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The Role of Eco-Driving Feedback Displays in Drivers' Information Processing and Energy Efficiency in Electric Vehicles

DISSERTATION

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Abstract

In the context of the transition to sustainable transportation, understanding the cognitive mechanisms that underlie energy-efficient driver behavior is critical. This cumulative dissertation investigates how ecodriving feedback displays influence drivers' information processing and achieved energy efficiency in battery electric vehicles. The main objective is to explain the psychological processes underlying operational (maneuver-based) ecodriving and to identify how ecodriving feedback displays can effectively support the acquisition of energy-related comprehension and improve driving behavior. Grounded in theories from engineering psychology and human factors, this work introduces and empirically validates the construct of *Energy Dynamics Awareness* (EnDynA)—a domain-specific adaptation of situation awareness tailored to electric vehicle driving. EnDynA captures drivers' awareness of current and anticipated energy flows and is a cognitive foundation for energy-efficient real-time decision-making.

The dissertation comprises four empirical articles combining online and driving simulator studies. Article 1 introduces the concept EnDynA and its assessment through subjective (experienced EnDynA) and objective (actual EnDynA) measures. The article demonstrates that feedback displays with higher informational value—such as instantaneous consumption displays extended with distance-based information—significantly improve experienced EnDynA. Article 2 extends this approach using a mental workload manipulation and a novel self-controlled occlusion paradigm. Results reveal that increased workload reduces visual attention to energy displays and impairs actual EnDynA, underscoring the role of attentional resources. Article 3 shows in a repeated-trials simulator experiment that richer feedback improves experienced EnDynA and leads to measurable gains in operational ecodriving performance. Article 4 compares instantaneous and predictive feedback systems and reveals a moderating effect of situation complexity: conventional feedback facilitates experiential learning under low complexity, whereas predictive guidance is more effective in high-demand conditions.

Together, the studies provide converging evidence that ecodriving feedback displays can support drivers' cognitive processing, learning, and behavior, particularly when designed to match informational needs and situational demands. Theoretically, the work contributes a domain-specific extension of situation awareness theory, called EnDynA. Methodologically, it introduces and refines tools for assessing energy-related awareness, attention, and behavior. Practically, it formulates actionable design recommendations for adaptive feedback systems in electric mobility.

In sum, this dissertation shows that ecodriving feedback displays, when designed with psychological theory in mind, can close the cognitive information processing loop between perception, comprehension, and action in electric vehicle driving. By fostering EnDynA, such systems enable drivers to regulate energy use more effectively, contributing to improved driver performance, enhanced user experience, and the broader goals of sustainable mobility.

Zusammenfassung

Im Kontext des Übergangs zu einer nachhaltigen Mobilität ist das Verständnis der kognitiven Mechanismen, die energieeffizientes Fahrverhalten bedingen, von zentraler Bedeutung. Diese kumulative Dissertation untersucht, wie Feedbackanzeigen für ökologisches Fahren (Ecodriving) die Informationsverarbeitung von Fahrer:innen sowie deren erreichte Energieeffizienz beim Fahren von Elektrofahrzeugen beeinflussen. Ziel ist es, die psychologischen Prozesse zu erklären, die dem operativen (manöverbasierten) Ecodriving zugrunde liegen, und aufzuzeigen, wie solche Feedbackanzeigen die Entwicklung eines energiebezogenes Verständnis und das energieeffiziente Fahrverhalten wirksam unterstützen können. Basierend auf Theorien der Ingenieurpsychologie und der Human Factors führt die Arbeit das Konzept des *Bewusstseins für Energiedynamiken* (EnDynA) ein und validiert es empirisch. EnDynA beschreibt die bewusste Wahrnehmung aktueller und antizipierter Energieflüsse/-verbräuche im Fahrzeug und bildet die kognitive Grundlage für effiziente Entscheidungen in Echtzeit.

Die Dissertation umfasst vier empirische Artikel in einer Kombination aus Online- und Fahrsimulationsstudien. Artikel 1 führt das Konzept EnDynA ein und dessen Beurteilung anhand subjektiver (erlebtes EnDynA) und objektiver (tatsächliches EnDynA) Messmethoden. Der Artikel zeigt, dass Feedbackanzeigen mit höherem Informationswert, wie Momentanverbrauchsanzeigen, die um distanzbasierte Informationen erweitert wurden, das erlebte EnDynA signifikant verbessern. Artikel 2 erweitert diesen Ansatz durch eine Manipulation der mentalen Arbeitsbelastung sowie ein neuartiges Paradigma für selbstgesteuerte Okklusion. Die Ergebnisse zeigen, dass eine erhöhte Arbeitsbelastung die visuelle Aufmerksamkeit gegenüber Energieanzeigen verringert und das tatsächliche EnDynA beeinträchtigt, was die Bedeutung verfügbarer Aufmerksamkeitsressourcen unterstreicht. Artikel 3 zeigt in einer Simulatorstudie mit wiederholten Fahrten, dass reichhaltigere Feedbackanzeigen das erlebte EnDynA verbessern und zu messbaren Leistungssteigerungen beim operativen Ecodriving führen. Artikel 4 vergleicht eine Momentanverbrauchsanzeige mit einer vorausschauenden Assistenzanzeige und identifiziert einen moderierenden Einfluss der Situationskomplexität: Konventionelles Verbrauchsfeedback unterstützt erfahrungsbasiertes Lernen unter geringer Komplexität, während vorausschauende Assistenz bei hoher Beanspruchung effektiver ist.

Insgesamt liefern die Studien übereinstimmende Evidenz dafür, dass bestimmte Ecodriving-Feedbackanzeigen die kognitive Verarbeitung, das Lernen und das Verhalten von Fahrer:innen unterstützen können, insbesondere dann, wenn sie an die Informationsbedarfe und situativen Anforderungen angepasst sind. Theoretisch leistet die Arbeit einen Beitrag zur Theorie des Situationsbewusstseins durch dessen domänenspezifische Erweiterung als EnDynA. Methodisch werden Instrumente zur Erfassung von EnDynA, Aufmerksamkeit und Fahrverhalten in kontrollierten Umgebungen eingeführt und weiterentwickelt. Praktisch werden Gestaltungsempfehlungen für adaptive Feedbacksysteme in der Elektromobilität formuliert.

Zusammenfassend zeigt diese Dissertation, dass Ecodriving-Feedbackanzeigen, wenn sie psychologisch fundiert gestaltet sind, die kognitive Informationsverarbeitungs-Schleife zwischen Wahrnehmung, Verstehen und Handlung im Elektrofahrzeug schließen können. Durch die Förderung von EnDynA ermöglichen solche Systeme eine effektivere Regulierung des Energieverbrauchs, und leisten so einen Beitrag zur individuellen Fahrleistung, zum Nutzererleben und zu den übergeordneten Zielen nachhaltiger Mobilität.

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Table of Contents

List of Abbreviations

ART ...... Action Regulation Theory
DALI ..... Driving Activity Load Idex
EnDynA .. Energy Dynamics Awareness
EV .... Electric Vehicle
GHG ..... Greenhouse gas
HCI ...... Human-Computer Interaction
HMI ..... Human-Machine Interface
ICD ...... Instantaneous Consumption Display
ICEV ..... Internal Combustion Engine Vehicle
kWh ..... Kilowatt-Hour
NASA-TLX NASA Task Load Index
OSD ..... Optimal Speed Display
PCT ...... Perceptual Control Theory
RO .... Research Objective
SA .... Situation Awareness
SAGAT ... Situation Awareness Global Assessment Technique
SART .... Situation Awareness Rating Technique
SPAM .... Situation-Present Assessment Method

1 General Introduction

”What contains more energy? A gallon of gasoline, a stick of dynamite, or a hand grenade?” With this quiz, Bill Gates (2021, p. 180) began his chapter on the analysis of how climate catastrophe is caused by transportation and traffic (among others). The answer is, for dramatic purposes, of course, the gallon of gasoline. Humans find it very difficult to perceive, understand, and compare energy quantities as we lack the sensory organs for these physical entities (Attari et al., 2010; Baird & Brier, 1981). We can only draw conclusions about energy from phenomena such as heat, movement, and light. Fortunately, we rarely have to choose between gasoline and dynamite in everyday life, but it does illustrate the challenges in other domains. For instance, when it comes to mobility, a gallon of gasoline allows a combustion vehicle to travel about 60 kilometers. But how far can the same energy, around 33 kWh, take you in an electric vehicle (EV)? How much energy would you save if you turned off your car’s headlights when they’re not needed? And how much energy do we waste with unnecessary accelerations before stopping at a traffic light?

A lack of understanding regarding energy quantities can impact decision-making. People often rely on heuristics, such as size, when estimating which household devices consume more or less energy (Steg et al., 2015). A clearer understanding of energy consumption can be enhanced through the use of technical sensors and support. For this reason, most vehicles are now equipped with displays that provide information on energy consumption. However, does this information actually contribute to improving energy efficiency? Additionally, how should these displays be designed for optimal effectiveness? These overarching questions and problems motivate the present dissertation.

This dissertation investigates the psychological mechanisms involved in energy-efficient driving behavior (*eco-driving* or *ecodriving*), with a particular focus on the effectiveness of ecodriving feedback displays in EVs. It seeks to develop and apply theory from engineering psychology to better understand how drivers interact with different types of feedback, how these interactions affect their energy-related decisions, and—based on those insights—how human-car interfaces (or human-machine interfaces, HMIs) can be designed to foster efficient and sustainable driving practices.

Chapter 1 introduces the research topic, with Section 1.1 motivating the research within the broader context of sustainable transportation, the growing importance of EVs, and their energy-efficient use. Section 1.2 introduces the concept of ecodriving, first in the context of combustion vehicles and then with regard to the specific characteristics and challenges of EVs. Section 1.3 introduces and discusses existing approaches and empirical studies to support ecodriving behavior, with a particular focus on HMIs that provide some sort of feedback to the driver. Section 1.4 summarizes the existing research gap that motivates the research focus of this dissertation.

Chapter 2 develops the theoretical foundation of the dissertation. It presents key psychological theories for understanding driver behavior and interaction with ecodriving displays. The text first introduces and discusses control and regulation theories (see Section 2.1), such as perceptual control theory, action regulation theory, and the skill-rule-knowledge framework. Additionally, it explores how these concepts have been adapted to the driving context. Section 2.2 focuses on human information processing, including attention and mental workload, while Section 2.3 addresses situation awareness and how it can be applied to the context of energy-relevant human-machine interaction. The chapter concludes with a synthesis (Section 2.4) that integrates the theoretical strands into a joint conceptual understanding of operational ecodriving and display support.

Chapter 3 introduces methodological considerations for empirically investigating ecodriving behavior. It discusses experimental paradigms to effectively capture ecodriving and related cognitive processes in a comparable, reliable, and valid way. It also discusses design implications for displays used as an independent variable operationalization.

Chapter 4 defines this dissertation's research objectives.

Chapter 5 summarizes the empirical studies of the articles included in the dissertation. I included four first-author manuscripts: one article published in the journal *Human Factors*, one peer-reviewed full-paper conference article published at the *Applied Human Factors and Ergonomics* (AHFE) Conference 2024, one article published as a preprint, and one article published as a preprint and submitted to the *International Journal of Human-Computer Interaction*.

Chapter 6 provides a general discussion of findings, contributions, and implications. It is structured around theoretical, methodological, and practical implications as well as a critical reflection on the articles with an outlook for future research.

Chapter 7 concludes the dissertation with regard to its research objectives and contributions.

After the synopsis, the included manuscripts are attached:

1. Gödker, M., Moll, V. E., & Franke, T. (2024a). Energy consumption displays in electric vehicles: Differential effects on estimating consumption and experienced energy dynamics awareness. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 00187208231222154. https://doi.org/10.1177/00187208231222154

2. Gödker, M., & Franke, T. (2024). Assessing energy-related situation awareness using self-controlled occlusion during electric vehicle driving scenes. In G. Praetorius, C. Sellberg, & R. Patriarca (Eds.), *Advances in Human Factors of Transportation. AHFE (2024) International Conference. AHFE Open Access* (pp. 286–296, Vol. 148). AHFE International. https://doi.org/10.54941/ahfe1005219

3. Gödker, M., Schrills, T. P. P., & Franke, T. (2025). *Improved ecodriving using instantaneous consumption displays in an electric vehicle driving simulator: The role of energy dynamics awareness*. PsyArXiv. https://doi.org/10.31234/osf.io/zusyx_v3

4. Gödker, M., Schmees, S., Bernhardt, L., Görges, D., & Franke, T. (2025). *Two types of eco-driving support - The effects of an instantaneous consumption and an optimal speed display on energy-efficient driving and energy dynamics awareness*. Open Science Framework. https://osf.io/297wv_v1

1.1 Background

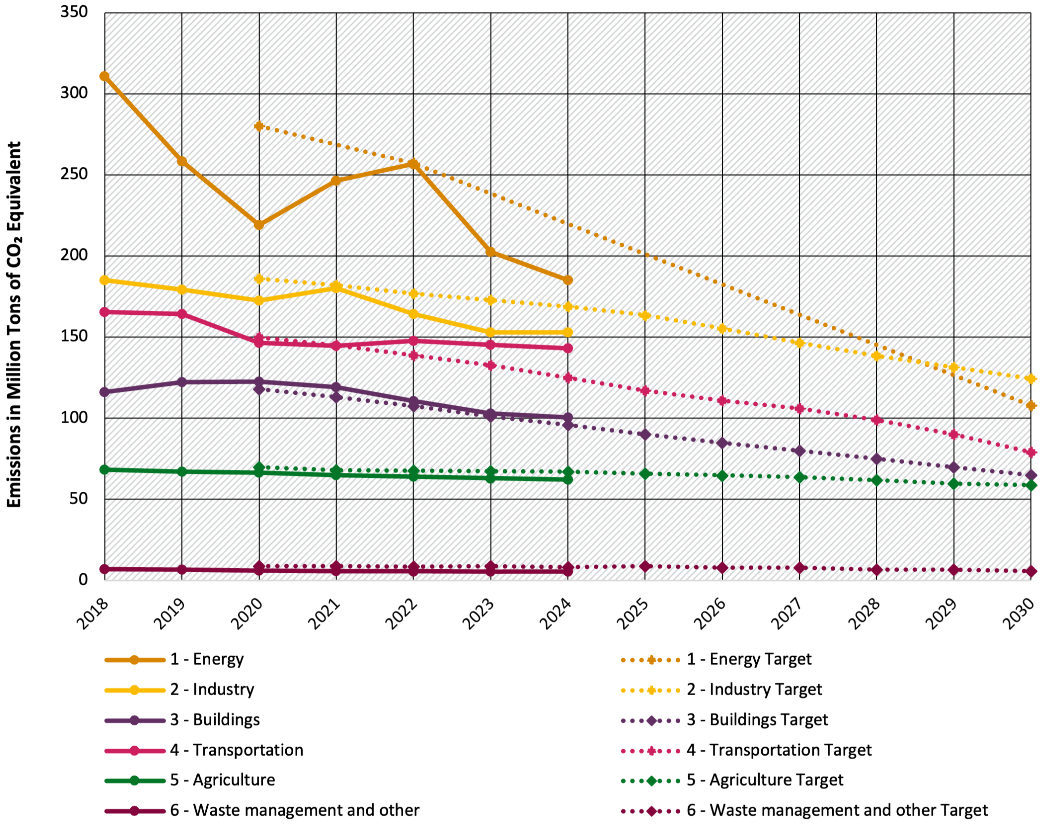
Anthropogenic climate change is a threat because global warming increases the likelihood of natural disasters and crop failures, making the planet uninhabitable in the long term (Intergovernmental Panel On Climate Change, IPCC, 2023). The last 10 years (until 2022) have also been the 10 years with the greatest temperature anomalies since 1850 (NOAA National Centers for Environmental Information, 2025). The reason for climate change is the emission of greenhouse gases (GHG; Intergovernmental Panel On Climate Change, IPCC, 2023), especially CO_2 (Friedlingstein et al., 2023). Worldwide, 107 countries have pledged themselves to achieve net-zero emissions to counteract climate change, including Germany (until 2045) and the USA (until 2050; United Nations Environment Programme et al., 2024). This goal encompasses many sectors and stakeholders and is extremely difficult to implement centrally, and therefore requires simultaneous efforts in all areas.

Of the global CO_2 emissions in 2023, the transport sector accounted for 21.1% (European Commission: Joint Research Centre et al., 2024), the second largest share after the energy industry and is therefore of central importance and appears to be especially challenging. While Germany has gradually reduced its CO_2 emissions, the transport sector is the only sector producing substantially (beyond the error margin) more CO_2 emissions than the path for the emission targets until 2030 allows (Umweltbundesamt, 2025, see also Figure 1). From 2021 to 2022, GHG emissions (in grams per person per kilometer; g/pkm) were reduced for every transportation mean except for e-bikes (+3) and cars (+4; Umweltbundesamt, 2024). This demands a rapid and significant reduction in CO_2 emissions, especially in individual car transportation (Axsen et al., 2020).

EVs are defined by F. Chen et al. (2015, p. 110) as "road vehicles that move [...] with electric propulsion." These vehicles offer "high energy efficiency" compared to Internal Combustion Engine Vehicles (ICEVs) and produce "zero tailpipe emissions." It's important to differentiate among the various types of EVs. Electric vehicles can be categorized in different ways (e.g., Da Costa et al., 2025), with the main types being:

Figure 1

Development of GHG Emissions per Sector in Germany and Their Targets



Note. From Umweltbundesamt (2025)

1. Battery electric vehicles (BEVs) operate entirely on electricity that is stored in a battery.

2. Hybrid electric vehicles (HEVs) feature both an electric motor and a combustion engine, which can work together or independently. The battery is recharged through regenerative braking.

3. Plug-in hybrid electric vehicles (PHEVs) are a type of HEV that can be charged using an external power source.

4. Fuel cell electric vehicles (FCEVs) generate electricity for the drivetrain by converting a synthetic fuel, such as hydrogen.

The discussion of which drivetrain technology holds advantages over others in specific operating scenarios, along with the calculations and assumptions involved, exceeds the scope of this dissertation. However, it can be stated that there is a broad agreement by life cycle analyses that—in general—BEVs emit less GHG compared to combustion engine vehicles (e.g., Bouter et al., 2020; Da Costa et al., 2025; Zhang et al., 2024). This advantage depends on several factors (Bauer et al., 2015). It is further supported by a small battery, small curb weight, usage in urban regions (Bouter et al., 2020), and renewable energies in production and usage. Best-case scenarios often presume positive developments in the carbon-neutrality of the electricity mix and estimate that BEVs can reduce life-cycle GHG emissions by, e.g., 80% (Bauer et al., 2015; Yasaka et al., 2017) compared to gasoline cars. For these reasons, BEVs are considered to be a central future technology. This dissertation will focus primarily on BEVs, and I will use the term EVs throughout the dissertation, but always refer to BEVs.

However, the benefits of energy efficiency go beyond reducing GHG emissions. It goes hand-in-hand with the transition to electric mobility and counteracts negative perceptions of electric mobility (Lot et al., 2025). Energy efficiency extends the vehicle's driving range (performant range; Franke & Krems, 2013). With that, energy efficiency helps to reduce overall range stress, a major technology acceptance factor for EVs (Franke, Rauh, et al., 2016). Consequently, comfort with smaller technical ranges increases and smaller batteries become necessary, reducing costs and CO_2 emissions in manufacturing and recycling the vehicle (Buberger et al., 2022). Moreover, saving energy directly reduces energy costs for drivers and fleet operators (Sivak & Schoettle, 2018). It contributes to lower demands in the electricity grid (Hasan et al., 2021)—an increasingly relevant factor with the growing share of renewable but fluctuating energy sources. These advantages underline the importance of promoting the energy-efficient use of EVs for both sustainability and economic goals.

Although EVs have, from a technological perspective, an advantage regarding their energy efficiency compared to other drivetrain technologies, some literature suggests that this is only the case if EVs are operated energy-efficiently (Bauer et al., 2015). The energy consumption of passenger vehicles depends on various factors, many of which are beyond drivers' control (e.g., weather, engine efficiency). Yet, one factor that has gained attention in many studies is the influence of driving behavior, referred to as *ecodriving*. This dependency of a technical system's energy efficiency on human behavior is a central principle for this dissertation and has previously been summarized by Franke, Görges, and Arend (2019, p. 36) as:

$$\textbf{Energy Efficiency} = \textbf{Technical Potential} \times \textbf{User Behavior}$$

This principle illustrates that optimal energy efficiency in mobility requires optimizing both technical potentials through engineering work *and* user behavior, especially in EVs, where drivers are supposed to have an even more considerable influence on energy efficiency than in ICEVs (Yan et al., 2021). To sum up, the electrification of vehicles and enhancing ecodriving are essential factors in reducing transport-related CO_2 emissions, optimizing transportation costs, and improving driver experience and acceptance. So naturally, the question of how to improve the energy-efficient operation of EVs arises.

1.2 Ecodriving

The purpose of this section is to explain ecodriving and its expected effects on energy savings in EVs. The idea that drivers themselves can significantly influence a vehicle's energy consumption is not new. In fact, early empirical studies have already identified behavioral patterns that affect fuel efficiency. For example, a study by Evans (1979) shows that changing driving goals—such as instructing drivers to ”minimize fuel consumption”—can influence individual driving styles in urban environments and, as a result, alter fuel consumption. Since then, extensive research has been conducted on ICEVs to quantify the impact of driving behavior on fuel usage.

1.2.1 Ecodriving in Combustion Engine Vehicles

Barkenbus (2010) presents ecodriving as a strategy to reduce GHG emissions through behavior change. He summarizes that ecodriving practices can yield reductions in fuel consumption of 10%, although the specific effects vary depending on context and driver adherence. Sivak and Schoettle (2012) take this notion further by estimating that if a driver adopts all optimal ecodriving decisions consistently, fuel savings of up to 45% are theoretically possible. These results highlight the substantial energy-saving potential of driver decisions.

More recent studies have taken a multivariate approach. Lois et al. (2019) analyzed multiple driving pattern variables—such as average speed, acceleration, and gear shifting—to understand their combined effects on fuel consumption in ICEVs. Their findings show that behavioral factors interact in complex ways and underscore the necessity of multifactorial models to fully capture ecodriving behavior.

Comprehensive reviews have further synthesized the state of the research: Z. Chen et al. (2022) conducted a thorough scientometric and bibliometric analysis of the ecodriving research landscape, examining 767 publications from the Web of Science Core Collection between 2001 and 2020. The study reveals that research on ecodriving has significantly increased over the past two decades. The authors identify two main development stages: an exploratory stage (2001–2010) and a prosperity stage (2011–2020). Through keyword clustering, they highlight five dominant research areas: energy-saving strategies, simulation-based research, driver decision-making, connected and automated environments, and human-machine cooperation. This indicates a clear scientific interest in understanding how drivers make decisions and how technological systems can support this process.

Ma et al. (2024) conducted a scoping review of energy-efficient driving behaviors. They identified eleven main behavioral and contextual features influencing fuel consumption, including speed, acceleration, pedal use, gear selection, and steering behavior, but also contextual factors such as road characteristics, weather, and traffic signals. This confirms that driver behavior is not isolated from context—it is part of a dynamic and situational system that jointly determines fuel efficiency.

In summary, research on ICEVs provides robust evidence that ecodriving is effective but depends on multiple driver-controlled behavior patterns in complex interaction with the environment. This evidence base also serves as an empirical foundation for understanding ecodriving in EVs.

1.2.2 Ecodriving in Electric Vehicles

The influence of driving behavior on energy consumption in ICEVs is well established, but do similar effects exist in EVs? The operational characteristics of EVs differ in key aspects from ICEVs, notably due to regenerative braking, the absence of idling, and different torque dynamics. Nevertheless, driver behavior seems to remain decisive in determining overall energy efficiency in EVs (Kato et al., 2013).

One of the earliest real-world investigations of this influence using consumption data was conducted by Knowles et al. (2012), who showed that energy consumption in EVs varies significantly with individual driving styles. Participants ($N = 11$) drove an EV on-road under controlled but naturalistic conditions, and results indicated up to 25% variations in efficiency between more and less energy-efficient drivers. Despite the small sample size, this study indicates that ecodriving in EVs under naturalistic conditions is advantageous. Additionally, individual characteristics, such as age, may help explain the observed variances. Subsequent studies have further substantiated these findings. For example, Bingham et al. (2012) demonstrated that acceleration behavior and braking frequency are among the most critical behavioral predictors of energy use in EVs. Similarly, Galvin (2017) analyzed data from EV dynamometer tests and highlighted the negative impact of aggressive driving, particularly sharp accelerations, on energy consumption. Importantly, regenerative braking was unable to recover the excessive energy consumed.

The quantitative potential for energy savings through optimized driving behavior has also been quantified in larger datasets. For example, Donkers et al. (2020) confirmed based on microscopic simulation and driving tests that, even after accounting for weather and traffic conditions, the driving style remained a strong predictor of consumption, suggesting a stable behavioral component. Braun and Rid (2018) used factor analysis based on extensive real-world tracking data of four vehicles to isolate driver-induced consumption patterns. The authors identified driving patterns, five of which were related to short-term acceleration and deceleration maneuvers, that showed significant intermediate correlations with energy efficiency.

From a simulation-based perspective, Jia et al. (2023) reported a 13% improvement in energy efficiency through adaptive driving assistance targeting optimal speed and acceleration profiles. Similarly, Lot et al. (2025) modeled optimal control strategies for EVs and showed that operational ecodriving can achieve substantial energy savings (10%-15%) without time loss.

Based on various research methods, the findings of the above-mentioned studies indicate that, beyond infrastructural, technical, and ecological factors, a significant portion of the variance in consumption is influenced by driving behavior. Even if the overview of the mentioned findings does not claim to be a systematic literature search, it can be stated with certainty that the relationship between driving behavior and energy efficiency in EVs is empirically confirmed and quantitatively significant. Although some ICEV ecodriving strategies—such as avoiding idling—are less relevant for EVs, new opportunities arise from regenerative braking (Cocron et al., 2013). These findings affirm that ecodriving is not only applicable to EVs but potentially even more critical due to the vehicles' sensitivity to dynamic driving patterns and the limited range that characterizes many EV use cases.

1.2.3 Ecodriving Behavior Models

Ecodriving includes various decisions and behaviors aimed at improving vehicle energy efficiency. Inspired by the hierarchical driving behavior model by Michon (1985), Sivak and Schoettle (2012) classify ecodriving into strategic, tactical, and operational decisions. Strategic decisions involve selecting and maintaining vehicles, tactical decisions pertain to route choice and vehicle loading, and operational decisions relate to how the vehicle is driven, including acceleration, braking, and speed control. Huang et al. (2018, p. 597) narrow down ecodriving as "the driving behaviors or the control a driver has over the vehicle during a journey that can influence fuel consumption and emissions". The authors argue in favor of these factors because they are most common and can be easily implemented by anybody without the need to buy a new vehicle. They cluster ecodriving into the following factors: "driving speed, acceleration/deceleration, idling, route choice, other factors in the control of the driver and other factors out of control of the driver." (Huang et al., 2018, p. 601).

Similarly, G. Wang et al. (2020, p. 2) categorized ecodriving behaviors into five key indicators: "Driving maneuver, travel planning and trip chaining, tradeoff between travel time and energy saving, route choice preference using navigations systems, in-vehicle-display (IVD)/on-board-system (OBS) technologies". Building on qualitative empirical data, G. Wang et al. (2020) were able to find differences between EV and ICEV drivers in some of these key indicators.

A particularly insightful model based on qualitative empirical data is provided by Franke, Arend, et al. (2016). Focusing on ecodriving experts, the authors interviewed $N = 39$ HEV drivers with high energy efficiency. The findings revealed that energy savings are influenced not only by a driver's skill and motivation but also by their technical knowledge. The authors also frame ecodriving as a dimension of driving style and propose a control-theoretic framework to understand ecodriving as a dynamic cycle: drivers monitor energy-relevant system variables, retrieve ecodriving strategies from a mental "strategy knowledge base," evaluate them based on expected utility (e.g., balancing efficiency against travel time), and implement them accordingly.

Ecodriving is not only a behavioral phenomenon but a multi-faceted psychological construct. It involves a mix of conscious and semi-automated behaviors shaped by individual beliefs, mental models of vehicle energy dynamics, and the driving context. Moreover, it is influenced by feedback and information available in the vehicle. Therefore, ecodriving is not just a set of behaviors but an ongoing decision-making process embedded in human-machine interaction.

For its potential for immediate implementation and its links to comprehension and short-term behavior, this dissertation focuses on *operational ecodriving* in EVs. I define it as the set of real-time driving behaviors drivers perform to directly regulate and optimize energy consumption during trips. Optimal operational ecodriving in EVs entails minimizing abrupt accelerations, maintaining steady speeds, exploiting regenerative braking, and adapting to the vehicle's specific energy dynamics. Franke, Görges, and Arend (2019, p. 37) accordingly formulate five simple rules of ecodriving, which are:

1. Keep vehicle velocity as low as possible.

2. Choose the vehicle velocity and acceleration such that the electric motor efficiency is high.

3. Avoid regenerative braking.

4. Avoid friction braking.

5. Avoid strong acceleration and braking.

Learning these behaviors, adapting them to new situations or vehicles, and refining their execution requires cognitive engagement and feedback interpretation, emphasizing the significance of vehicle interfaces. In sum, ecodriving in EVs is relevant and necessary for maximizing energy efficiency. The potential for driver behavior to shape energy outcomes is significant, creating an opportunity and a challenge for interface design. The following section will explore how HMIs can support ecodriving behavior by providing effective feedback and guidance.

1.3 Ecodriving Human-Machine Interfaces

This section presents approaches to support ecodriving, especially feedback displays, and their empirical tests. I argue that visual displays of ecodriving feedback offer especially great potential to enhance operational ecodriving, but significant research gaps are still to be investigated to fully understand their effect and optimally design them in a human-centered way.

1.3.1 Approaches to Support Ecodriving

Various interventions have been proposed and evaluated to support drivers adopting ecodriving behaviors. These range from training programs (Y. Wang & Boggio-Marzet, 2018) to the provision of ecodriving tips (Sureth et al., 2019), or brief cognitive primes aimed at activating relevant mental models before driving (Pampel et al., 2017). Other approaches focus on haptic feedback integrated into the driving pedal to physically guide drivers toward more energy-efficient behavior (Jamson et al., 2013).

Comprehensive overviews of these diverse interventions can be found in recent review articles (Allison et al., 2021; Xu et al., 2021), which discuss the theoretical underpinnings, practical implementations, and consequences of ecodriving systems. For example, Xu et al. (2021) claim that in-vehicle feedback can support ecodriving behavior, but safety, user acceptance, and feedback timing remain central concerns. Tu et al. (2022) provide a comprehensive review of ecodriving guidance systems, distinguishing between static (e.g., training, brochures) and dynamic (e.g., real-time feedback) interventions. Results showed that dynamic guidance leads to greater energy savings, while the effects of static guidance often diminish over time. The authors present key psychological challenges such as knowledge–action disconnect, safety issues, and motivational variability across drivers. Their contribution lies in outlining critical design trade-offs and formulating a research agenda, including calls for adaptive, customized feedback systems, context-aware integration, and more psychologically grounded HMI strategies. Although these insights provide key challenges, the paper does not formalize constructs or mechanisms that would constitute a general theory of energy feedback design that HMI designers could easily apply. Thus, this work offers an overview to support the development of more comprehensive models in future research. It also highlights the importance of dynamic displays.

Designing energy feedback displays that are both human-centered and psychologically grounded poses significant challenges. When visualizations are dynamic and accurate metrics are used, they can introduce biases in perception. For instance, Larrick and Soll (2008) showed that the–in the USA commonly used–"miles per gallon" metric can systematically mislead consumers due to its non-linear relationship with fuel savings, leading to an underestimation of the benefits of small miles per gallon improvements. Similarly, Moll and Franke (2021) demonstrated that drivers tend to overestimate energy consumption when viewing instantaneous consumption displays with high peaks, especially when these peaks are short in duration. Their findings suggest that drivers often rely on simplifying heuristics rather than accurately integrating magnitude over time, which can distort their understanding of energy efficiency differences between driving strategies. Thus, even well-intentioned feedback displays can unintentionally bias driver perception and behavior and must, therefore, be designed and used thoughtfully and empirically tested for their effectiveness.

In the following, I will present empirical approaches to test the design of ecodriving feedback displays on energy efficiency in driving and discuss their implications and limitations. In general, interventions can be distinguished between EVs and ICEVs. Empirical studies on both categories provide valuable insights for the objectives of the present dissertation. Therefore, this section regards EV *and* ICEV displays.

1.3.2 Empirical Evidence on Feedback Displays

In an EV driving simulator study, Kim et al. (2011) investigated how a power-flow gauge—a visual feedback interface—affects drivers' acceleration and braking behavior. The bar gauge indicated "economic" vs. "non-economic" driving behavior in real-time by changing length and color from green (efficient) to red (inefficient). $N = 16$ drivers completed four driving sessions (city or highway and with or without the gauge) while the stability of the pedal behavior was measured as a metric of ecodriving. Results showed that the gauge significantly increased acceleration stability, especially during highway driving. The study was able to demonstrate the effect of the display. However, the comparison of display vs. no display does not indicate whether this is due to knowledge acquisition or simply to the prompting character triggered by the mere presence of any display. Also, the simulation lacked direct energy consumption measurements, leading to the necessity of creating an artificial normative indicator in the power flow gauge (”economic” vs ”non-economic”) based on pedal level changes. Yet, it is unclear whether this indicator is still valid outside the norm context of this particular driving simulator and scenarios, e.g., on a street where more instability in the pedal is simply due to the road characteristics.

In a field study by Stillwater and Kurani (2013), $N = 46$ PHEV drivers tested personalized energy feedback interfaces over two weeks. Their subjective responses obtained in interviews provided insights into the potential benefits of different elements of the displays. The drivers reported that real-time energy economy feedback encouraged experimentation, learning, and motivation, helping drivers understand the impact of their actions. Personalized goals (like consumption targets) seemed to be a key motivational driver—even default values influenced behavior via anchoring effects. Many drivers described the interface as creating a game-like experience, increasing engagement, and encouraging high-efficiency driving. Also, drivers stated that displaying real-time use of gasoline, electricity, and regenerative braking helped drivers understand the hybrid system. While a small reduction in fuel consumption was detected (Kurani et al., 2013), the lack of a control group leaves it unclear whether this effect really stems from the displays. Due to the wide variety of feedback, it's also unclear which display or information element accounts for what improvement.

Both publications share a common issue: they report results but fail to integrate empirical findings into a comprehensive theory that explains and generalizes the effects of display design elements. Also, as Wickens et al. (2021, p. 3) put it in words, knowing *how* performance can be improved is not sufficient for engineering psychologists, who are more interested in ”*why* performance might be changed.” The need for a more ”general design theory for ecodriving feedback information systems” is precisely what motivated Dahlinger and Wortmann (2016,

p. 1) to review the literature to identify core dimensions of feedback displays. However, they do not present a complete or formal theory in this paper, as it should be based on cumulative, generalizable, and theory-driven empirical work. Instead, they offer a structured review and highlight key dimensions (feedback type, timing, channel, etc.) on which such a theory could potentially be based. Additionally, the authors point out underrepresented dimensions and denounce methodological issues, especially small sample sizes. Lastly, the authors urge the human-computer interaction (HCI) communities to contribute to this general theory.

A good example of an empirical study that follows this path comes from the authors themselves (Dahlinger et al., 2018). They conducted a large-scale field experiment to investigate how the level of abstraction in ecodriving feedback interfaces influences driver behavior. Grounded in construal-level theory (Trope & Liberman, 2010), the study hypothesized that abstract feedback (e.g., a growing tree symbolizing efficient driving) would activate higher-level motivational goals and lead to more energy-efficient behavior than concrete feedback (e.g., direct data on acceleration or fuel consumption). Results from $N = 56$ professional drivers revealed that only abstract feedback led to significant fuel savings, particularly on longer trips. This study thus offers an empirical validation of construal-level theory in applied HCI and contributes to the theoretical foundation for ecodriving feedback design. However, limitations include confounding interface designs (abstract and concrete differed on multiple dimensions), a non-neutral control condition, and limited generalizability due to the use of professional drivers. Nevertheless, this approach better integrates motivation theory with display design and empirical research. It serves as a good example of what could address the gap in psychological ecodriving feedback design research.

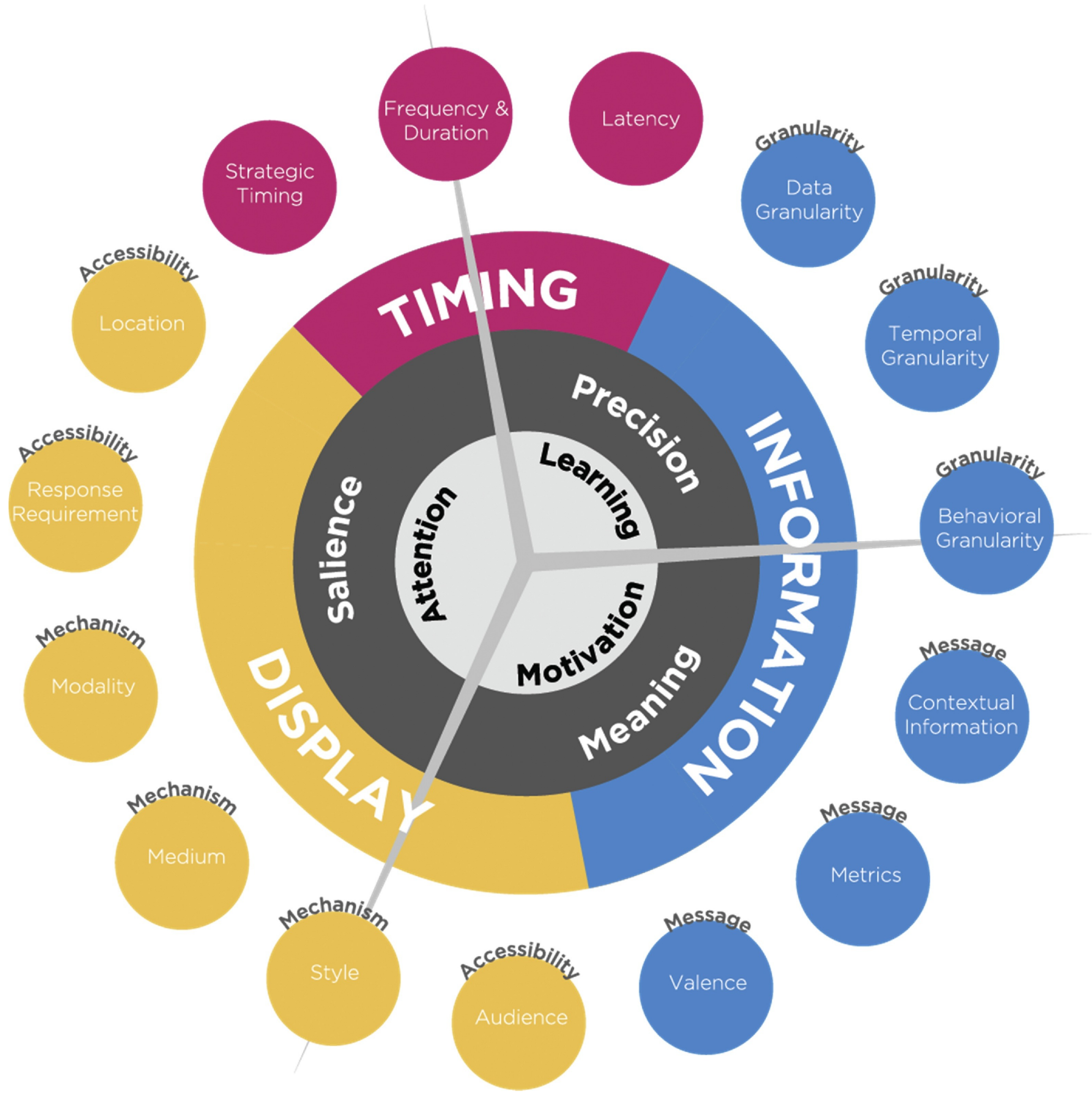
1.3.3 Approaches Towards Ecodriving Design Frameworks

The previous subsection discussed that while many studies have investigated specific feedback designs or tested interface variations empirically, there is a notable lack of integrated theoretical frameworks that guide the systematic design of ecodriving feedback displays. Some authors, however, have laid significant theoretical groundwork. Franke, Görges, and Arend (2019) provide a transdisciplinary synthesis of technical and psychological determinants of energy efficiency in EVs and derive actionable design principles for so-called "action-integrated" energy interfaces. Their conceptualization emphasizes the need to align energy information with human perceptual capacities, cognitive heuristics, and real-time control demands during driving. Yet, this work does not include empirical studies. In a similar vein, Sanguinetti et al. (2017, 2018, 2020) present a design-behavior framework (Figure 2) rooted in eco-feedback theory, which relates feedback content, display properties, and timing to behavior change mechanisms such as attention, learning, and motivation.

Despite differences in terminology and focus, both strands of research converge on the idea that energy feedback displays must integrate behavioral science and system dynamics. Yet, these

Figure 2

Design-Behavior Framework of Ecodriving Feedback



Note. From Sanguinetti et al. (2018, p. 58)

frameworks remain primarily theoretical and still lack empirical confirmation. As such, they represent crucial steps toward a design theory of energy feedback—but further empirical validation is necessary.

1.4 Research Focus and Gap

Based on the presented findings that show the high potential of supporting maneuver-based operational ecodriving (Huang et al., 2018) with dynamic (Tu et al., 2022) displays providing energy information (Franke, Görges, & Arend, 2019; Sanguinetti et al., 2020), this dissertation focuses—not exclusively—on a specific type of real-time feedback: *instantaneous consumption displays* (ICDs). These displays present immediate energy consumption values—typically in the form of a dynamic bar, gauge, or trace—and are among the most widely implemented energy feedback formats in ICEVs and EVs. ICDs are commonly embedded into the instrument cluster and update in real-time as the driver accelerates, decelerates, or coasts.

The central rationale for focusing on ICDs is their potential to support high-frequency energy efficiency regulation by providing timely and specific feedback. As Franke, Görges, and Arend (2019) argue, energy-efficient driving constitutes a continuous control problem, in which drivers must dynamically regulate their behavior based on perceived energy flows. Instantaneous feedback is uniquely suited to support such fine-grained adjustments. It contributes to what the authors term "action-integrated interfaces"—systems that support perception, decision-making, and action execution within a cognitive control loop. Similarly, Sanguinetti et al. (2017, 2018) emphasize the importance of *temporal immediacy* in feedback design. Their design-behavior framework links short feedback delays (and not longer ones) to improved attention allocation and learning, particularly in complex contexts. ICDs are a foundational building block of many ecodriving systems and have been widely adopted in HMI design. Despite their widespread implementation, ICDs have not yet been empirically validated in the context of EVs. Understanding their psychological impact is therefore essential—not only for validating existing interfaces but also for informing the development of future adaptive and user-centered feedback systems.

Many existing studies focus on technical feasibility or compare modalities (e.g., haptic vs. visual feedback) without grounding the display designs in psychological theory. As a result, ICDs are rarely used as operationalizations of theoretically relevant constructs, making it difficult to systematically test psychological hypotheses. In many studies, the effects of displays are supported by qualitative user statements—not behavioral data—or reduced to external performance indicators such as energy consumption. Psychological constructs like mental models, perceived control, or energy awareness are seldom measured, and theoretically meaningful covariates (beyond workload measures like NASA-TLX) are often missing. Consequently, while ICDs are *assumed* to be supportive, empirical evidence for their actual effectiveness in EVs remains scarce, and investigations about why and when they work are missing. As such, the generalizability of existing findings remains limited, and the mechanisms by which ICDs affect driver behavior remain poorly understood.

This dissertation addresses this gap by empirically investigating human drivers using ecodriving feedback displays—especially ICDs—in EVs. By applying a theoretically grounded psychological framework, appropriate measurements, and advanced empirical methods, this dissertation aims to describe and explain how displays influence drivers' cognitive states and operational ecodriving.

2 Theoretical Framework

”No comprehensive model of driving behavior has been developed, and, given the wide variety of driving situations and associated combinations of component skills, it is unlikely that one will soon emerge” Ranney (1994, p. 746). Although quite old, this quote still summarizes this dissertation’s challenge in creating an appropriate theoretical framework to tackle the research gaps. A further challenge arises from the fact that most driver theories aim to explain safety-relevant driving behavior and help predict or prevent accidents rather than explain and support energy-efficient driving.

Literature offers various driver models derived from different psychological theories. It is necessary to carefully select models to understand ecodriving behavior and provide explanations and prognoses of ecodriving display effects. In other words, a psychological conceptualization of energy-efficient driving behavior is necessary to better understand what can be supported by ecodriving displays and why. In the following chapters, I will present general psychological theories and driving behavior models that provide valuable insights for explaining successful energy-efficient driving behavior and allow for deriving optimal design strategies for ecodriving displays.

2.1 Control and Regulation Theories

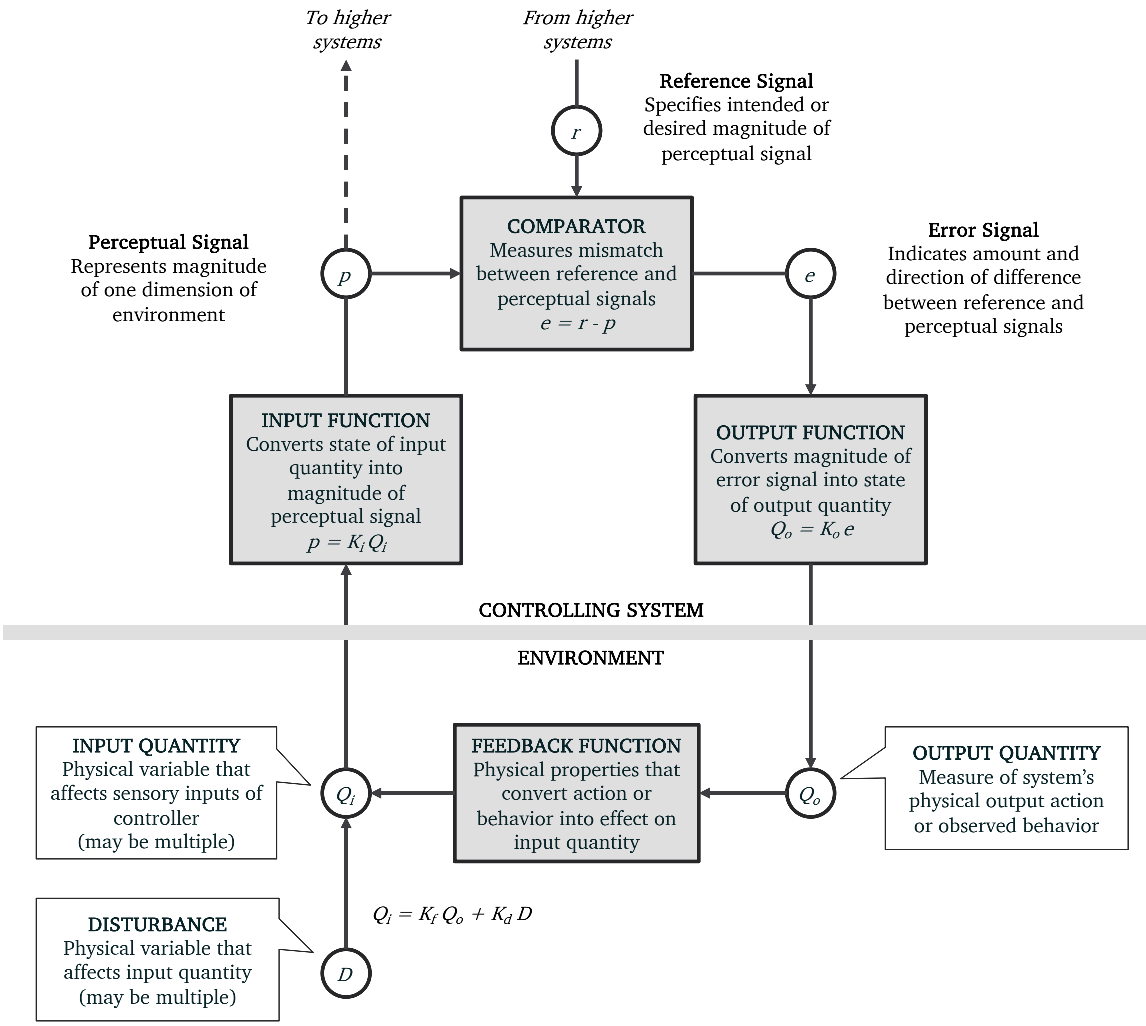
In his seminal work on the human operator in control systems, Craik (1947) proposed an important perspective to the explanation of human errors in the work context. The author conceptualized the human as an “intermittent correction servo”, emphasizing that human control behavior—such as in target tracking—follows a pattern of discrete, ballistic corrections rather than continuous fine-tuning. Drawing analogies from engineering systems, he suggested that human operators could be modeled using feedback loops, time delays, and gain adjustments. The ideas of Craik (1947) were foundational in shifting the study of behavior from linear stimulus-response paradigms to closed-loop control frameworks, laying the groundwork for later developments in cybernetic models of regulation and control.

2.1.1 Perceptual Control Theory

Perceptual control theory (PCT) offers a foundational cybernetic framework for understanding self-regulation in humans. Originally introduced by Powers et al. (1960a, 1960b) and later expanded by Powers et al. (2011), PCT conceptualizes behavior as the process by which organisms control their perception of environmental variables through a closed-loop negative feedback system. The core of a PCT model is a negative feedback loop (see Figure 3) that consists of a *reference signal* (goal), an *input function* (perception of the current state), a *comparator*, and an *output function* (behavior). The comparator determines the difference between the reference and the perceived value and generates an error signal that drives behavior to reduce this discrepancy. Importantly, PCT emphasizes that it is not behavior that is controlled, but perception—what an individual *sees, hears, or feels* is the target of regulation.

Figure 3

Basic Organization of a Negative Feedback Control System



Note. From Powers et al. (2011, p. 2)

Carver and Scheier (1982) and Carver and Scheier (2000) extended this cybernetic notion into psychological self-regulation, proposing that such control loops operate across different levels of abstraction—from concrete motor actions to abstract identity goals. In driving, for instance, one might simultaneously strive to maintain a certain speed (low-level control) while adhering to an overarching principle of driving efficiently (high-level control). Their work also advanced the theory by tieing these mechanisms to emotional responses: successful regulation leads to positive affect (e.g., satisfaction or relief), while persistent failure triggers negative affect (e.g., frustration or anxiety).

This hierarchical organization of control—where outputs of higher-order loops define goals for lower-level loops—is a central aspect of PCT. For instance, the goal of *reducing energy consumption* may manifest in lower-level actions such as *accelerating gently* or *coasting toward red lights*. In this view, ecodriving is a continuous control task requiring real-time adaptation based on perceptual feedback, making it a suitable context for applying PCT.

However, classical PCT assumes a steady-state structure that describes behavior *after learning has occurred*. It does not explain well how new goals are formed or how control systems develop. Furthermore, the theory alone does not specify what kinds of feedback are most effective for supporting energy-efficient behavior. These limitations suggest the need for complementary perspectives. Action regulation theory (ART) accounts for the dynamics of learning, adaptation, and conscious strategy use in complex tasks like ecodriving and might therefore provide useful supplementary explanations.

2.1.2 Action Regulation Theory

ART provides a cognitive-ergonomic framework for understanding how humans plan, execute, and adapt goal-directed activities in complex environments. Originally developed in the context of work psychology (Frese & Zapf, 1994; Hacker, 2003; Hacker & Sachse, 2014), ART is particularly valuable for analyzing how individuals regulate their actions when faced with dynamic feedback and competing demands—conditions typical of the driving task. ART conceptualizes human activity as a cyclical process consisting of *goal formation*, *orientation*, *planning*, *execution*, *monitoring*, and *feedback evaluation*. These regulatory steps are organized across multiple levels of abstraction:

1. *Sensorimotor skill level:* At this level, actions are performed automatically without conscious cognitive effort. In driving, this includes habitual activities such as steering or braking in familiar situations.

2. *Flexible action patterns:* This level involves recognition of environmental cues and application of learned patterns, such as adapting speed based on road conditions or anticipating traffic flow.

3. *Intellectual or conscious level:* When faced with novel or complex situations, drivers engage in deliberate planning and reasoning. This occurs when interpreting new ecodriving displays or adjusting strategies based on energy feedback.

4. *Meta-cognitive heuristics:* At this highest level, drivers reflect on their strategies, evaluate their performance, and adjust overarching driving goals. This process is essential for long-term improvements in ecodriving behavior.

Each level forms part of a hierarchical-sequential structure in which higher levels define goals for subordinate control layers.

Vor(weg)nahme-Veränderungs-Rückkopplungseinheiten (VVR-Units, Hacker & Sachse, 2014) are a particularly important theoretical refinement in ART, which describes the functional internal structure of regulatory action units. In each VVR-Unit, a discrepancy between the current and desired state triggers the formation of a goal (Vornahme) and its anticipated outcome (Vorwegnahme), which guides the execution of behavior through internal programs. The resulting effects are monitored and compared with these internal reference structures, forming a feedback loop. Unlike formal control models, this concept integrates psychological content—such as intentions and expectations—into the regulation process, emphasizing the anticipatory nature of human action regulation (Hacker & Sachse, 2014). In complex activities or tasks, VVR-Units can be interlinked across the hierarchy levels.

Another key feature of ART is the notion of the *action-oriented mental model*—a dynamic internal representation of task-relevant knowledge, strategies, and environmental contingencies across all regulatory levels. This model allows drivers to link perceived information with ecodriving goals and behavioral strategies, facilitating flexible adaptation in varying traffic and energy contexts. Importantly, ART also emphasizes the importance of *complete activities*—tasks that are both sequentially and hierarchically complete—in fostering motivation, learning, and effective performance. In the ecodriving context, well-designed feedback displays can contribute to such completeness by bridging perception, goal-setting, and execution.

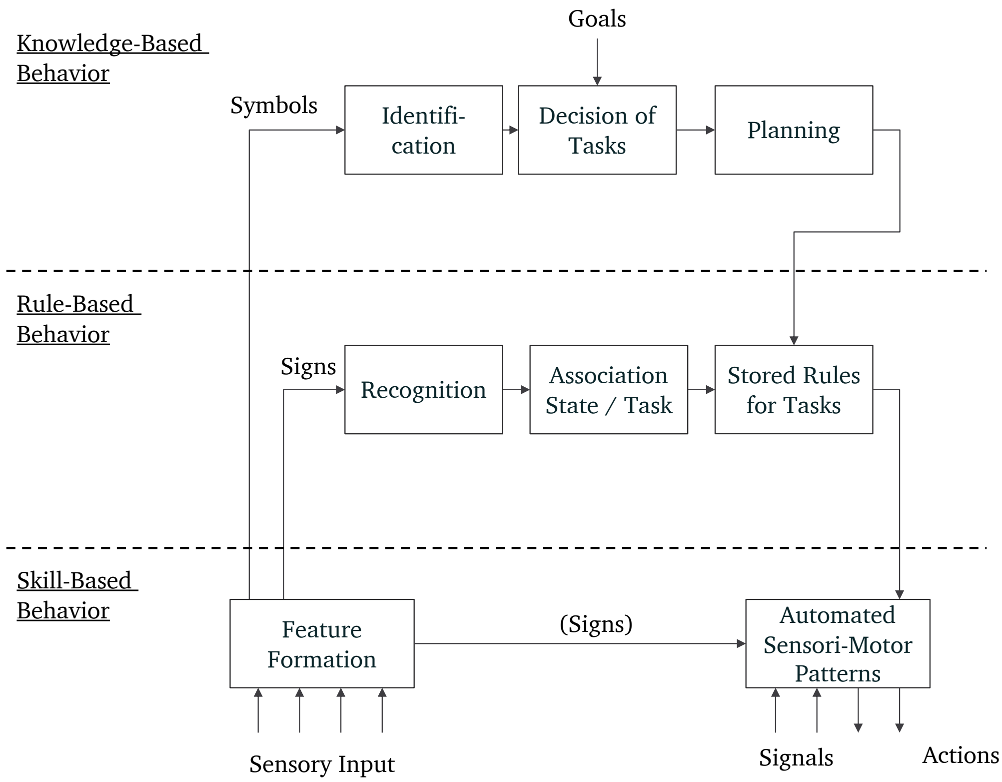
Moreover, ART underscores the role of errors as learning opportunities. Mistakes in action regulation are seen not merely as failures but as critical triggers for feedback integration and strategy refinement—an insight highly relevant to the iterative process of optimizing ecodriving behavior. Taken together, ART provides a structured theoretical lens for understanding how drivers actively regulate their behavior in response to energy feedback and how interfaces can support this process through design.

2.1.3 Skill-Rule-Knowledge Framework

Complementing psychological action and control theories, Rasmussen's *skill–rule–knowledge* framework provides an influential engineering psychology perspective on human performance in complex systems (J. Rasmussen, 1983). It distinguishes three levels of behavior (Figure 4) based on the nature of cognitive control and the structure of mental representations: *skill-based* behavior is highly automated and sensorimotor-driven, relying on dynamic internal models for execution without conscious deliberation. *Rule-based* behavior involves the application of learned procedures in familiar contexts triggered by environmental signs. *Knowledge-based* behavior emerges in novel or uncertain situations and depends on problem-solving and reasoning using symbolic representations. Crucially, Rasmussen links these behavioral levels to different modes of information perception: *signals* are time-space patterns used in skill-based sensorimotor control, *signs* serve as conventional cues for triggering rules, and *symbols* support abstract reasoning and mental simulation of unfamiliar situations. These distinctions underscore that the same display or feedback can be perceived differently depending on the operator's mode of control. For the design of ecodriving feedback systems, the model implies that interface elements should be tailored to the driver's cognitive level—supporting automated adjustments through perceptual signals (e.g., pedal feel), reinforcing procedural strategies with clear signs (e.g., color-coded speed recommendations), and enabling reflective understanding via symbolic representations (e.g., consumption graphs or range estimations).

Figure 4

Three Levels of Performance in the Skill-Rule-Knowledge Framework



Note. From J. Rasmussen (1983, p. 258)

2.1.4 Adaptations to Driving

Control and regulation theories have laid the foundation for many influential models of driving behavior. Early efforts to describe the cognitive structure of driving tasks include the hierarchical model by Michon (1985), which categorizes driver behavior into three distinct levels: strategic (planning and route choice), tactical (maneuvering), and operational (vehicle control). This model has proven influential in separating long-term decision-making from real-time control, aligning well with the idea of hierarchically organized feedback loops in both PCT and ART. Expanding on such structural frameworks, Ranney (1994) reviewed a variety of cognitive and behavioral models of driving and emphasized the relevance of integrating multiple control layers to capture the complexity of real-world driving.

Fuller (2005, 2011) proposed the “task-capability interface” model, a dynamic theory of driver behavior grounded in control theory. The author views driving as a continuous loop of perceived task demand and available capabilities. Drivers attempt to maintain equilibrium between these forces to avoid overload or underload. This framework is conceptually compatible with negative feedback models in PCT and ART, where mismatches between actual and desired states (e.g., energy use) trigger compensatory adjustments. Summala (2007) adds a motivational and emotional dimension to driver behavior by introducing the notion of “comfort through satisficing.” Rather than maximizing driving efficiency or minimizing risk, drivers often regulate their behavior to remain within personally acceptable bounds of comfort and effort. This satisficing strategy provides a psychological rationale for why drivers may not pursue optimal ecodriving performance, especially when faced with competing goals or ambiguous feedback. The idea resonates with control models that incorporate flexible reference standards and context-sensitive trade-offs.

Specific to the context of EVs and ecodriving, Franke, Arend, et al. (2016) and Franke and Krems (2013) offer a detailed application of self-regulation theory to range-related driving behavior. They introduce the “adaptive control of range resources” framework, which describes how EV drivers develop and calibrate their reference values for the remaining range as a function of different psychological aspects of the range, that is, the competent, performant, and comfortable range levels. These, in turn, are based on experience, personality traits, and system knowledge. This model explicitly adopts the language of control theory, framing ecodriving as a continuous self-regulation process in which drivers compare perceived range buffers to personal thresholds and adapt behavior accordingly.

Taken together, these contributions show that theoretical models of driving have consistently drawn upon core concepts from control and regulation theory, including goal formation, feedback loops, hierarchical action structures, and dynamic resource balancing. These models also help contextualize ecodriving as a cognitively demanding, goal-regulated activity where real-time feedback—such as that provided by ICDs—can support improved energy efficiency when it aligns with the driver’s self-regulatory processes and individual bounds of comfort and effort.

2.2 Human Information Processing

Successful ecodriving is a matter of human performance. From an engineering psychology perspective, *information processing* offers a useful framework for understanding human performance in interaction with complex systems—such as vehicles. As Wickens and Carswell (2021, p. 114) point out, “information processing lies at the heart of human performance.”

Wickens’ model of human information processing stages conceptualizes performance as the product of several distinct but interconnected stages describing how sensory input is transformed into action. These stages include *sensory processing*, *perception*, *memory and cognition*, *decision and response selection*, and *response execution* (Wickens & Carswell, 2021, see Figure 5). A central element in this stage model is *feedback*. Feedback refers to the information generated by the system or environment in response to the driver’s action. For example, applying the accelerator may increase speed and reveal new environmental information (e.g., a hidden traffic light). This creates a feedback loop in which driver actions affect the system and influence future perceptions.

While the model is often visualized as a left-to-right sequence of mental operations, it is essential to recognize that the stages do not necessarily operate in a strict linear fashion. As Wickens (2015, p. 92) note, “there is no reason at all to assume that stages must run in a strictly left-right fashion.” The boundaries between perception and working memory, for example, are particularly soft. Despite its schematic nature, the stage-based model is a tool for analyzing performance-related tasks, identifying sources of error, and generating engineering solutions. As emphasized in Wickens et al. (2021), the model aids in “analyzing tasks, describing principles and recommending solutions [...].”

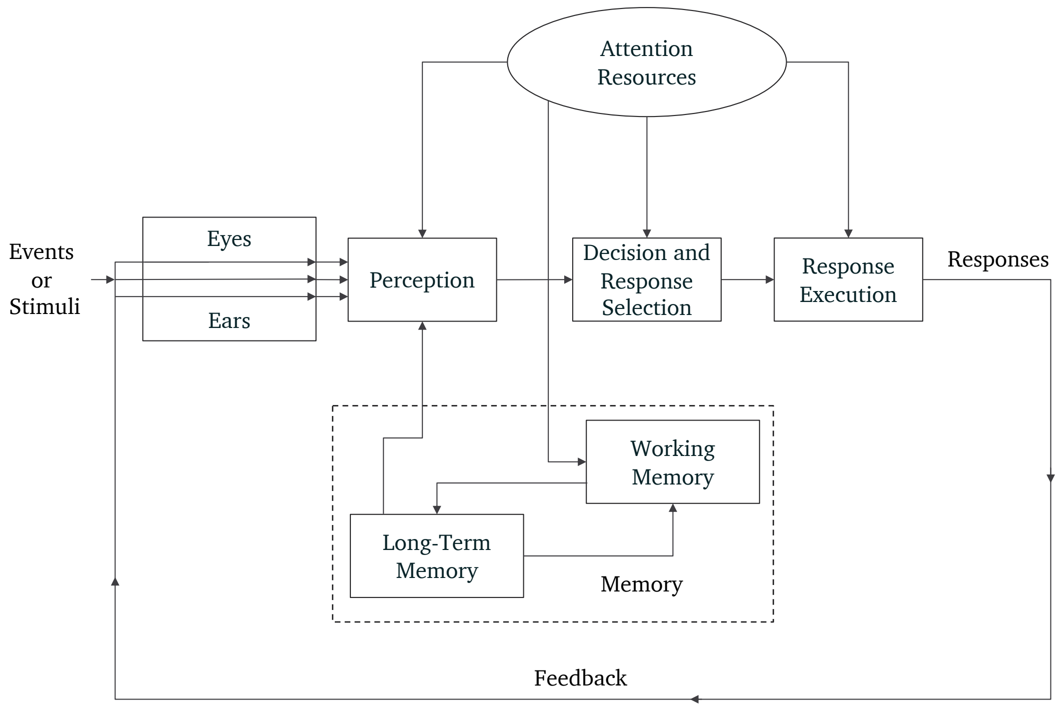
2.2.1 Attention

Attention is a core component of human information processing, serving both as a *filter* and a *fuel* (Wickens & Carswell, 2021). As a filter, attention governs which elements of the environment are selected for deeper cognitive processing—an essential function when drivers are faced with a visually rich and dynamically changing scene. For example, a driver might attend to a consumption bar graph on an ecodriving display while ignoring concurrent auditory stimuli such as a conversation or background music. As fuel, attention represents a limited pool of mental resources that can be allocated across competing tasks. High-demand situations, such as interpreting unfamiliar ecodriving feedback while navigating complex traffic conditions, may exceed these limits and impair both safety-related driving performance and ecodriving.

In the context of ecodriving, *selective visual attention* is particularly important due to the abundance of information available and the necessity to prioritize among it. Wickens et al. (2021)

Figure 5

A Model of Human Information Processing Stages



Note. From Wickens and Carswell (2021, p. 116).

characterizes six types of visual attention tasks relevant to driving: (1) general orientation and scene scanning, (2) supervisory control, (3) noticing, (4) searching, (5) reading, and (6) confirming. Of these, *supervisory control*—actively monitoring and adjusting behavior based on dynamic displays—is particularly central to the effective use of ecodriving feedback systems.

The *SEEV model* (Horrey et al., 2006) provides a theoretical framework for understanding how drivers allocate their visual attention under such demands. According to SEEV, gaze behavior is influenced by four factors: *salience*, *effort*, *expectancy*, and *value*. Salience refers to how visually conspicuous a display is (e.g., bright or blinking elements), effort denotes the physical ease of shifting gaze to a particular location, expectancy reflects how frequently changes occur at that location, and value captures the relevance of the information to current goals. These factors jointly determine the likelihood that a driver will attend to a specific element of the interface. The control of visual attention is crucial for ecodriving interfaces, where feedback displays must remain secondary to primary driving tasks due to limited attentional resources. If such displays are not designed with attentional constraints in mind, they may be ignored or impose excessive cognitive load.

Understanding attention as both a scarce resource and a strategic mechanism highlights the importance of design principles taylored to attation in developing ecodriving feedback systems.

These systems must be optimized to align with drivers' attentional capacities and tendencies, especially under varying cognitive demands and driving contexts.

2.2.2 Mental Workload

A key factor in reducing errors and increasing performance in demanding tasks is the management of mental workload (Longo et al., 2022). Appropriate workload levels are crucial in the context of driving—and specifically ecodriving. The feedback display must be informative and helpful without causing cognitive overload, and it must not interfere with more critical tasks such as ensuring safety. This balancing act makes workload regulation a vital aspect of interface design and driver support systems.

In the present context, the mental workload can be understood as the mental effort required by an individual to fulfill specific task requirements in human-machine systems (Seitz, 2022). Longo et al. (2022) have undertaken a literature search and extracted various key aspects of the definition of mental workload. Although their definition is extensive, it makes clear how diffuse and, at the same time, important the concept of mental workload is for the entire field of engineering psychology:

> *Mental workload [...] represents the degree of activation of a finite pool of resources, limited in capacity, while cognitively processing a primary task over time, mediated by external dynamic environmental and situational factors, as well as affected by static definite internal characteristics of a human operator, for coping with static task demands, by devoted effort and attention.* (Longo et al., 2022, p. 18)

Mental workload is determined by the relationship between the demands of a task and the available cognitive resources of the individual performing it (Wickens et al., 2021). When task demands exceed the operator's available capacity, performance typically degrades. Conversely, well-calibrated workload levels allow efficient task execution and lower error rates. Therefore, designing ecodriving displays that are supportive without being intrusive requires a careful understanding of cognitive limits.

There are several ways to measure mental workload, both subjectively and objectively. Among the most commonly used subjective tools is the NASA Task Load Index (NASA-TLX), which quantifies six dimensions of perceived task load: mental, physical, temporal demand, own performance, effort, and frustration (Hart & Staveland, 1988). Due to ongoing debates about the validity and specificity of such multidimensional scales, some studies have used single-item variants focusing specifically on the ”mental demand” dimension (von Janczewski et al., 2022). Other validated instruments include the Driving Activity Load Index (DALI; Pauzié, 2008), which has been developed specifically for driving contexts.

Mental workload can be experimentally manipulated in driving research by increasing situational complexity or introducing secondary tasks (Wolfe et al., 2019). For example, workload increases in urban traffic compared to highway driving due to the complexity of navigation and interaction with other vehicles (Fastenmeier & Gstalter, 2007; Paxion et al., 2014). Additionally, novice drivers often experience higher workloads because they lack automated routines, requiring more cognitive effort to maintain acceptable performance levels (Paxion et al., 2014). According to workload theories, such as the single and multiple resource models, limited cognitive resources are allocated across tasks, and performance suffers when demands exceed capacity (Wickens et al., 2021).

This implies a design challenge for ecodriving feedback displays: the system must not increase workload unnecessarily and should ideally help reduce it. This means that display elements must be intuitive, relevant, and well-integrated into the driver's perceptual and cognitive flow. Ecodriving interfaces that introduce excessive visual or cognitive complexity risk compromising their effectiveness by overloading the user. Additionally, the complexity of the situation and the driver's experience may influence mental workload. Hence, demands posed by interfaces might vary across different situations and individuals.

2.3 Situation Awareness

The construct of *situation awareness* (SA) has become one of the most influential concepts in engineering psychology and human factors. As Wickens (2015, p. 90) emphasized, "the situation awareness (SA) construct is [...] one of the most important constructs in engineering/applied psychology to emerge in the 65 years since our discipline was started." Originally introduced in aviation and military domains, SA has since been widely applied to complex, dynamic environments such as healthcare, process control, and driving. Refer to Figure 6 for the original detailed illustration.

SA is key for situation comprehension in dynamic contexts and commonly defined following Endsley (1995b, p. 36) as the "perception of the elements in the environment withing a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future." This conceptualization divides SA into three hierarchical levels:

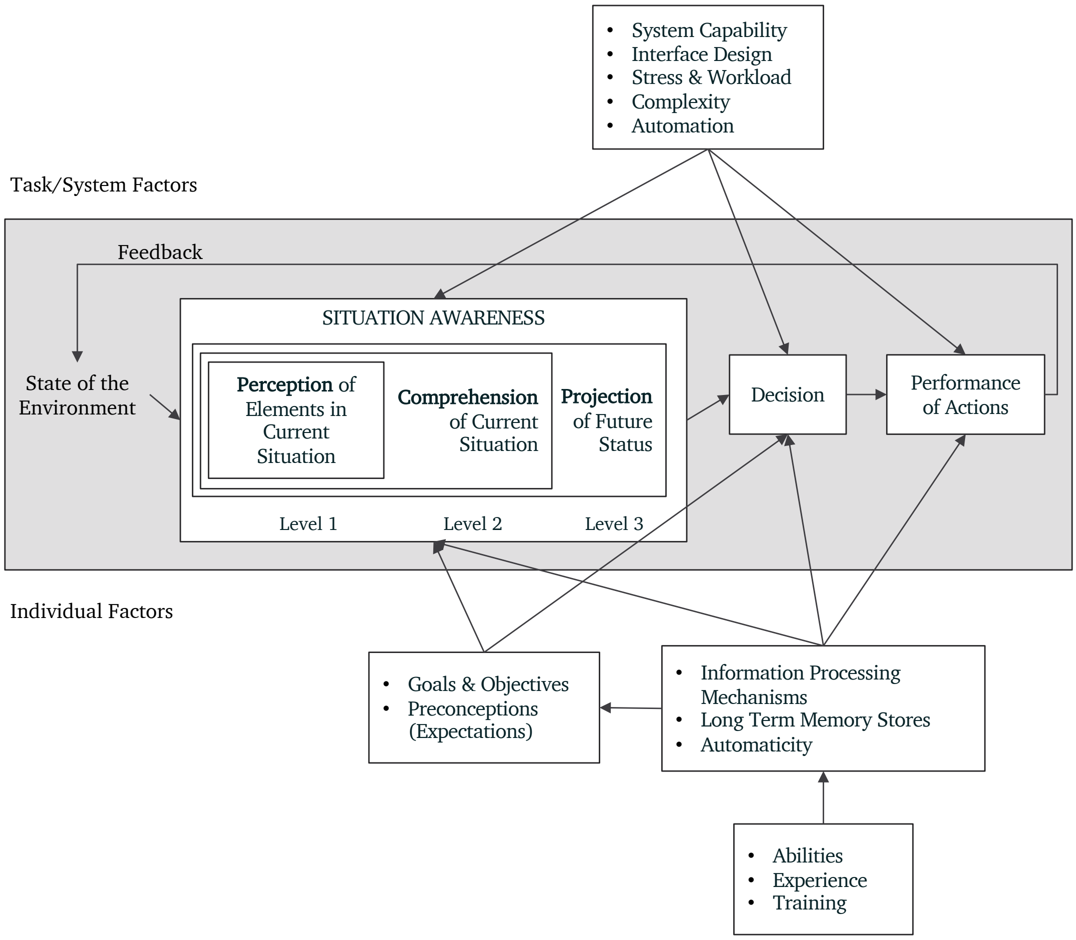
1. *Level 1: Perception* of relevant elements (e.g., other vehicles, speed signs)

2. *Level 2: Comprehension* of the current situation based on perceived information (e.g., these many slow vehicles are a traffic jam)

3. *Level 3: Projection* of future states (e.g., estimating if I will crash into another vehicle given my speed and the speed of the other road users)

Figure 6

Model of SA in Dynamic Decision Making



Note. From Endsley (2015, p. 5).

In his critical analysis, Wickens (2015) supports this framework while pointing out several clarifying statements. First, SA must be separated from decision-making and action. SA refers to the internal state of understanding, while decisions and actions follow from it. Second, Wickens underlines the role of *working memory* in maintaining SA, especially for dynamic environments. Updating and integrating information in real time—what he refers to as the ”bandwidth of change”—is essential for sustaining SA. Third, achieving *Level 3 SA*, the ability to anticipate future states, remains cognitively demanding but critical for proactive behavior in time-sensitive contexts like driving.

The theoretical foundation of SA has prompted extensive methodological development. SA measurement instruments can be categorized as indirect or direct and objective or subjective measurements (Endsley, 1995a). *Subjective measures* typically rely on self-ratings or expert observer evaluations, offering ease of administration but often lacking accuracy and diagnosticity due to biases or limited access to internal mental states. *Objective measures*, by contrast, involve external assessments such as knowledge probes/questions or performance outcomes, providing more reliable data but often only task-specific indicators. *Indirect methods*, including physiological indicators or global performance scores, can assess SA-related processes but do not capture SA as a state of knowledge. In contrast, *direct methods* aim to elicit explicit knowledge about the perceived situation, enabling detailed, element-by-element evaluations of SA levels across perception, comprehension, and projection (Endsley, 1995a).

The most validated and widely used method is the *Situation Awareness Global Assessment Technique* (SAGAT; Endsley, 1995a), a direct, objective measurement. SAGAT uses freeze probes during task simulations to assess the accuracy of a participant's knowledge across all three SA levels. Answers are scored against ground truth to provide a direct measure of SA. A complementary direct and objective measurement to SAGAT is the *Situation-Present Assessment Method* (SPAM; Durso et al., 1998), which offers real-time probes without pausing the task. However, SPAM introduces dual-task demands that can interfere with primary task performance and bias sampling toward low-workload moments (Endsley, 2021). Subjective SA is most often assessed using the *Situation Awareness Rating Technique* (SART; Endsley, 2020), which evaluates perceived attentional demand, supply, and understanding. Yet, meta-analytic reviews show weak and often inconsistent correlations between subjective and objective SA measures (Endsley, 2020). This discrepancy is partly due to poor metacognitive insight—people often do not know what they do not know.

SA has become a core concept between human perception, memory, and decision-making. It reflects the quality of the cognitive representation formed about the environment and future trajectories of relevant variables. In complex tasks like driving, SA serves as a foundation for planning, response selection, and strategy adaptation. As such, it is increasingly regarded as a central criterion in system design.

Among other factors, like training and individual and system factors, SA is supported by HMIs (Endsley, Bolté, & Jones, 2003). SA theory also provides a framework for developing design guidelines for HMIs (Endsley, Bolté, & Jones, 2003). A key challenge in designing these interfaces to support SA is referred to by Endsley (2000) as the *information gap*. This gap occurs when the environment presents a large amount of information, but users only require a few relevant pieces to achieve their task objectives. Therefore, a display must convey as much necessary information as possible in a user-friendly manner while avoiding the inclusion of irrelevant data. In the context of operational ecodriving, the primary objective is to regulate actions efficiently and promote ecodriving by identifying both efficient and inefficient driving maneuvers. Consequently, every ecodriving feedback display should minimize the information gap to support this goal.

2.3.1 Situation Awareness in Driving

SA in the driving context refers to a driver's ability to perceive, comprehend, and project elements in the dynamic traffic environment. Driving requires continuous monitoring of the vehicle, other road users, traffic infrastructure, and environmental cues under conditions of uncertainty and time pressure. A breakdown in SA has been identified as an influencing part of traffic incidents, highlighting its role in safe and adaptive driver behavior (Salmon et al., 2012). Empirical work has demonstrated the sensitivity of SA to both driver-related and environmental variables. For example, Kaber et al. (2012) showed that hazard exposure and roadway complexity significantly affect SA. Older drivers exhibit greater speed reductions in response to dynamic hazards compared to younger drivers. Such findings underscore the need to consider influencing factors such as age, experience, task demands, and context.

While Endsley's model has been highly influential, alternative perspectives have emphasized the need to specify the underlying cognitive mechanisms of SA more precisely. Baumann and Krems (2007, 2009) propose a comprehension-based model that conceptualizes SA as an outcome of dynamic cognitive processes akin to discourse comprehension. Their model describes how perceived information activates associated knowledge structures in long-term memory, which are then integrated into a coherent situation model through constraint-satisfaction mechanisms. This representation supports both the comprehension of the current situation and the anticipation of future developments. Unlike Endsley's framework, which distinguishes SA from decision-making and action, this model posits that perception, comprehension, and action are interwoven in a continuous loop. This integration is particularly relevant for driving, where effective behavior relies on the dynamic interplay between environmental cues and driver intentions.

In sum, SA can help understand driver cognition and behavior. The comprehension-based approach provides complementary insights into how SA is formed and maintained in the driving task. These models collectively offer a framework for analyzing the cognitive mechanisms of ecodriving behavior and driver-vehicle interaction in EVs.

2.3.2 Energy Dynamics Awareness in EV Driving

Recent work has begun to transfer the concept of SA to energy-related domains. Thill and Riveiro (2015) conceptually explored SA in ecodriving, emphasizing the need for awareness of energy-relevant environmental and vehicular factors and calling for SA-based interface designs. Beyond driving, Ren et al. (2015) applied SA theory to smart home energy systems, identifying goal awareness, system comprehension, and energy consequence projection as central elements for promoting efficient user behavior. Nienhüser et al. (2012) underlined the potential of designing an assistance system that perceives, interprets, and anticipates dynamic traffic scenarios to match driving tasks. In maritime transport, H. B. Rasmussen et al. (2018) showed that shared

SA and communication are key to effective energy management, extending SA theory to distributed teams operating complex energy systems. Together, these studies demonstrate that SA is suitable as a theoretical foundation for analyzing and supporting energy-efficient behavior in a range of interactive systems.

The idea to investigate SA as a comprehension-based concept for dynamic situations that explains the effectiveness of ecodriving feedback displays is underrepresented in the current research literature. Either SA is not observed in ecodriving studies that directly investigate energy consumption, or SA does not serve as a guideline for designing the ecodriving feedback displays that are evaluated for their effectiveness.

Based on these considerations, I previously introduced the concept of *energy dynamics awareness* (EnDynA) as a domain-specific extension of SA and developed a corresponding measurement scale to assess drivers' awareness of dynamic energy states in EVs (Gödker et al., 2019). I used the abbreviation "EDA" for energy dynamics awareness in my earlier works. However, I now consistently use "EnDynA" to eliminate any potential confusion with other psychological and physical concepts. The concept of EnDynA explicitly accounts for the awareness of dynamic energy-related states that are crucial for efficient EV operation. As energy consumption in EVs is influenced by a complex interplay of driving behavior, vehicle systems, and environmental factors, drivers must maintain an accurate and actionable internal representation of the energy situation.

EnDynA refers to a driver's awareness of the current and anticipated energy flows and consumption of the vehicle, including the comprehension of influencing factors and the ability to act accordingly to optimize energy efficiency. The concept builds upon the three-level structure of SA (Endsley, 1995b) but specifies it for energy-related information: (1) *Perception* of energy-relevant cues such as battery state of charge, topography, and acceleration; (2) *Comprehension* of their meaning in terms of energy impact; and (3) *Projection* of future energy states under continued or alternative actions. For example, a driver with high EnDynA might anticipate that continued acceleration on a hilly segment will lead to unnecessary energy loss and decide to adjust their behavior proactively.

EnDynA is not a break from the established SA framework; instead, it serves as a specification. It encompasses the elements that are relevant in the context of ecodriving, how drivers can comprehend their meaning with respect to energy efficiency, and how this enables anticipatory control over driving strategies. As such, EnDynA provides a conceptual lens through which driver cognition, interface design, and energy efficiency can be jointly analyzed in EVs. It forms the central theoretical construct of this dissertation and serves as a foundation for the empirical investigations presented in the following chapters.

2.4 Synthesis

The theoretical approaches outlined in this chapter—ranging from cybernetic control frameworks such as PCT and ART to information-processing models, workload theory, and SA—have not only shaped individual lines of research in human factors but have also been successfully combined in applied psychology. The situation awareness model (Figure 6) itself contains elements identical to the information processing model (e.g., memory, feedback), PCT (goals), and ART (expectations). Parasuraman et al. (2008) argue, SA, mental workload, and trust in automation represent empirically validated constructs that, when integrated, provide powerful tools for understanding and designing human-system interaction in complex environments. Similarly, Johnson et al. (2017) propose a closed-loop model that synthesizes visual attention, mental workload, and SA within a continuous feedback cycle. In his influential overview, Wickens (2015) advocates for explicitly embedding SA within an information-processing framework, locating it at the intersection of perception and cognition rather than action execution. These overlaps support the motivation to use SA as a theoretical model for understanding cognitive performance in time-sensitive environments.

This integration supports the core premise of this dissertation: that (operational) ecodriving in EVs can be well understood as a cognitive control activity guided by internal representations of dynamic energy states—what I conceptualize as EnDynA. This work applies and extends existing constructs from engineering psychology and human factors research to the domain of energy-efficient behavior. The models reviewed in this chapter converge on several key theoretical principles that guide the empirical components of the dissertation:

- **Hierarchical control and action regulation:** Theories such as ART and PCT emphasize that human action unfolds across multiple levels of abstraction—ranging from sensorimotor routines to strategic, goal-directed reasoning. These levels form a nested control hierarchy in which high-level goals (e.g., energy-efficient driving) are translated into lower-level behaviors (e.g., coasting, gentle acceleration). Understanding how drivers regulate behavior across these levels is central to the design of ecodriving feedback displays (Hacker & Sachse, 2014; Zacher & Frese, 2018).

- **Feedback loops:** All presented major theories assume a closed-loop structure in which perception, action, and feedback are continuously cycled. In ecodriving, this loop is often broken due to the invisibility of energy consumption. Interfaces must, therefore, close the loop by transforming technical system states into perceptible, actionable feedback (Craik, 1947; Powers et al., 2011).

- **Knowledge-based internal states and awareness:** At the core of both SA and EnDynA is the formation of an internal knowledge state that allows for the comprehension and projection of relevant environmental dynamics. Similar concepts exist in ART. I refer to energy-specific SA as EnDynA, which determines optimal ecodriving decisions and actions. (Gödker et al., 2019).

- **Cognitive resources, attention, and workload:** Ecodriving feedback systems must take the primary task of driving safely into account and consider limited attentional resources. Models such as the SEEV model (Horrey et al., 2006) and its closed-loop extension by Johnson et al. (2017) show that attention allocation depends on perceived information value and uncertainty. Mental workload theories provide further constraints on interface design by highlighting the trade-offs between information provision and cognitive load (Longo et al., 2022).

- **HMI impact:** The theories presented for this framework often imply a supportive effect of HMIs and formulate display design needs (Endsley, Bolté, & Jones, 2003; J. Rasmussen, 1983). This dissertation applies an integrative perspective to the design of feedback displays that enhance EnDynA while managing attentional demand and workload.

Taken together, these principles form a coherent conceptual foundation for the subsequent empirical investigations. They justify the development of EnDynA as a key cognitive construct for ecodriving and provide a multifactorial lens through which both driver behavior and interface design can be understood and optimized in EVs. Furthermore, I will clarify some of the key terms and their interrelations:

Operational ecodriving is the primary focus of this dissertation, defined by the goal to reduce energy consumption during manual EV driving by performing driving maneuvers, specifically choosing and executing optimal speed profiles by longitudinal control of the vehicle, comparabel to the lowest levels of driving behavior of Michon (1985) and Sivak and Schoettle (2012). Operational ecodriving encompasses all levels of action regulation, from unconscious to conscious decision-making, as well as a complete feedback loop, including goal-setting and all stages of information processing. Central psychological variables (EnDnyA, memory, mental models, attention) are part of operational ecodriving, as well as the desired outcome behavior **energy-efficient driving**, which is defined as driving optimal speed profiles. *EnDynA* is understood to be a central psychological variable in a fuzzy relationship/overlap to the information processing stages sensory processing and perception as proposed by Wickens (2015). **Energy consumption** is a consequence of operational ecodriving and depends not only on energy-efficient driving but also on the vehicle and the environment. In controlled experiments, where both the environment and vehicle conditions remain constant, energy consumption can be used as an indicator for energy-efficient driving. **Ecodriving feedback displays** are tools that can enhance operational ecodriving by providing real-time, detailed feedback on driving behavior and its consequences, including energy consumption. Their information is perceived and can support various aspects of operational ecodriving (perception, decision-making, memory, etc.).

3 Methodological Considerations for the Investigation of Ecodriving

Research on ecodriving can be carried out using several methods, including on-road driving experiments, driving simulation studies, numerical modeling, and surveys (see Huang et al., 2018, for a comprehensive overview). The requirements for studying energy-efficient driving can differ significantly from those needed for safety-related research. The instruments and standardized paradigms to investigate operational ecodriving empirically are scarce. Therefore, I develop and create suitable methods and instruments in this dissertation. In this section, I will address the methodological challenges and implications for display design that are relevant across multiple articles of this dissertation.

3.1 Experiment Requirements

Choosing an appropriate research method for investigating ecodriving behavior involves careful consideration of both ecological validity and experimental control. Results will not be directly comparable if influencing factors change between measurements (e.g., servicing of vehicles, vehicle type, weather, traffic situation, type of work, loaded weight; af Wåhlberg, 2007). Different methods allow for the control of these factors to varying degrees.

Field studies offer the highest ecological validity, as energy consumption can be measured directly under real driving conditions using vehicle sensor data. However, they also introduce substantial methodological challenges: the lack of experimental control, high situational disturbances, and safety concerns make it difficult to isolate the effects of display manipulations. Field studies are, therefore, more suitable for evaluating mature ecodriving feedback systems with a high level of technological readiness and operational reliability.

Driving simulation studies combine advantages regarding realism and control. They allow for the systematic manipulation of driving scenarios and display types under safe conditions. Although simulation platforms can replicate traffic and vehicle dynamics with considerable fidelity, minor variations in vehicle trajectories—driven by participants' behavior—can still affect what drivers perceive across trials. Moreover, energy consumption simulation is often based on simplified models, meaning the resulting consumption data may not fully reflect real-world vehicle physics. Driving simulation studies are particularly suitable when investigating functionally advanced displays that still require a safe and controlled testing environment.

Video-based studies offer the highest degree of experimental control. In this method, all participants are exposed to identical perceptual input, making the approach especially valuable for isolating the effects of display designs. Moreover, videos derived from real driving data can retain high ecological validity as consumption can be measured via vehicle sensors, ensuring realistic feedback dynamics. But, it is impossible to observe actual ecodriving behavior. Due to their simplicity and scalability, video studies are especially well-suited for early-stage evaluation of display concepts, including online experiments with large and diverse participant samples. This method has been used for studies regarding ecodriving displays before (Lin & Wang, 2022; Moll & Franke, 2021).

In this dissertation, the primary goal was to systematically investigate the psychological effects of ecodriving feedback displays, which were used as the manipulated independent variable across studies. To achieve high controllability while working with display concepts that were still in an early stage of technological readiness, I chose to combine *video-based studies* and *driving simulation experiments*. This dual-method approach struck a balance between experimental controllability and ecological representativeness, while the simulator experiments allowed for the observation of actual ecodriving behavior.

Measuring drivers' EnDynA introduces further methodological challenges, as no measurement method was directly applicable for the present studies. SA measurement instruments can be categorized as indirect or direct and objective or subjective measurements (Endsley, 1995a). In general, self-rating scales are versatile and easy to administer but may be inaccurate due to a lack of introspective access, misinterpretation of confidence, or conflation with workload. Objective performance in the context of EnDynA could be to let participants estimate how much energy was consumed and measure the estimates' accuracy. Another option would be to let participants rank trips according to their energy consumption as a measure that does not depend on precise numbers. Consumption estimation and efficient trip identification circumvent the limitations of subjective measures but assess EnDynA only task-specific and do not allow for a separate evaluation of the three levels of perception, comprehension, and projection. Physiological methods such as gaze behavior are increasingly popular but prone to situational and individual variance, making them difficult to interpret in novel or unconstrained experimental paradigms. In combination, however, these methods can provide converging evidence and help to counterbalance their respective weaknesses. I, therefore, apply multiple complementary assessment methods across studies in this dissertation to evaluate EnDynA comprehensively. As Endsley (2020) states, subjective measures might better correspond with *SA confidence*; it is also possible to let participants rate how confident they are in their SA (direct) or SA-related performance (indirect) to better triangulate EnDynA. In this dissertation, the term *experienced EnDynA* refers to an individual's subjective perception of their own EnDynA state, as assessed through self-ratings using the EnDnyA scale (see Section 5.1). In contrast, *actual EnDynA* denotes the conventional understanding of EnDynA itself, representing the knowledge-based state that can be quantified using specific probe questions.

In driving simulation studies, ecodriving research poses specific methodological challenges that differ from safety-focused research. Since energy efficiency is only one of several goals that drivers balance in real-world settings, experimental designs must carefully define task goals while maintaining enough behavioral variability to detect display effects. The core challenge lies in inducing realistic goal-setting that allows for the evaluation of operational ecodriving behavior without overly constraining participants.

Time Constraints Because lower driving speeds generally improve energy efficiency, participants may adopt unrealistic driving strategies in the absence of time pressure (e.g., driving 30 km/h on highways). Yet, time constraints must be carefully calibrated. Overly strict limits can suppress natural behavior and confound display effects. An overly strict time constraint will lead to too many trials where the observed driving behavior change will only be attributable to drivers trying to meet the time constraint instead of improving ecodriving, which is not the behavior change of interest. Another problem in setting specific time constraints is, that it is impossible for drivers to estimate how much time is left when driving a scenario for the first time. So, any time constraint must remain intuitive and not depend on precise time estimation skills. One practical approach is communicating a *time budget*, e.g.: "You must complete the route in X.Y minutes. This is the time a driver needs while always driving 20% of the current speed limit." This allows drivers to always judge their current time limit adherence while allowing room for strategy and ecodriving improvement.

Traffic Rule Compliance To ensure externally valid behavior and to avoid "cheating", traffic rules such as speed limits or lane keeping must be enforced. However, strictly enforcing minor violations (e.g., brief +5 km/h speeding) may not reflect naturalistic driving. A more realistic approach is to implement thresholds that define rule violations in terms of severity, duration, or frequency (e.g., speeding more than 10% for over 5 seconds or repeatedly across segments). This allows participants to drive flexibly while keeping behavior within acceptable limits. Rule compliance can be monitored either through software-based thresholds or by human observers.

Balancing Competing Goals Once constraints and rules are set, participants must balance goals to reflect real-world trade-offs. This includes choosing between ecodriving, time efficiency, and rule compliance. While monetary incentives are often used to influence goal pursuit, they can introduce ethical concerns—especially if experimental conditions differ in their baseline difficulty—and reduce intrinsic motivation. Moreover, participants' real-world cost–benefit considerations may override the experimental incentives. An alternative is to appeal to task compliance norms by framing instructions as part of an evaluative study. Informing participants that failure to follow task rules could invalidate their data often suffices to promote adherence. Non-monetary incentives such as post-task feedback or performance comparisons (e.g., gamified dashboards) can also foster engagement. If penalties are applied (e.g., "lives" for rule violations), these must be carefully designed to avoid compromising measurement validity—for example, by influencing behavior in later task segments or by making test sections non-independent. Such frameworks should be transparent to researchers but not necessarily communicated to participants to avoid strategic gameplay.

When creating driving scenarios (as maps) for driving simulation, they need to be diagnostic (induce operational ecodriving) and reliable. Refer to Gödker, Schmees, Bernhardt, et al. (2024) for a detailed discussion on how to create a diagnostic driving environment. For driving data comparability, a scenario needs to start and end at the same speed level to avoid disturbance due to potential energy gains and losses.

3.2 Display Design

A central premise of this dissertation is that ecodriving displays should not only serve applied purposes but also be conceptualized as operationalizations of theoretically informed independent variables. This allows for the formulation of testable hypotheses grounded in the theoretical framework and, in turn, enables the generalization of findings regarding the psychological effects of specific display elements. Designing displays under this dual constraint—serving both theoretical and applied aims—poses specific methodological challenges. It should also be noted that although some of the types of displays used in this dissertation already exist in EVs, their use under specific instructions or in the particular design of this study could compromise safe driving. Therefore, they should not be utilized in real traffic until further testing is conducted.

Following the design principles outlined by Endsley, Bolstad, et al. (2003) and Endsley, Bolté, and Jones (2003), all displays in this dissertation were developed with the goal of supporting drivers' EnDynA. A critical challenge in this regard is the so-called *information gap*: users typically require only a small, context-relevant subset of available environmental information to effectively accomplish a task. Consequently, an effective display must maximize the delivery of task-relevant information while minimizing extraneous or distracting content.

In this research, the independent variable across studies is defined by the display's *informational value*—that is, the extent and quality of information relevant to achieving the task goal of energy-efficient driving. This is supposed to optimally address the information gap. More specifically, informational value is conceptualized as the ratio of relevant to irrelevant information. The manipulation of this ratio across display types (e.g., flow, bar, or trace displays; conventional feedback vs. predictive feedback) forms the experimental basis for testing their effects on EnDynA and operational ecodriving. Thus, each interface is not merely a visual design artifact but a theoretically specified variable operationalization.

Another important consideration is the definition of the control group. In general, a control group could be to have no display at all or to have a display with the exact same visual demands while presenting no feedback. In general, the latter seems favorable as it only manipulates the transmitted information and keeps all other influences constant. However, it is difficult to keep drivers regularly looking at the display while only presenting irrelevant information. Hence, it will be almost impossible to imitate the same visual demands without introducing a parallel or secondary task only for the sake of the control group. Therefore, I decided on a control group that has no display at all, which is a rather extreme control group and will be further discussed in Section 6.2.

4 Research Objectives

The overall objective of the present research is to empirically investigate humans using ecodriving displays in order to describe and explain how different ecodriving displays influence operational ecodriving behavior and drivers' cognitive states and experiences. More specifically, the research objectives (ROs) of this cumulative dissertation are as follows:

RO1. **Develop and validate the concept of EnDynA**
EnDynA is introduced as a domain-specific adaptation of SA in the context of energy consumption. This dissertation seeks to define and empirically validate EnDynA as a theoretical construct of the drivers' informed mental state by examining how drivers perceive, comprehend, and predict energy dynamics in EVs.

RO2. **Develop and refine methods and instruments for investigating drivers' operational ecodriving**
This dissertation aims to create and validate methodological approaches for a reliable and valid assessment of drivers' cognitive and behavioral aspects of operational ecodriving. This includes the development of experimental paradigms, self-report instruments, and behavioral measures that facilitate a deeper understanding of how drivers interact with energy feedback displays.

RO3. **Examine the effects of different ecodriving feedback displays on drivers' operational ecodriving**
This research evaluates the effectiveness of different ecodriving feedback displays, including real-time energy feedback displays such as ICDs (e.g., bar or trace displays) and predictive guidance (optimal speed displays, OSDs), in enhancing psychological variables related to the concepts of the theoretical framework, especially in improving energy-efficient driving performance.

RO4. **Assess the impact of mental workload and attentional processes on operational ecodriving**
Driving is a cognitively demanding task, and attention allocation plays a crucial role in interpreting energy feedback. This dissertation investigates how mental workload influences drivers' ability to process energy information and improve operational ecodriving.

RO5. **Integrate findings from empirical studies to formulate recommendations for future ecodriving feedback systems**
This dissertation aims to provide actionable recommendations for developing human-centered ecodriving interfaces by synthesizing findings across multiple studies.

With these objectives, this research will contribute to engineering psychology, human factors, cognitive ergonomics, and sustainable transportation by advancing the understanding of how interface design can support energy-efficient behavior in EVs. The findings can affect automotive HMI design, driver training programs, and the transition to sustainable mobility solutions. The resulting methods and tools contribute to the broader fields of engineering psychology, human factors, and HCI by establishing empirical methodologies applicable to sustainability-oriented traffic research.

5 Summary of Included Manuscripts in the Dissertation

The following section provides a concise summary of the main findings of each article included in this dissertation. It outlines each article's specific contribution (see Table 1 for an overview) to the overarching ROs and clarifies all co-authors' individual contributions.

Table 1

Overview of the Articles' Contributions

Article	RO1	RO2	RO3	RO4	RO5
Article 1	✓	✓	✓		✓
Article 2	✓	✓		✓	✓
Article 3	✓	✓	✓		✓
Article 4	✓	✓	✓	✓	✓

5.1 Article 1: Differential Effects of Energy Interfaces

Publication

This article was published in the journal *Human Factors: The Journal of the Human Factors and Ergonomics Society*:

Gödker, M., Moll, V. E., & Franke, T. (2024a). Energy consumption displays in electric vehicles: Differential effects on estimating consumption and experienced energy dynamics awareness. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 00187208231222154. https://doi.org/10.1177/00187208231222154

Summary of the Empirical Research

This study investigated how three different types of ICDs in EVs—a flow display, a bar display, and a trace display—differentially affect drivers' EnDynA. It introduced the novel subjective self-report *EnDnyA Scale* to measure *experienced EnDynA* and examined its relationship to objective indicators such as consumption estimation and the identification of efficient trips (*actual EnDynA*). Also, the confidence in the actual EnDnyA estimates was measured. The study employed a video-based online experiment in which $N = 82$ participants watched standardized EV driving scenes, each featuring one of the three energy displays. After each scene, they had to estimate how much energy was consumed on this trip. Each participant viewed six driving scenes in total (two per display type). After both scenes per display type, participants answered the self-report scales and identified the more efficient trip.

Results showed that the type of energy display influenced experienced EnDynA and the confidence ratings, with the trace display being rated most supportive, followed by the bar display and then the flow display. However, no significant differences were found between displays regarding both actual EnDynA measures. Nonetheless, experienced EnDynA correlated positively with confidence ratings and the ability to identify efficient driving behaviors, supporting its conceptual relevance. These findings underscore the importance of displays' informational value in shaping drivers' subjectively experienced EnDynA. The study introduced a reliable measurement tool (EnDynA Scale) and novel paradigm for evaluating energy-specific SA, contributing to SA theory and HMI design.

Contribution to ROs

This article makes foundational contributions to several core objectives of the dissertation. Most notably, it directly addresses **RO1** by introducing and empirically testing the theoretical concept of EnDynA and investigating the convergent validity of different EnDnyA measurement methods. It contributes to **RO2** by developing a reliable self-report instrument—the EnDynA Scale—to assess experienced EnDynA. Additionally, the article reports the development of a controlled video-based experimental paradigm that enables the standardized assessment of energy-related perception and comprehension using two judgment-based objective EnDynA assessment methods (consumption estimation and efficient trip identification). Concerning **RO3**, the study evaluates the effects of three different ICD types on experienced EnDynA, demonstrating that displays with a high information value, such as trace displays, can enhance drivers' subjective experience of EnDynA. Objective performance measures were not significantly affected. Regarding **RO5**, the article makes a primary contribution by showing that adding a distance dimension in ICDs can enhance their informational value. However, the initial hypothetical construct of informational value requires further development and discussion. Thus, this article forms the conceptual and methodological starting point for the dissertation's overarching investigation into energy-related driver information processing and HMI design in EVs.

Author Contributions

CRediT statement: **Markus Gödker**: conceptualization; data curation; formal analysis; investigation; methodology; supervision; visualization; writing – original draft; writing – review & editing. **Vivien Moll**: conceptualization; writing – original draft; writing – review & editing. **Thomas Franke**: funding acquisition; resources; supervision; writing – review & editing.

I contributed by developing the research idea and conceptualizing EnDynA, the displays, and the videos. I created the experimental design and the questionnaires, which included the EnDynA scale and the other EnDynA measurement methods. I collected and analyzed the data and wrote the manuscript with support from the co-authors. Please note that Jan Heidinger and Lukas Bernhardt contributed to this research as student research assistants, although they are not listed as co-authors. Lukas Bernhardt was responsible for collecting driving data and recording the videos. Jan Heidinger implemented the ICDs based on provided instructions and synchronized the videos, driving data, and displays to create the driving scenes.

5.2 Article 2: Assessing Energy-Related Situation Awareness

Publication

This article was presented at the *15th International Conference on Applied Human Factors and Ergonomics* (AHFE 2024) and published in the conference proceedings:

Gödker, M., & Franke, T. (2024). Assessing energy-related situation awareness using self-controlled occlusion during electric vehicle driving scenes. In G. Praetorius, C. Sellberg, & R. Patriarca (Eds.), *Advances in Human Factors of Transportation. AHFE (2024) International Conference. AHFE Open Access* (pp. 286–296, Vol. 148). AHFE International. https://doi.org/10.54941/ahfe1005219

Summary of the Empirical Research

As an extension of the study in Article 1, this study investigated how mental workload influences EnDynA in the context of ecodriving. It tested a novel self-controlled occlusion method to assess visual attention (using the metric *uncertainty*) and investigated its relations to performance-based and subjective measures of EnDynA under different workload conditions. A total of $N = 29$ participants completed a video-based online experiment featuring simulated EV driving scenes (from Article 1) with an ICD. During the scenes, participants simultaneously performed either a low (0-back) or high (1-back) visual-manual n-back task. They could manually occlude either the driving view (including the n-back task) or the energy display to simulate gaze allocation in an actual vehicle, thereby allowing for the inference of visual attention. As in Article 1, EnDynA was assessed via three complementary approaches: (1) absolute consumption estimation tasks, (2) efficiency identification decisions, and (3) an adjusted version of the self-report EnDynA Scale.

Results confirmed that the mental workload manipulation was successful and significantly influenced performance: Under high workload, participants estimated consumption less accurately and sampled the display less frequently using self-controlled occlusion. Hence, the derived uncertainty metric also increased under high workload, indicating reduced energy-related information acquisition. However, the different EnDynA measures (performance-based, self-report, gaze-behavioral) did not correlate with each other, suggesting a divergence between subjective and objective awareness. These findings offer a novel and technically efficient method for capturing visual attention and energy information processing in low-cost online settings. They also contribute to the theoretical debate on how different types of awareness measures relate—or fail to relate—to one another in ecodriving contexts.

Contribution to ROs

This article advances multiple objectives of the dissertation. In direct support of **RO2**, it refines and extends methodological tools for assessing drivers' energy-related information processing by introducing self-controlled occlusion as an innovative, low-cost proxy for visual attention. Furthermore, a visual-manual n-back task was successfully used to induce different workload conditions. This contributes significantly to the empirical toolkit for studying ecodriving feedback systems in controlled settings. Furthermore, the study empirically examines how EnDynA is affected by workload and attention, addressing **RO4** by demonstrating that cognitive demands reduce display engagement and impair estimation accuracy. The dissociation between subjective and objective measures raises important conceptual questions, contributing to the theoretical development of EnDynA within **RO1**. Finally, the results suggest implications for adaptive and attention-aware interface design, thus indirectly informing **RO5**.

Author Contributions

CRediT statement: Markus Gödker: conceptualization; data curation; formal analysis; investigation; methodology; resources; validation; visualization; writing – original draft; writing – review & editing. **Thomas Franke**: Conceptualization; Funding acquisition; Supervision; Writing – review & editing.

My contribution was developing the research idea. I further advanced the concept of EnDynA and its measurement based on the first article. I created the experimental design and the questionnaires and collected the data. I analyzed the data and wrote the manuscript with support from the co-author. Please note that Hannah Küpper, Mona Dietzel, and Philipp Steinschulte contributed to this research as student research assistants and as students for their Bachelor's theses, yet they are not listed as co-authors. Philipp Steinschulte expanded upon the driving scenes from Article 1 (created by Jan Heidinger and Lukas Bernhardt) and implemented the n-back task and self-controlled occlusion based on the provided instructions. Hannah Küpper and Mona Dietzel supported developing the research idea, creating the experimental design and the questionnaires, as well as the data collection.

5.3 Article 3: Improved Ecodriving

Publication

This article has been published as a preprint on PsyArXiv and currently in the submission process:

Gödker, M., Schrills, T. P. P., & Franke, T. (2025). *Improved ecodriving using instantaneous consumption displays in an electric vehicle driving simulator: The role of energy dynamics awareness*. PsyArXiv. https://doi.org/10.31234/osf.io/zusyx_v3

Summary of the Empirical Research

This study investigates how ICDs affect energy-efficient driving behavior and EnDynA in an EV driving simulator. The central aim was to explore whether ICDs differing in information extent and quality provision (similar to the independent variable of Article 1) improve operational ecodriving and EnDynA across repeated driving trials. $N = 77$ participants were randomly assigned to one of three groups: trace display (high information provision), bar display (medium information provision), or control (no display, low information provision). Participants completed eight driving trials (5 trials on Route A, 3 on Route B) under consistent conditions. The first two runs served as baseline trials without any display. Throughout the experiment, experienced EnDynA (self-reported) and actual EnDynA (consumption change estimation accuracy) were collected alongside average energy consumption to assess operational ecodriving. Further, the study evaluated participants' intention to improve their understanding of energy dynamics and how they experienced their display contributed to improving EnDynA (*EnDynA Enabling Scale*).

The results demonstrated that participants improved their energy-efficient driving and their experienced and actual EnDynA across trials. Notably, the most substantial gains in energy efficiency and experienced EnDynA were observed in the trace display group, which provided the richest energy information. However, no significant differences emerged between groups in improving the estimation accuracy, and the expected negative correlation between experienced EnDynA and the intention to improve it was reversed. Interestingly, experienced EnDynA correlated negatively with energy consumption, suggesting that higher awareness might support ecodriving. A high correlation between experienced EnDynA and the EnDynA Enabling Scale was observed, indicating that participants attribute their improved understanding to the displays. These findings provide strong experimental support that ICDs can improve drivers' energy efficiency by enhancing their EnDynA. Thus, they demonstrate the critical role of information provision quality in human-machine interaction design for sustainable mobility.

Contribution to ROs

This study directly contributes to validating the EnDynA concept (**RO1**) by showing that experienced EnDynA is a meaningful predictor of ecodriving performance and that it most likely originates from effective display design (as indicated by a high correlation to the EnDynA Enabling Scale). The study also contributes to **RO1** by showing that higher experience in EnDynA is associated with an increased intention to improve EnDynA, providing initial insights into the motivational potential of EnDynA. The study advances the methodological toolkit for investigating ecodriving behavior by applying a driving simulator experiment design and advancing reliable scales for measuring EnDynA, including an adapted version of the EnDynA Scale, a new *EnDynA Enabling* Scale, and a scale to measure the *intention to improve EnDynA* **RO2**). Third, the experiment demonstrates that the ICD design affects operational ecodriving and drivers' experiences (**RO3**). Moreover, the study highlights the role of subjective cognitive states—like experienced EnDynA—as key mediators of interface effectiveness. This finding informs theoretical considerations and provides recommendations for energy feedback systems in EVs (**RO5**) by emphasizing that an ICD with a distance dimension improves information provision quality and drivers' energy comprehension. The article substantially advances the overarching goal of a psychologically grounded understanding of energy-efficient driving behavior by combining display design, consumption measurement, and psychological concepts in a controlled experimental setting.

Author Contributions

CRediT statement: **Markus Gödker**: conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; software; validation; visualization; writing – original draft; writing – review & editing. **Tim Schrills**: conceptualization; funding acquisition; methodology; resources; writing – original draft; writing – review & editing. **Thomas Franke**: conceptualization; funding acquisition; project administration; resources; supervision; writing – original draft; writing – review & editing.

I contributed by developing the research idea with the support of Tim Schrills and advancing the concept of EnDynA with the support of Tim Schrills. I designed the displays and the driving scenario, and created the experimental design and the questionnaires. I collected the data with significant assistance from student research assistants. I analyzed the data and wrote the manuscript with support from the co-authors. Please note that this research was conducted as part of the AMORi project and only possible through the contribution of the entire AMORi team: Lukas Bernhardt, Jan Heidinger, Elise Banach, Dennis Fares, Leonardt Wagner, Tobias Harms, Anton de Vries, Tobias Reins, and many others. In particular, the technical implementation of the study design in the laboratory (driving simulator including route creation, data processing, study management program, displays, etc.) and large parts of the data collection were carried out by the AMORi team.

5.4 Article 4: Two Types of Support

Publication

This article has been submitted to the *International Journal of Human-Computer Interaction* and is currently being assessed. It has been published as a preprint on OSF:

Gödker, M., Schmees, S., Bernhardt, L., Görges, D., & Franke, T. (2025). *Two types of eco-driving support - The effects of an instantaneous consumption and an optimal speed display on energy-efficient driving and energy dynamics awareness*. Open Science Framework. https://osf.io/297wv_v1

Summary of the Empirical Research

This study examined the effects of two types of ecodriving feedback displays—an ICD and an OSD—on energy-efficient driving and EnDynA in EVs. The study employed a repeated-measures driving simulator experiment using the EcoSimLab, the EcoDrivingTestPark sectors, and a simulated Renault Zoe EV. $N = 94$ participants were randomly assigned to one of three groups: ICD, OSD, or control (no display). After two baseline trials without any display, participants completed two additional trials according to their display condition. These two trials of each measurement differed in situation complexity as indicated by the DALI mean scores and a newly created Situation Complexity Short Scale. In each trial, behavioral and self-report measures were collected, including experienced EnDynA, energy consumption, and deviation from the optimal speed. Additionally, an in-situ experienced EnDynA measurement was introduced as a single-item EnDynA Scale.

Both display groups significantly improved in experienced EnDynA, average consumption, and optimal speed deviation better than the control group. The ICD showed particular benefits in low-complexity scenarios (e.g., slow and straight road) by fostering experiential learning. In contrast, the OSD was most effective in complex scenarios (e.g., highway exit with transition to stop sign), supporting action regulation through forward-looking guidance. This provided insights into the displays' functions and their optimal environmental conditions. The study suggests that adaptive ecodriving feedback systems—capable of switching between real-time and predictive feedback—can effectively support energy-efficient driving and driver EnDynA improvement.

Contribution to ROs

This article contributes to all ROs of the dissertation. It directly supports **RO1** by further validating the concept of EnDynA, showing that different feedback displays influence drivers' experienced EnDynA. In line with **RO2**, the study extends and refines methodological tools for assessing EnDynA, including a refined version of the EnDynA Scale, a single-item scale that can be administered verbally during driving, and a Situation Complexity Short Scale to assess driving situations' complexity. It addresses **RO3** by empirically showing that an ICD and an OSD support drivers' EnDynA and operational ecodriving. Furthermore, ICDs support experiential learning in low-complexity scenarios, while OSDs facilitate proactive regulation under high complexity. These results also inform **RO4** by demonstrating how attentional demands and task complexity interact with display type to influence drivers' ability to drive energy-efficiently. Finally, the study contributes to **RO5** by arguing in favor of the adaptive design of ecodriving feedback systems—suggesting that a context-sensitive combination of real-time and predictive feedback may be most effective in supporting sustainable driving behavior in EVs.

Author Contributions

CRediT statement: **Markus Gödker**: conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; resources; validation; visualization; writing – original draft; writing – review & editing. **Steffen Schmees**: data curation; methodology; resources; software; validation; writing – original draft; writing – review & editing. **Lukas Bernhardt**: data curation; investigation; project administration; resources; software; writing – original draft; writing – review & editing. **Daniel Görges**: conceptualization; funding acquisition; project administration; supervision; writing – review & editing. **Thomas Franke**: conceptualization; funding acquisition; project administration; supervision; writing – review & editing.

I contributed by developing the research idea and advancing the concept of EnDynA. I designed the displays with the support of Leonardt Wagner and created the experimental design and the questionnaires. I collected the data with significant assistance from student research assistants. I analyzed the data and wrote the manuscript with support from the co-authors. Please note that this research was conducted as part of the AMORi project and only possible through the contribution of the entire AMORi team: Lukas Bernhardt, Jan Heidinger, Vivien Moll, Elise Banach, Anne Tichy, Leonardt Wagner, Tobias Harms, and others. In particular, the technical implementation of the study planning in the laboratory (driving simulator, including route sectors and data processing, study management program, displays, etc.) and the data collection were carried out by the AMORi team. Parts of the experimental design for this study were developed with the support of team members (Tim Schrills, Marthe Gruner, and Mourad Zoubir) during the grant proposal writing process.

5.5 Cross-Study Summary of Empirical Findings

This dissertation delivered empirical evidence across four complementary studies investigating drivers' energy-related awareness and behavior and the influence of ecodriving feedback displays. This section organizes the key findings thematically, highlighting commonalities and divergences across experiments.

All studies assessed **EnDynA as a multi-faceted construct** comprising *experienced EnDynA*, measured via self-report, and *actual EnDynA*, measured via objective performance-based tasks such as consumption estimation and efficient trip identification. Articles 1–4 gradually revised and used the self-report **EnDynA Scale** to measure experienced EnDynA with high internal consistency. Articles 1, 2, and 3 employed objective measures to evaluate actual EnDynA, such as **consumption estimation** and **efficient trip identification**, or a combination of both measures into a single consumption change estimation item.

Articles 1, 3, and 4 found significant differences in **experienced EnDynA** between display types. Displays with higher levels of information provision (e.g., trace ICD or OSD) received higher EnDynA Scale scores than those with lower information provision (such as flow ICD or bar ICD). Additionally, in Article 1, confidence in actual EnDynA differed across display types. Experienced EnDynA demonstrated relationships with other relevant psychological concepts: It correlated with efficient trip identification and confidence in actual EnDynA (Article 1), intention to improve EnDnyA, energy consumption, and the EnDynA Enabling Scale (Article 3).

An effect of the display type on **energy-efficient driving** was observed in Article 3 (energy consumption) and Article 4 (energy consumption and optimal speed difference). **Mental workload** was successfully induced in Article 2 by the visual-manual n-back task (checked by the NASA-TLX mental load item) and in Article 4 (checked by the Situation Complexity Short Scale and DALI). Mental workload influenced consumption estimation and visual attention in Article 2 and moderated the effect of the display type on energy consumption in Article 4.

No significant effect of display type on **actual EnDynA** was observed in Articles 1 and 3. In Article 3, actual EnDynA improved across trials, but this improvement was independent of the display condition. Correlational analyses revealed mixed patterns: In Article 1, experienced and actual EnDynA were positively correlated. However, no such relationship was found in Articles 2 and 3. Additionally, in Article 3, actual EnDynA did not correlate with energy consumption.

Together, the findings provide a structured empirical basis for understanding how feedback displays, attention, and subjective awareness measures relate to drivers' performance and energy-related cognition across multiple experimental contexts.

6 Discussion

6.1 Contributions

In the following section, I will discuss the theoretical, methodological, and practical implications of the current results while also addressing the five ROs.

6.1.1 Theoretical Implications

RO1. Develop and validate the concept of EnDynA Across the studies, the EnDynA construct has evolved conceptually as a meaningful and measurable construct to describe drivers' knowledge state related to the current energy consumption and energy flows. As an energy-specific adaptation of SA, EnDynA was piloted in an early publication (Gödker et al., 2019) and has been developed and empirically tested in studies related to energy-efficient driving in this dissertation. The studies showed that EnDynA is sensitive to the informational value of different ecodriving feedback designs (as defined by Endsley, Bolté, & Jones, 2003) and to different workload conditions. EnDynA relates to other relevant constructs like confidence in EnDynA, energy consumption, intention to improve EnDynA, and ratings of how displays help to improve EnDynA (assessed by the EnDynA Enabling Scale).

The sensitivity of EnDynA to the informational value of the displays supports the assumptions outlined in the general theory of SA, as noted by Endsley (1995b) and further discussed by Endsley, Bolté, and Jones (2003). Additionally, the correlation with energy consumption, which can be seen as evidence of criterion validity, reinforces the theory of SA because it is assumed to drive optimal decisions and actions, as highlighted by (Endsley, 2000). In sum, the concept of EnDynA, as measured by the instruments of this dissertation, demonstrates aspects of content, convergent, and criterion validity and therefore supports SA theory.

The difference between subjective (self-reported) and objective (behaviorally assessed) EnDynA emerges as a conceptual issue. Across all studies, results regarding experienced EnDynA were quite consistent, while the results regarding actual EnDynA were rather mixed. Actual EnDynA was less sensitive to the informational value of the displays, and only efficient trip identification correlated with measures of experienced EnDynA in Article 1. Consistent with prior debates in the SA literature (e.g., Endsley, 2020), the present studies illustrate that subjective awareness and objective behavior/performance do not always align.

There is more than one approach to explain this divergence based on the present findings and the literature. First, it could simply be a matter of the individual measurement instruments used.

I will discuss this along with other issues regarding the method of consumption estimation and efficient trip identification in Section 6.1.2. Second, according to Endsley (2020), subjective SA should be reconceptualized as *confidence in SA*, which is therefore conceptually different from SA and has less performance-predictive value. This assumption is supported by the significant correlation between experienced EnDynA and confidence in actual EnDynA in Article 1. This would imply that experienced EnDynA should rather be understood as one's confidence in EnDynA. Third, experienced EnDnyA and actual EnDynA may evolve at different rates and are therefore not yet aligned in the present experiments. According to Endsley (2020), individuals with poor SA and who have high confidence in their inaccurate SA are likely to take actions that are inappropriate or ineffective and result in bad outcomes. Yet, in Article 3, the results showed that regardless of the actual EnDynA accuracy, higher experienced EnDynA was associated with better ecodriving outcomes. This challenges this assumption and suggests that there may still be a conceptual relationship between experienced and actual EnDnyA, and a different temporal scale would explain the divergent findings. Experienced EnDynA might simply evolve *faster* than actual EnDnyA, or actual EnDnyA has different requirements, e.g., the type of feedback. Taken together, this highlights the need for models of EnDynA that validly account for both aspects of EnDynA. Moreover, ecodriving feedback displays designed to support EnDynA should regard both aspects and try to calibrate the subjective and objective aspects of EnDynA.

I propose that EnDynA, as evaluated by the instruments developed in this dissertation, serves as a valuable indicator of the informed cognitive state that drivers develop while utilizing ecodriving feedback displays and supports the learning process associated with ecodriving. While this aligns closely with the theory of SA, it does not imply that the theoretical model of EnDynA is completely accurate, nor does it rule out other possible explanations for the observed effects. As mentioned in Section 2.4, SA and information processing stages may overlap (Wickens, 2015). It is indeed possible to conceptualize this cognitive state in various ways. This dissertation provides evidence that it is crucial to investigate whether drivers can accurately perceive, understand, and anticipate the information presented in ecodriving displays and whether they can effectively use this information to optimize their energy-efficient driving behaviors. It is, however, important to further investigate and discuss whether EnDynA remains a useful construct for describing perception and cognition in processing energy information in comparison to other conceptualizations.

RO3. Examine the effects of different ecodriving feedback displays on drivers' operational ecodriving Ecodriving feedback displays help drivers to enhance their operational ecodriving and ultimately save energy. Articles 3 and 4 are among the first to demonstrate through a driving simulator study that this improvement applies to EVs and not only ICEVs. This supports and expands the findings reported by Sanguinetti et al. (2020) and Sanguinetti et al. (2018), which assume a beneficial effect of consumption feedback displays on information precision and, consequently, learning. Additionally, across the studies, various aspects of operational ecodriving showed differences based on the type of display used. In Article 1, experienced EnDnyA and confidence in actual EnDynA were significantly influenced by the type of display. These findings are one explanation for the supportive effect of ecodriving feedback displays and verify the theoretical framework for operational ecodriving (as described in Section 2.4).

The central design variable of the display that explains its supportive effect may be the informational value of the feedback, particularly in addressing the information gap associated with EV driving, as proposed by Endsley, Bolté, and Jones (2003). By enhancing the informational value, such as incorporating the distance dimension in the trace ICD or predictive information in the OSD, operational ecodriving was supported. The significant differences observed in experienced EnDynA further support that EnDynA is the central variable explaining the display effect.

However, explanations beyond the scope of SA theory can also validly explain the observed findings. In addition to the display conditions that operationalized the informational value of the displays, control groups that received no energy information at all were included in Articles 3 and 4. If operational ecodriving is understood as a negative feedback loop (Powers et al., 2011) or a VVR-Unit (Hacker & Sachse, 2014), this would mean that the current and the goal state (actual and desired consumption) cannot be compared in the comparator of the control loop, thereby disrupting the loop. While in Article 3 (Figure 5, bottom right) no energy consumption improvement can be observed at all for the control group—supporting this assumption—there is a little improvement for the control group in Article 4 (Figure 3, middle). One possible explanation for this finding is that drivers' lower-level control loops related to vehicle handling are able to reduce the discrepancy a bit slower in Article 4 compared to Article 3 (due to the rapidly changing driving environment). In other words, drivers in Article 4 are slower in adapting to handle the driving simulator to execute their desired speed profiles than those in Article 3. The confounding effects of learning/adaptation processes (that are not of primary interest) are a key challenge in shorter driving simulation experiments. Still, this issue should be addressed to better isolate the effect of ecodriving feedback displays on operational ecodriving. However, as the display groups still outperformed the control groups in the present experiments, we can assume an effect of the ecodriving displays beyond mere adaptation to the simulator.

Extending on the perspective of action regulation theory (Hacker & Sachse, 2014) and the skill-rule-knowledge framework (J. Rasmussen, 1983), at least two explanations for the effect of the displays may be valid:

First, energy feedback provides input information that enables goal discrepancy assessment at *lower levels of control or action*, specifically at the level of flexible action patterns. This facilitates associative, rule-based behavior adaptations toward energy-efficient driving. From this perspective, the displays serve as a *sign* rather than a *symbol*. In the case of the present displays, these signs could be a rapid movement with high amplitude in the bar ICD, a large colored area in the trace ICD, or the green action cue in the OSD. The corresponding rule-based behavior or pattern reaction would be to immediately stop acceleration or to follow the green action cue to minimize discrepancy. Previous research also provides indications that ICDs can trigger heuristic reasoning (Moll & Franke, 2021), which resembles rule-based behavior.

The second explanation suggests that the ecodriving displays support comprehension through iterative hypothesis generation and testing at *higher levels of control and action*. This operates on the intellectual, conscious, and knowledge-based level by providing symbols. In this sense, the ecodriving displays offer symbolic information that allows drivers to consciously link behavior patterns, such as variations in acceleration, with their consequences, like energy consumption, thereby constructing robust mental models and strategies.

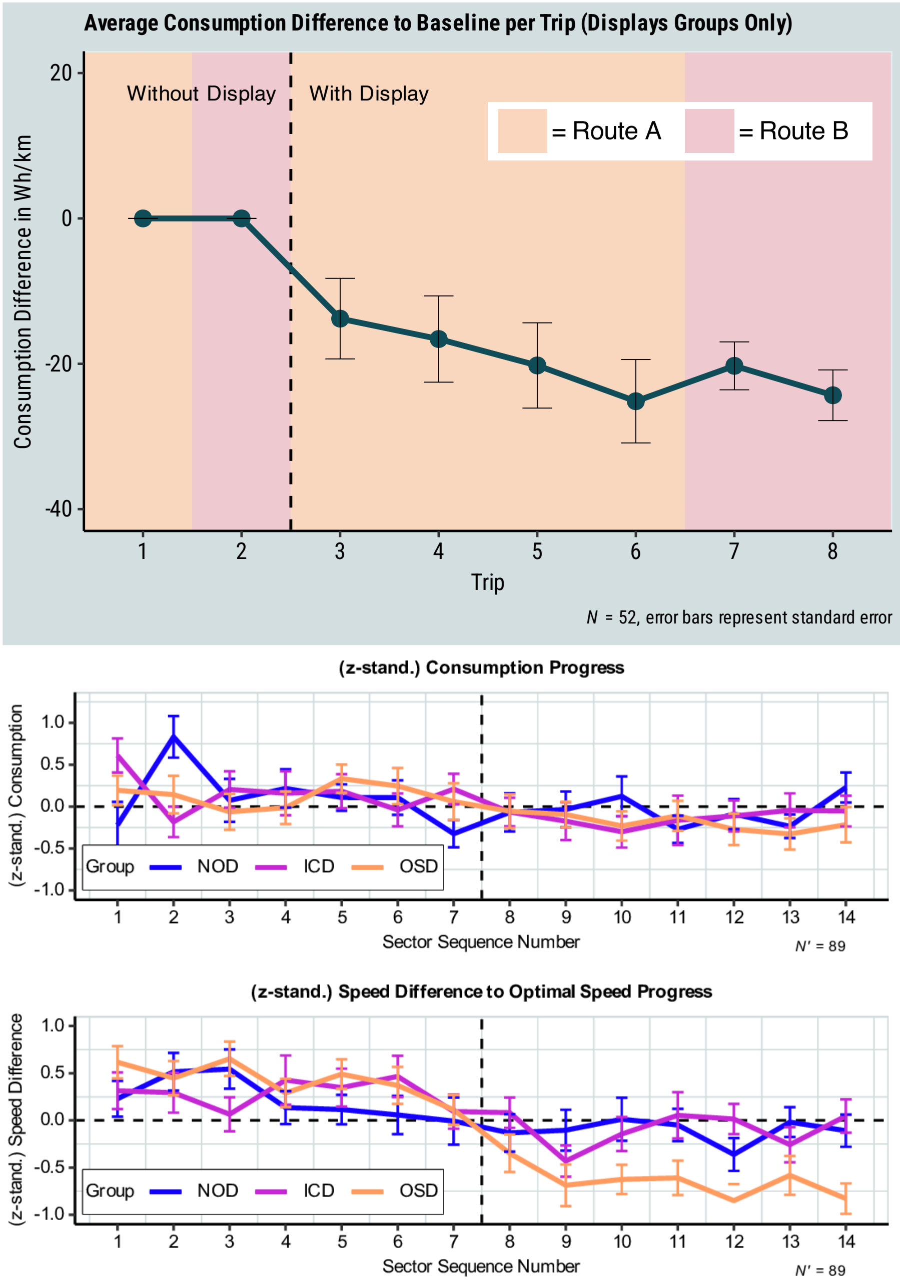
These two explanations do not need to be exclusive. In fact, the data from Articles 3 and 4 suggest that multiple mechanisms may be at work in parallel, operating at different temporal scales (Figure 7). For instance, the consumption data per trial for the display groups in Article 3 reveals a rather fast improvement between trips 2 and 3—after the displays have been introduced—likely driven by immediate behavior adjustments (reactions) based on the displays' signs. A more gradual improvement across trips 3 to 6 may hint towards another slower learning process based on symbolic information. Similarly, in Article 4, the OSD group exhibits a rapid behavioral adaptation in the optimal speed deviation following the display intervention. At the same time, the improvement in the ICD group may be more gradual, suggesting a slower, comprehension-oriented mechanism. If we assume that, according to the skill-rule-knowledge framework of J. Rasmussen (1983), the OSD communicates more signs and fewer symbols compared to the ICD, the rate of improvement in optimal speed may point towards two different levels of behavior adjustment. The fact that the ICD performs better in low-complexity situations (with lower cognitive demands) and the OSD in high-complexity situations (with higher cognitive demands) further supports this hypothesis. It also provides a theoretical account for the divergence observed between subjective and objective EnDynA measures in Articles 1 and 3. Drivers may *feel* more aware due to the fast, supportive feedback process, while performance improvements in tasks such as energy estimation require slower, conscious comprehension.

These findings may be an empirical hint towards a 2-layered effect of feedback displays: First, a fast effect for low-level adjustments. Prolonged exposure facilitates the development of higher-level comprehension through learning and reflection. Not only does the framework of this dissertation allow this interpretation. Moreover, it aligns with motor learning theories that distinguish between implicit, procedural learning and explicit, declarative knowledge acquisition (e.g., Buchanan & Wang, 2012; Schmidt & Wulf, 1997; Taylor & Ivry, 2012).

Overall, this dissertation extends the work by Sanguinetti et al. (2018) by linking design features of ecodriving feedback to the underlying cognitive mechanisms of information processing in driving. While the present findings offer only preliminary empirical evidence for the two distinguished processes of ecodriving feedback support, they open the door to future research on the temporal dynamics of feedback-supported learning. Key questions remain, such as which display elements activate which processes, how these processes interact, and whether their effects persist after feedback is temporarily removed.

Figure 7

Trial-Wise Results From Articles 3 and 4



Note. Trial-wise results from the study in Article 3 (top) and from Figure 5 in Article 4 (middle and bottom; Gödker, Schmees, Bernhardt, et al., 2025, p. 11). The top figure only includes data from the display groups, not the control group.

RO4. Assess the impact of mental workload and attentional processes on operational ecodriving Mental workload shapes drivers' ability to process energy information, influences operational ecodriving, and moderates the effect of ecodriving feedback displays. Articles 2 and 4 successfully varied mental workload demands by introducing a visual-manual n-back task (Article 2) and two different situation complexity conditions. In both cases, this affected operational ecodriving.

In Article 2, the high workload condition resulted in reduced visual attention toward the ICD despite the visual demands remaining constant (with no additional visual information introduced). The SEEV model (Horrey et al., 2006) does not explicitly account for this change in visual attention since all influencing factors (SEEV) remained the same. This raises the question of why the shift in visual attention towards the n-back task occurred. One possible explanation is that participants may have altered their task priorities, even though they were instructed that all tasks were equally important. In the high workload condition, the n-back task took on greater priority, which affected the perceived value of the windshield perspective. Additionally, participants demonstrated lower accuracy in their consumption estimations during the high workload condition (which is an indicator of actual EnDynA). Both findings would support the idea of *satisficing* by Summala (2007) that presumes more flexible boundaries of higher-level goal-states. In summary, under high workload conditions, drivers tend to limit their cognitive and visual engagement with energy information. This suggests that EnDynA relies on attention as a finite resource and is susceptible to interference.

Interestingly, subjective EnDynA ratings were not reduced under high workload, even though objective performance declined. This dissociation mirrors findings in the SA literature, where subjective ratings fail to reflect actual knowledge states due to limited metacognitive access (Endsley, 2020). It suggests that drivers may rely on heuristics such as the display's potential supportiveness to assess their awareness, leading to a potential mismatch.

Finally, building on the discussion above, the interaction between task complexity and display type, as observed in Article 4, points to the importance of matching displays to mental workload demands. While ICDs were particularly effective in low-complexity environments—where drivers had spare attentional capacity—the OSD proved more effective under high complexity, supporting action regulation on rule-based behavior level.

In sum, these findings support the assumption that the EnDynA construct is shaped not only by what information is available but also by how attentional and cognitive constraints govern the ability to perceive, comprehend, and project energy-related dynamics in real-time.

6.1.2 Methodological Implications and Learnings

RO2. Develop and refine methods and instruments for investigating drivers' operational ecodriving This dissertation contributes several methodological advancements to the empirical investigation of driver behavior, particularly in the context of energy-efficient driving and energy-related cognitive processes. The experimental paradigms, measurement tools, and study designs developed across the included studies offer insights for future research in ecodriving, HMI evaluation, and engineering/traffic psychology.

Two types of experimental paradigms were successfully employed. First, video-based online experiments proved to be effective in early-stage display testing, allowing for the controlled presentation of perceptual input, and were successfully extended to include both workload manipulations and self-controlled occlusion (Articles 1 and 2). Second, driving simulator studies—implemented both on a longer continuous route (Article 3) and on a modular test environment (EcoDrivingTestPark; Article 4)—demonstrated feedback display manipulation effects. These frameworks offer adaptable and scalable platforms for assessing ecodriving displays under different levels of control, realism, and complexity, particularly prior to conducting field studies.

A key methodological contribution of this work is the development and validation of multiple instruments for assessing EnDynA. For experienced EnDynA, three self-report tools were iteratively tested and refined:

1. The 8-item *EnDynA Scale* to retrospectively assess experienced EnDynA gained during driving or display interaction.

2. A *single-item EnDynA Scale* for in-situ measures, offering minimal intrusiveness and easy administration.

3. The 8-item *EnDynA Enabling Scale*, capturing the experienced ability of a display to support the formation of EnDynA, enabling direct display evaluations from the user perspective.

Despite the advances in subjective EnDynA assessment, measuring actual EnDynA—i.e., drivers' capacity to accurately perceive, comprehend, and predict energy dynamics—remains challenging. Objective methods, such as consumption estimation and efficient trip identification, demonstrate methodological limitations. Average consumption estimation is difficult without some form of energy consumption feedback on more aggregated levels. In Article 3, participants received general information in the instructions about expected consumption ranges under normal circumstances to help in estimations (see Appendix A in Article 3). However, in modular environments, as in the EcoDrivingTestPark (Article 4), variability across sectors makes such general statements impossible. Similarly, efficient trip identification can only be meaningful when the route, or at least the consumption distribution, is tightly similar (as in Articles 1 and 2). Moreover, the data is very rough—large amounts of video material are required to produce

Table 2

Energy Dynamics Awareness (EnDynA) Scale

Item	Text
1	I have a very good overview of the energy dynamics of the system.
2	I can precisely estimate the influence of different factors on energy consumption.
3	I understand which of my actions influence the energy dynamics.
4	I am able to correctly predict energy consumption in future situations.
5	I know exactly how to optimize energy consumption.
6	I am sure I can notice errors in my energy-efficient behavior.
7	I feel confident in choosing energy-efficient actions.
8	I feel confident in optimizing energy consumption.

Note. The instructions explained the rating scheme ("Please indicate your level of agreement with the following statements."). The agreement to the eight items had to be indicated on a 6-point Likert scale reading: *completely disagree*, *largely disagree*, *slightly disagree*, *slightly agree*, *largely agree*, *completely agree*, coded as 1–6 for data analysis. From Gödker, Schmees, Bernhardt, et al. (2025, p. 5), see Appendix A in Article 4 for original German items.

minimal discriminative data. These limitations underscore the value and necessity of subjective measures.

In the context of EnDynA, two supplementary measurement instruments were developed and tested: the EnDynA Enabling Scale and a scale dedicated to assessing the intention to improve EnDynA. Both of these instruments proved to be reliable, demonstrating consistent results across various applications. The EnDynA Enabling Scale is designed to allow drivers to rate their experiences with the display after use. This rating seems to be linked to the overall effectiveness of the display to support experienced EnDynA. The intention to improve EnDynA Scale serves as a valuable tool for sampling the motivational magnitude to learn and improve one's action regulation among drivers. By assessing users' intentions to engage with the system, this scale can contribute to a more effective implementation of EnDynA-supporting displays in practical settings.

The subjective measurement of mental workload and situational complexity also yielded valuable insights. The NASA-TLX workload scale showed limited sensitivity in certain contexts: only the mental demand item consistently captured workload differences in Article 2. In contrast, the Driving Activity Load Index (DALI) was more responsive to complexity variation and proved more useful in driving contexts, as shown in Article 4. For situation complexity, a short scale adapted from Banach and Gödker (2024) was successfully implemented and offers a promising and reliable tool to rate the expected cognitive demands in driving situations for future driving research.

Finally, the dissertation yielded insights into simulator setup and user experience. In Article 3, 15 of 97 participants dropped out due to simulator sickness, whereas only 4 of 105 did so in Article

4—despite the latter involving more maneuver-intensive scenarios. While chance effects cannot be ruled out, possible contributing factors include technical improvements (e.g., lower latency, optimized camera perspective) but, more importantly, the introduction of a structured tutorial track that gradually introduced longitudinal and lateral control, followed by elevation. These findings emphasize the importance of scenario design and participant onboarding for ensuring data quality and participant retention.

The dissertation also highlights the importance of carefully selected scenarios and standardized instructions. Especially in simulator-based experiments, scenario composition directly affects the reliability of ecodriving measurements. Repeated route designs (as used in Article 3) facilitated the detection of within-subject improvements but lacked representativeness. Conversely, sector-based modular test parks (Article 4) increased realism and variety but introduced difficulties in comparing energy consumption across trials because the baseline consumption distribution differs from situation to situation. These trade-offs underline the need for methodological designs that balance experimental control with ecological validity.

6.1.3 Practical Implications

RO5. Integrate findings from empirical studies to formulate recommendations for future ecodriving feedback systems The empirical findings of this dissertation yield a set of actionable design implications for ecodriving feedback systems that are grounded in cognitive theory and experimental evidence.

First, feedback systems should aim not only to instruct drivers toward more efficient behavior but also to support their comprehension of energy flows and their temporal dynamics. A design criterion could be defined as ”informational value,” which refers to the quality and extent of information provided that is relevant to task goals. In this dissertation, this was done, for example, through the addition of a spatial (distance-based) dimension to ICDs, which transforms raw energy flow data into two-dimensional visual areas that better reflect real-world consumption amounts. This design allows drivers to better associate the amount of energy consumed with the duration of the maneuver, thereby reducing perceptual biases such as peak bias and facilitating a more accurate understanding of energy dynamics (Franke, Görges, & Arend, 2019; Moll & Franke, 2021). In contrast, conventional bar displays may be easier to interpret at a glance but require drivers to aggregate instantaneous values over time, a cognitively demanding task that increases susceptibility to perceptual and memory distortions.

Experienced EnDynA plays a motivational role. As Article 3 showed, drivers with higher levels of experienced EnDynA also expressed stronger intentions to continue using feedback information to improve their understanding. This finding highlights the potential of interface designs that not only convey energy data but also promote a sense of insight and control. The EnDynA

Enabling Scale provides a useful tool for evaluating this capacity during the early stages of interface development.

A key design challenge lies in balancing *simplicity* and *transparency*. In complex traffic conditions, feedback that reduces cognitive demands—such as the OSD in Article 4—may be more effective by guiding immediate behavior. However, such simplified feedback may have limited learning value and could lose its effectiveness once the display is removed. Conversely, detailed feedback that supports internal model building—such as temporally extended ICDs—may facilitate long-term learning but is likely more effective under conditions of low workload. Therefore, the balance between cognitive load and informational depth must be carefully adjusted according to the context of use and the desired psychological manipulation.

The varying effectiveness of displays across driver states and situational demands suggests considerable potential for adaptive feedback systems. Article 2 showed that drivers under high workload conditions were less likely to attend ICDs, leading to reduced EnDynA. While this does not imply that such feedback is ineffective under load, it suggests that drivers' capacity to perceive and process energy-relevant information fluctuates. Future interfaces may use vehicle sensor data (e.g., low steering or acceleration activity) to detect low workload windows and adjust the timing or modality of feedback accordingly. Such adaptive systems could enhance both attention allocation for safety and EnDynA.

A further finding from Article 4 illustrates that OSDs can effectively guide drivers toward optimal speed behavior, even if the resulting improvements in energy consumption are less pronounced (see Figure 7, middle). This suggests that the behavioral guidance is effective, but the underlying optimization algorithm may require further refinement. With continued advances in vehicle sensors, V2X communication, and data-driven route modeling, the precision and personalization of such guidance displays could be significantly enhanced in future systems. In summary, the studies presented in this dissertation contribute to a psychologically grounded design of feedback displays in the context of ecodriving.

6.2 Critical Reflection and Outlook

While the findings of this dissertation offer meaningful theoretical and practical contributions to the study of ecodriving and human-machine interaction in EVs, several limitations should be acknowledged. These limitations point to concrete directions for future research and further methodological refinement.

One core challenge concerns the operationalization of the independent variable—namely, the informational value of ecodriving feedback displays. Theoretical foundations such as Endsley's SA framework (Endsley, Bolté, & Jones, 2003) provide important guidance, but they remain abstract in terms of actionable design parameters. In this dissertation, display manipulations were based on conceptual distinctions in feedback content (e.g., conventional vs. predictive, one- vs. two-dimensional representations). However, it remains difficult to assess the validity of these manipulations with high precision. This difficulty resembles the challenges other ecodriving HMI research had before (e.g., Dahlinger et al., 2018). Future research should aim to further formalize and quantify display characteristics that contribute to informational value to enable more rigorous operationalization of ecodriving feedback interventions.

The sample population used in the driving simulator studies mainly comprised university students, a relatively uniform group with limited driving experience. This sample characteristic can help to better investigate the initial learning process. However, it also significantly limits the relevance of the findings to the general driving public, which includes a much wider range of demographics and driving behaviors. To enhance the robustness and relevance of future research, it is essential to replicate and expand upon the existing results with a more diverse sample. Ideally, this study would include participants from various age groups, along with individuals of different driving experience levels—from beginners to experienced drivers. Incorporating a sample with varying levels of Affinity for Technology Interaction (Franke, Attig, & Wessel, 2019) could provide valuable insights into how this factor influences ecodriving learning, as correlational studies have highlighted the importance of Affinity for Technology Interaction in ecodriving (Gödker, Moll, & Franke, 2024b).

Another limitation is the short-term scope of the studies. Interventions were introduced within single-session online or simulator experiments, typically lasting 90 to 105 minutes. While this duration is cognitively demanding—especially in driving simulations—it does not allow conclusions about long-term learning or behavioral change. Long-term field studies or longitudinal experiments, which may include driver training modules or repeated exposures, would be valuable next steps for assessing the durability of EnDynA development and its impact on sustained energy efficiency. However, a recent literature review indicates that not only does the duration of exposure affect learning, but also the sequence and quality of the experiences involved (Nkusi et al., 2025). This observation supports the approach taken in this dissertation and encourages a deeper reflection on the situations and driving scenarios that participants encounter.

The ecological validity of the simulator studies is limited by several factors. First, the absence of physical acceleration cues (e.g., G-forces) and limited peripheral visual information may reduce validity. It not only diminishes immersion but also impacts energy information processing, as these elements are typically used as indirect indicators of the physical phenomenon of energy. Certain advanced driving simulations with kinematics and enhanced degrees of freedom can address this limitation during later stages of display development, although they are significantly more expensive (see Bruck et al., 2021, for a driving simulation technology review). Second, although already validated to some degree (Gödker, Schmees, Bernhardt, et al., 2024; Heidinger et al., 2023), the simulated energy consumption models may deviate from real-world data, particularly when using simplified vehicle physics. These models have been used to generate the data for the ICDs and for measuring energy consumption as a dependent variable. This raises questions about the fidelity of consumption feedback and the validity of the observed energy consumption as a dependent variable. However, from an experimental design standpoint, as long as the energy consumption values are not completely unrealistic, simplified models can still be useful. It is essential to ensure that the consumption information provided by the ICD aligns with the average consumption used as a dependent variable. This allows drivers to reduce their average consumption with the help of the ICD. Even real EVs can vary in terms of how different driving behaviors affect energy consumption, requiring drivers to adapt their ecodriving practices to suit each specific electric motor. Yet, future studies could validate results by combining test-track experiments with real vehicle telemetry and high-fidelity driving simulators with even more validated energy models.

The EnDynA Scale was developed as an energy domain-specific adaptation of SA assessment techniques. While the scale demonstrated reliability and validity across studies, it remains an open question how precisely it maps to SA theory. Some items may insufficiently reflect the three-level SA structure or may overlap with constructs such as confidence, motivation, or perceived usefulness. Further psychometric validation with more sophisticated convergent and discriminant validity testing is needed to refine the conceptual and empirical boundaries of EnDynA measurement.

Additionally, certain experimental design aspects impose constraints on interpretation, e.g., the control group definition. Articles 1 and 2 used a within-subject design without a control group, limiting effect interpretation. Across the other studies, the control condition was typically defined as the absence of any display, which represents an extreme case. Including alternative control groups—such as non-informative or fake data displays—would allow more nuanced comparisons and help isolate the cognitive effects of perceived feedback versus actual information content.

The usefulness and relevance of the driving scenarios in Articles 3 and 4 require more detailed consideration. While scenarios were designed to be comparable across participants, their representativeness of real-world ecodriving situations remains uncertain. Future work could benefit from diagnostic scenario design frameworks, in which scenarios are both highly sensitive to feedback-induced behavior changes and statistically representative of real-world driving contexts. Another approach would be to create an experiment with only highly diagnostic scenarios but quantify the representativeness of these diagnostic scenarios (e.g., they account for 60 % of real-world driving situations) to estimate the assumed efficiency effect on everyday driving.

One important omission in the current research is the lack of safety-related performance metrics (Duan & Abbas, 2019; Green, 2013). A comprehensive risk-benefit analysis of ecodriving displays—especially under complex or distracted conditions (Fastenmeier & Gstalter, 2007)—remains to be conducted. This is essential for ensuring that energy efficiency gains do not compromise driving safety.

Finally, the role of ecodriving in the context of increasing vehicle automation warrants further investigation and discussion. Even in automated driving modes, drivers will have goals related to time, energy, or comfort. Ecodriving feedback displays should then still provide drivers with information that helps them to make appropriate higher-level decisions to achieve their goals. Moreover, in everyday driving, there may occur critical range situations in which energy-aware manual intervention is beneficial or necessary. Understanding how EnDynA can be supported—or how ecodriving feedback should adapt—in automated vehicles represents a promising avenue for future work.

6.3 Brief Summary of the Key Takeaways

Ecodriving feedback displays can improve ecodriving—But context matters This dissertation provides the first controlled empirical evidence that ecodriving feedback display can improve operational ecodriving in EVs. In particular, the provision of information for task-relevant goals (informational value) seems to constitute a central design criterion in ecodriving feedback displays. The present studies showed that ICDs—a type of ecodriving display that has been included in vehicles' interior design for many years—support energy-efficient behavior in EVs. This is particularly true in low-complexity environments. However, the effectiveness of such displays is not guaranteed across all contexts. As demonstrated in Articles 2 and 4, higher workload or situational complexity can reduce drivers' attention to energy displays and attenuate their effectiveness. This highlights the importance of adapting display design to the cognitive context of driving.

Ecodriving displays that provide predictive guidance are a relatively novel HMI approach and have demonstrated promising effects in Article 4. These types of displays might excel in high-complexity environments in particular.

In future implementations, the alternation or adaptation between conventional consumption feedback (ICD) and predictive guidance (OSD) may be a promising strategy to maintain both effectiveness and driver engagement across conditions. In addition, preparatory training—either in driving simulators or test-track settings—can build foundational awareness of energy dynamics that can transfer to real-world behavior.

What it means to comprehend energy This dissertation applied engineering psychology theory to explain what it means to comprehend energy for ecodriving in psychological terms. I conceptualize EnDynA as an informed cognitive state that reflects drivers' perception, comprehension, and anticipation of energy consumption. The findings support—in general—the theories proposed in the present theoretical framework. SA theory and other engineering psychology theories are capable of explaining much of the findings of this dissertation and integrating them into a general understanding of ecodriving.

An additional theoretical contribution of this dissertation is the psychological framing of energy comprehension as a process involving both rule-based reactions and more conscious understanding. Different forms of feedback appear to target different cognitive levels: while fast, sign-based feedback supports low-level behavioral adjustments, symbolic, temporally extended feedback fosters deeper learning and mental model development. This layered perspective might also explain the observed divergence between subjective and objective EnDynA and suggests that comprehension is shaped by both the structure of the interface, the demands of the context, and with different temporal rates. As such, comprehension of energy in ecodriving should not be viewed as a unitary outcome but as a temporally and situationally dependent process with varying persistence and transferability.

These interpretations are justifiable by engineering psychology theories and might therefore also be generalizable to other domains of human-energy interaction, e.g., household appliances or industry.

Advancing the methodological toolbox for ecodriving research This dissertation also makes several methodological contributions that enhance the empirical investigation of ecodriving behavior and driver cognition. It introduces and validates new experimental paradigms. This includes a video-based experiment that allows for the investigation of driver cognition in a low-cost, scalable way. Interfaces can be tested in early development stages in a controlled setting. Moreover, the combination with a visual-manual n-back task allows for the manipulation of mental workload to mimic real-world cognitive demands. Also, this dissertation created driving simulation experiments considering the distinct requirements for the valid comparison of driving data in ecodriving research. Experimental design trade-offs are presented for future experiments (see Section 3.1). These experimental paradigms allow researchers to examine driver attention, energy comprehension, and feedback effectiveness with high experimental control and varying levels of realism.

In addition, a range of novel measurement instruments were developed and tested, including (1) the 8-item *EnDynA Scale* and its single-item version, (2) the *EnDynA Enabling Scale* for evaluating display support, (3) the scale to assess *intention to improve EnDynA*, (4) the Situation Complexity Short Scale, (5) the *self-controlled occlusion paradigm* as a low-cost proxy for attention, and (6) judgment-based tasks such as *consumption estimation* and *efficient trip identification*. Together, these instruments offer a scalable and transferable toolkit for researchers and practitioners aiming to assess cognitive and behavioral effects of ecodriving support systems, especially during early development stages.

7 Conclusion

This cumulative dissertation investigates humans using ecodriving feedback displays and describes how they affect drivers' cognitive processing and energy efficiency in EVs. The dissertation focuses on advancing theoretical understanding, methodological rigor, and interface design. Anchored in psychological theories of control and regulation, human information processing, and SA, the present research conceptualized and empirically investigated EnDynA—a domain-specific adaptation of SA tailored to energy-relevant driver cognition in EVs.

The research objectives were addressed through four manuscripts, each contributing uniquely to the overarching research objective. Article 1 laid the conceptual foundation for EnDynA, introducing and validating the EnDynA self-report scale and demonstrating that experienced EnDynA varies meaningfully across different ICD designs. Article 2 extended this work by integrating visual attention theory and workload manipulation, showing that cognitive demand impairs energy-related estimation accuracy and alters visual attention patterns, even when display information remains constant. Article 3 transitioned from perceptual studies to behavioral measurement, revealing that ICDs with high informational value enhance drivers' subjective awareness and improve operational ecodriving over time in a driving simulator environment. Article 4 compared real-time (ICD) and predictive (OSD) feedback mechanisms, showing that each display type supports energy-efficient driving under different situational complexities, thereby underscoring the value of adaptive feedback systems.

The manuscripts provide converging evidence that ecodriving feedback displays can support energy-efficient behavior and awareness in EVs, yet their effectiveness depends on the interplay of informational value, cognitive workload, and driver goals. Drivers rated displays with greater informational value (e.g., trace ICDs and OSDs) as more helpful for forming EnDynA, and these displays were associated with improved behavioral outcomes under appropriate conditions. Furthermore, the development and application of multiple measurement tools—including the EnDynA Scale, consumption estimation tasks, trip identification measures, and self-controlled occlusion paradigms—enabled a more nuanced understanding of how drivers perceive and use energy feedback in real time.

From a cumulative perspective, the included manuscripts demonstrate conceptual coherence by advancing a joint theoretical framework, empirical integration through a consistent measurement strategy, and thematic continuity in their focus on EnDynA and feedback design. While each manuscript addressed distinct research questions, they collectively advance the understanding of the psychological mechanisms through which feedback displays shape energy-related behavior and cognition in EVs.

This dissertation contributes to the growing body of sustainability-related research in human factors (i.e., *green ergonomics*; Thatcher, 2013) and transportation by showing how interface design can act as a psychological lever for promoting energy comprehension and energy-efficient behavior. It also underscores the importance of theory-driven, methodologically sound, and context-sensitive approaches to understanding human–machine interaction in mobility settings.

In conclusion, this cumulative dissertation supports the assumption that ecodriving feedback displays, if thoughtfully designed, can close the cognitive control loop encompassing drivers and the energy dynamics of their vehicles. By enhancing drivers' EnDynA, these displays foster a more informed and energy-efficient vehicle control. Looking ahead, future research should extend these findings to longitudinal studies in the field and explore how such displays can integrate into increasingly automated driving environments. Fostering a human-centered and psychologically grounded design is crucial to enhance energy efficiency, as it depends not only on technical potential but also on user behavior.

8 References

af Wåhlberg, A. E. (2007). Long-term effects of training in economical driving: Fuel consumption, accidents, driver acceleration behavior and technical feedback. *International Journal of Industrial Ergonomics*, *37*(4), 333–343. https://doi.org/10.1016/j.ergon.2006.12.003

Allison, C. K., Fleming, J. M., Yan, X., Lot, R., & Stanton, N. A. (2021). *Assisted eco-driving: A practical guide to the design and testing of an eco-driving assistance system (EDAS)* (1st ed.). CRC Press.

Attari, S. Z., DeKay, M. L., Davidson, C. I., & Bruine de Bruin, W. (2010). Public perceptions of energy consumption and savings. *Proceedings of the National Academy of Sciences*, *107*(37), 16054–16059. https://doi.org/10.1073/pnas.1001509107

Axsen, J., Plötz, P., & Wolinetz, M. (2020). Crafting strong, integrated policy mixes for deep CO2 mitigation in road transport. *Nature Climate Change*, *10*, 809–818. https://doi.org/10.1038/s41558-020-0877-y

Baird, J. C., & Brier, J. M. (1981). Perceptual awareness of energy requirements of familiar objects. *Journal of Applied Psychology*, *66*(1), 90–96. https://doi.org/https://doi.org/10.1037/0021-9010.66.1.90

Banach, E. S., & Gödker, M. (2024). Assessing driving situation complexity: Development and pilot evaluation of a short questionnaire with traffic psychology experts. In T. M. Buzug, H. Handels, C. Hübner, A. Mertins, S. Müller, P. Rostalski, & N. Bunzeck (Eds.), *Student conference proceedings 2024*. Infinite Science Publishing.

Barkenbus, J. N. (2010). Eco-driving: An overlooked climate change initiative. *Energy Policy*, *38*(2), 762–769. https://doi.org/10.1016/j.enpol.2009.10.021

Bauer, C., Hofer, J., Althaus, H.-J., Del Duce, A., & Simons, A. (2015). The environmental performance of current and future passenger vehicles: Life cycle assessment based on a novel scenario analysis framework. *Applied Energy*, *157*, 871–883. https://doi.org/10.1016/j.apenergy.2015.01.019

Baumann, M., & Krems, J. F. (2007). Situation awareness and driving: A cognitive model. In P. C. Cacciabue (Ed.), *Modelling driver behaviour in automotive environments* (pp. 253–265). Springer. https://doi.org/10.1007/978-1-84628-618-6_14

Baumann, M., & Krems, J. F. (2009). A comprehension based cognitive model of situation awareness. In V. G. Duffy (Ed.), *Digital human modeling* (pp. 192–201). Springer.

Bingham, C., Walsh, C., & Carroll, S. (2012). Impact of driving characteristics on electric vehicle energy consumption and range. *IET Intelligent Transport Systems*, *6*(1), 29–35. https://doi.org/10.1049/iet-its.2010.0137

Bouter, A., Hache, E., Ternel, C., & Beauchet, S. (2020). Comparative environmental life cycle assessment of several powertrain types for cars and buses in France for two driving cycles: “worldwide harmonized light vehicle test procedure” cycle and urban cycle. *The International Journal of Life Cycle Assessment*, *25*(8), 1545–1565. https://doi.org/10.1007/s11367-020-01756-2

Braun, A., & Rid, W. (2018). Assessing driving pattern factors for the specific energy use of electric vehicles: A factor analysis approach from case study data of the Mitsubishi i–MiEV minicar. *Transportation Research Part D: Transport and Environment*, *58*, 225–238. https://doi.org/10.1016/j.trd.2017.11.011

Bruck, L., Haycock, B., & Emadi, A. (2021). A Review of Driving Simulation Technology and Applications. *IEEE Open Journal of Vehicular Technology*, *2*, 1–16. https://doi.org/10.1109/OJVT.2020.3036582

Buberger, J., Kersten, A., Kuder, M., Eckerle, R., Weyh, T., & Thiringer, T. (2022). Total CO2-equivalent life-cycle emissions from commercially available passenger cars. *Renewable and Sustainable Energy Reviews*, *159*, 112158. https://doi.org/10.1016/j.rser.2022.112158

Buchanan, J. J., & Wang, C. (2012). Overcoming the guidance effect in motor skill learning: Feedback all the time can be beneficial. *Experimental Brain Research*, *219*(2), 305–320. https://doi.org/10.1007/s00221-012-3092-x

Carver, C. S., & Scheier, M. F. (1982). Control theory: A useful conceptual framework for personality–social, clinical, and health psychology. *Psychological Bulletin*, *92*(1), 111–135. https://doi.org/10.1037/0033-2909.92.1.111

Carver, C. S., & Scheier, M. F. (2000). On the structure of behavioral self-regulation. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 41–84). Elsevier. https://doi.org/10.1016/B978-012109890-2/50032-9

Chen, F., Taylor, N., & Kringos, N. (2015). Electrification of roads: Opportunities and challenges. *Applied Energy*, *150*, 109–119. https://doi.org/10.1016/j.apenergy.2015.03.067

Chen, Z., Xiong, S., Chen, Q., Zhang, Y., Yu, J., Jiang, J., & Wu, C. (2022). Eco-driving: A scientometric and bibliometric analysis. *IEEE Transactions on Intelligent Transportation Systems*, *23*(12), 22716–22736. https://doi.org/10.1109/TITS.2022.3200588

Cocron, P., Bühler, F., Franke, T., Neumann, I., Dielmann, B., & Krems, J. F. (2013). Energy recapture through deceleration – regenerative braking in electric vehicles from a user perspective. *Ergonomics*, *56*(8), 1203–1215. https://doi.org/10.1080/00140139.2013.803160

Craik, K. J. W. (1947). Theory of the human operator in control systems. *British Journal of Psychology. General Section*, *38*(2), 56–61. https://doi.org/10.1111/j.2044-8295.1947.tb01141.x

Da Costa, V. B. F., Bitencourt, L., Dias, B. H., Soares, T., De Andrade, J. V. B., & Bonatto, B. D. (2025). Life cycle assessment comparison of electric and internal combustion vehicles: A review on the main challenges and opportunities. *Renewable and Sustainable Energy Reviews*, *208*, 114988. https://doi.org/10.1016/j.rser.2024.114988

Dahlinger, A., & Wortmann, F. (2016). Towards the design of eco-driving feedback information systems – A literature review. In S. Straßburger, D. Fischer, V. Niessen, & D. Stelzer (Eds.), *Multikonferenz Wirtschaftsinformatik (MKWI) 2016* (pp. 801–812). Universitätsverlag Ilmenau.

Dahlinger, A., Wortmann, F., Ryder, B., & Gahr, B. (2018). The impact of abstract vs. concrete feedback design on behavior insights from a large eco-driving field experiment. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–11. https://doi.org/10.1145/3173574.3173953

Donkers, A., Yang, D., & Viktorović, M. (2020). Influence of driving style, infrastructure, weather and traffic on electric vehicle performance. *Transportation Research Part D: Transport and Environment*, *88*, 102569. https://doi.org/10.1016/j.trd.2020.102569

Duan, X., & Abbas, M. (2019). Safety assessment of ecodriving vehicles on following traffic. *Transportation research record*. https://doi.org/10.1177/0361198119843090

Durso, F. T., Hackworth, C. A., Truitt, T. R., Crutchfield, J., Nikolic, D., & Manning, C. A. (1998). Situation Awareness as a Predictor of Performance for En Route Air Traffic Controllers. *Air Traffic Control Quarterly*, *6*(1), 1–20. https://doi.org/10.2514/atcq.6.1.1

Endsley, M. R. (1995a). Measurement of situation awareness in dynamic systems. *Human Factors*, *37*(1), 65–84. https://doi.org/10.1518/001872095779049499

Endsley, M. R. (1995b). Toward a theory of situation awareness in dynamic systems. *Human Factors*, *37*(1), 32–64. https://doi.org/10.1518/001872095779049543

Endsley, M. R. (2000). Theoretical underpinnings of situation awareness: A critical review. In M. R. Endsley & D. J. Garland (Eds.), *Situation awareness analysis and measurement* (pp. 3–32). Lawrence Erlbaum Associates Publishers.

Endsley, M. R. (2015). Situation awareness misconceptions and misunderstandings. *Journal of Cognitive Engineering and Decision Making*, *9*(1), 4–32. https://doi.org/10.1177/1555343415572631

Endsley, M. R. (2020). The divergence of objective and subjective situation awareness: A meta-analysis. *Journal of Cognitive Engineering and Decision Making*, *14*(1), 34–53. https://doi.org/10.1177/1555343419874248

Endsley, M. R. (2021). A systematic review and meta-analysis of direct objective measures of situation awareness: A comparison of SAGAT and SPAM. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *63*(1), 124–150. https://doi.org/10.1177/0018720819875376

Endsley, M. R., Bolstad, C. A., Jones, D. G., & Riley, J. M. (2003). Situation awareness oriented design: From user's cognitive requirements to creating effective supporting technologies. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *47*, 268–272. https://doi.org/10.1177/154193120304700304

Endsley, M. R., Bolté, B., & Jones, D. G. (2003). *Designing for situation awareness: An approach to user-centered design* (1st ed.). Taylor & Francis.

European Commission: Joint Research Centre, Crippa, M., Guizzardi, D., Pagani, F., Banja, M., Muntean, M., Schaaf, E., Monforti-Ferrario, F., Becker, W., Quadrelli, R., Risquez Martin, A., Taghavi-Moharamli, P., Köykkä, J., Grassi, G., Rossi, S., Melo, J., Oom, D., Branco, A., San-Miguel, J., … Pekar, F. (2024). *GHG emissions of all world countries*. Publications Office of the European Union. https://doi.org/10.2760/4002897

Evans, L. (1979). Driver behavior effects on fuel consumption in urban driving. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *21*(4), 389–398. https://doi.org/10.1177/001872087902100401

Fastenmeier, W., & Gstalter, H. (2007). Driving task analysis as a tool in traffic safety research and practice. *Safety Science*, *45*(9), 952–979. https://doi.org/10.1016/j.ssci.2006.08.023

Franke, T., Arend, M. G., McIlroy, R. C., & Stanton, N. A. (2016). Ecodriving in hybrid electric vehicles – Exploring challenges for user-energy interaction. *Applied Ergonomics*, *55*, 33–45. https://doi.org/10.1016/j.apergo.2016.01.007

Franke, T., Attig, C., & Wessel, D. (2019). A personal resource for technology interaction: Development and validation of the affinity for technology interaction (ATI) scale. *International Journal of Human–Computer Interaction*, *35*(6), 456–467. https://doi.org/10.1080/10447318.2018.1456150

Franke, T., Görges, D., & Arend, M. G. (2019). The energy interface challenge. Towards designing effective energy efficiency interfaces for electric vehicles. *Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 35–48. https://doi.org/10.1145/3342197.3344526

Franke, T., & Krems, J. F. (2013). Interacting with limited mobility resources: Psychological range levels in electric vehicle use. *Transportation Research Part A: Policy and Practice*, *48*, 109–122. https://doi.org/10.1016/j.tra.2012.10.010

Franke, T., Rauh, N., Günther, M., Trantow, M., & Krems, J. F. (2016). Which factors can protect against range stress in everyday usage of battery electric vehicles? Toward enhancing sustainability of electric mobility systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *58*(1), 13–26. https://doi.org/10.1177/0018720815614702

Frese, M., & Zapf, D. (1994). Action as the core of work psychology: A German approach. In *Handbook of industrial and organizational psychology* (2nd ed., pp. 271–340). Consulting Psychologists Press.

Friedlingstein, P., O'Sullivan, M., Jones, M. W., Andrew, R. M., Bakker, D. C. E., Hauck, J., Landschützer, P., Le Quéré, C., Luijkx, I. T., Peters, G. P., Peters, W., Pongratz, J., Schwingshackl, C., Sitch, S., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S. R., Anthoni, P., … Zheng, B. (2023). Global Carbon Budget 2023. *Earth System Science Data*, *15*(12), 5301–5369. https://doi.org/10.5194/essd-15-5301-2023

Fuller, R. (2005). Towards a general theory of driver behaviour. *Accident Analysis & Prevention*, *37*(3), 461–472. https://doi.org/10.1016/j.aap.2004.11.003

Fuller, R. (2011). Driver control theory. In B. E. Porter (Ed.), *Handbook of traffic psychology* (pp. 13–26). Elsevier. https://doi.org/10.1016/B978-0-12-381984-0.10002-5

Galvin, R. (2017). Energy consumption effects of speed and acceleration in electric vehicles: Laboratory case studies and implications for drivers and policymakers. *Transportation Research Part D: Transport and Environment*, *53*, 234–248. https://doi.org/10.1016/j.trd.2017.04.020

Gates, B. (2021). *How to avoid a climate disaster: The solutions we have and the breakthroughs we need* (1st ed.). Alfred A. Knopf.

Gödker, M., Dresel, M., & Franke, T. (2019). EDA scale - Assessing awareness for energy dynamics. In F. Alt, A. Bulling, & T. Döring (Eds.), *Mensch und Computer 2019 - Tagungsband*. ACM. https://doi.org/10.1145/3340764.3344891

Gödker, M., & Franke, T. (2024). Assessing energy-related situation awareness using self-controlled occlusion during electric vehicle driving scenes. In G. Praetorius, C. Sellberg, & R. Patriarca (Eds.), *Advances in Human Factors of Transportation. AHFE (2024) International Conference. AHFE Open Access* (pp. 286–296, Vol. 148). AHFE International. https://doi.org/10.54941/ahfe1005219

Gödker, M., Moll, V. E., & Franke, T. (2024a). Energy consumption displays in electric vehicles: Differential effects on estimating consumption and experienced energy dynamics awareness. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 00187208231222154. https://doi.org/10.1177/00187208231222154

Gödker, M., Moll, V. E., & Franke, T. (2024b). Feeling comfortable? Exploring the relation between personality, competence, and range interaction in electric vehicles. https://doi.org/10.54941/ahfe1005220

Gödker, M., Schmees, S., Bernhardt, L., Görges, D., & Franke, T. (2025). *Two types of eco-driving support - The effects of an instantaneous consumption and an optimal speed display on energy-efficient driving and energy dynamics awareness*. Open Science Framework. https://osf.io/297wv_v1

Gödker, M., Schmees, S., Bernhardt, L., Heidinger, J., Görges, D., & Franke, T. (2024). Driving simulation for energy efficiency studies: Analyzing electric vehicle eco-driving with EcoSimLab and the EcoDrivingTestPark. *Proceedings of the 16th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 32–42. https://doi.org/10.1145/3640792.3675706

Gödker, M., Schrills, T. P. P., & Franke, T. (2025). *Improved ecodriving using instantaneous consumption displays in an electric vehicle driving simulator: The role of energy dynamics awareness*. PsyArXiv. https://doi.org/10.31234/osf.io/zusyx_v3

Green, P. (2013). Standard definitions for driving measures and statistics: Overview and status of recommended practice J2944. *Proceedings of the 5th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 184–191. https://doi.org/10.1145/2516540.2516542

Hacker, W. (2003). Action regulation theory: A practical tool for the design of modern work processes? *European Journal of Work and Organizational Psychology*, *12*(2), 105–130. https://doi.org/10.1080/13594320344000075

Hacker, W., & Sachse, P. (2014). *Allgemeine arbeitspsychologie: Psychische regulation von tätigkeiten* (3rd ed.). Hogrefe. https://doi.org/10.15496/publikation-84601

Hart, S. G., & Staveland, L. E. (1988). Develpoment of NASA-TLX (task load index): Results of empirical and theoretical research. *Advances in Psychology*, *52*, 139–183. https://doi.org/10.1016/S0166-4115(08)62386-9

Hasan, M. M., Avramis, N., Ranta, M., Saez-de-Ibarra, A., El Baghdadi, M., & Hegazy, O. (2021). Multi-objective energy management and charging strategy for electric bus fleets in cities using various ECO strategies. *Sustainability*, *13*(14), 7865. https://doi.org/10.3390/su13147865

Heidinger, J., Bernhardt, L., & Franke, T. (2023). Ecosimlab - A low-cost driving simulator environment for examining human factors in vehicle energy efficiency. *Adjunct Proceedings of the 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 66–70. https://doi.org/10.1145/3581961.3609881

Horrey, W. J., Wickens, C. D., & Consalus, K. P. (2006). Modeling drivers' visual attention allocation while interacting with in-vehicle technologies. *Journal of Experimental Psychology: Applied*, *12*(2), 67–78. https://doi.org/10.1037/1076-898X.12.2.67

Huang, Y., Ng, E. C., Zhou, J. L., Surawski, N. C., Chan, E. F., & Hong, G. (2018). Eco-driving technology for sustainable road transport: A review. *Renewable and Sustainable Energy Reviews*, *93*, 596–609. https://doi.org/10.1016/j.rser.2018.05.030

Intergovernmental Panel On Climate Change, IPCC. (2023). *Climate change 2021 – The physical science basis: Working group I contribution to the sixth assessment report of the intergovernmental panel on climate change* (1st ed.). Cambridge University Press. https://doi.org/10.1017/9781009157896

Jamson, H., Hibberd, D. L., & Merat, N. (2013). The design of haptic gas pedal feedback to support eco-driving. *Proceedings of the 7th international driving symposium on human factors in driver assessment, training, and vehicle design*, 264–270. https://doi.org/10.17077/drivingassessment.1499

Jia, Y., Abdelkarim, A., Klingbeil, X., Savelsberg, R., & Görges, D. (2023). Performance evaluation of energy-optimal adaptive cruise control in simulation and on a test track. *IFAC-PapersOnLine*, *56*(2), 4994–5000. https://doi.org/10.1016/j.ifacol.2023.10.1276

Johnson, A. W., Duda, K. R., Sheridan, T. B., & Oman, C. M. (2017). A closed-loop model of operator visual attention, situation awareness, and performance across automation mode transitions. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *59*(2), 229–241. https://doi.org/10.1177/0018720816665759

Kaber, D., Zhang, Y., Jin, S., Mosaly, P., & Garner, M. (2012). Effects of hazard exposure and roadway complexity on young and older driver situation awareness and performance. *Transportation Research Part F: Traffic Psychology and Behaviour*, *15*(5), 600–611. https://doi.org/10.1016/j.trf.2012.06.002

Kato, H., Ando, R., Kondo, Y., Suzuki, T., Matsuhashi, K., & Kobayashi, S. (2013). Comparative measurements of the eco-driving effect between electric and internal combustion engine vehicles. *2013 World Electric Vehicle Symposium and Exhibition (EVS27)*, 1–5. https://doi.org/10.1109/EVS.2013.6914843

Kim, S.-H., Dandekar, H., Camez, E., & Harrelson, H. (2011). Assessing the effect of a power-flow gauge on driving behaviors affecting energy consumption. In J. A. Jacko (Ed.), *Human-computer interaction. towards mobile and intelligent interaction environments* (pp. 411–417, Vol. 6763). Springer.

Knowles, M., Scott, H., & Baglee, D. (2012). The effect of driving style on electric vehicle performance, economy and perception. *International Journal of Electric and Hybrid Vehicles*, *4*(3), 228. https://doi.org/10.1504/IJEHV.2012.050492

Kurani, K. S., Stillwater, T., Jones, M., & Caperello, N. (2013). *EcoDrive I-80: A large sample fuel economy feedback field test* (tech. rep. No. ITS-RR-13-15). Institute of Transportation Studies University of California, Davis. Davis, CA, USA.

Larrick, R. P., & Soll, J. B. (2008). The MPG illusion. *Science*, *320*(5883), 1593–1594. https://doi.org/10.1126/science.1154983

Lin, R., & Wang, P. (2022). Intention to perform eco-driving and acceptance of eco-driving system. *Transportation Research Part A: Policy and Practice*, *166*, 444–459. https://doi.org/10.1016/j.tra.2022.10.017

Lois, D., Wang, Y., Boggio-Marzet, A., & Monzon, A. (2019). Multivariate analysis of fuel consumption related to eco-driving: Interaction of driving patterns and external factors. *Transportation Research Part D: Transport and Environment*, *72*, 232–242. https://doi.org/10.1016/j.trd.2019.05.001

Longo, L., Wickens, C. D., Hancock, G., & Hancock, P. A. (2022). Human mental workload: A survey and a novel inclusive definition. *Frontiers in Psychology*, *13*, 883321. https://doi.org/10.3389/fpsyg.2022.883321

Lot, R., Fleming, J., Chen, B., & Evangelou, S. (2025). Eco-driving optimal control for electric vehicles with driver preferences. *Transportation Engineering*, 100302. https://doi.org/10.1016/j.treng.2025.100302

Ma, Z., Jørgensen, B. N., & Ma, Z. (2024). A scoping review of energy-efficient driving behaviors and applied state-of-the-art AI methods. *Energies*, *17*(2), 500. https://doi.org/10.3390/en17020500

Michon, J. A. (1985). A critical view of driver behavior models: What do we know, what should we do? In L. Evans & R. C. Schwing (Eds.), *Human behavior and traffic safety* (pp. 485–524). Springer. https://doi.org/10.1007/978-1-4613-2173-6_19

Moll, V. E., & Franke, T. (2021). Biased energy efficiency perception based on instantaneous consumption displays – Indication for heuristic energy information processing. *Applied Ergonomics*, *94*, 103399. https://doi.org/10.1016/j.apergo.2021.103399

Nienhüser, D., Bär, T., Kohlhaas, R., Schamm, T., Zimmermann, J., Gumpp, T., Strand, M., Bringmann, O., & Zöllner, J. M. (2012). Energy efficient driving and operation strategies based on situation awareness and reasoning. *it - Information Technology*, *54*(1), 5–16. https://doi.org/10.1524/itit.2012.0658

Nkusi, E. M., Grabbe, N., & Bengler, K. (2025). Long-term is no term: A systematic review of learning effects and the understanding of “long-term” in the context of driver-vehicle interaction. *Transportation Research Part F: Traffic Psychology and Behaviour*, *112*, 111–137. https://doi.org/10.1016/j.trf.2025.03.027

NOAA National Centers for Environmental Information. (2025). Climate at a glance: Global time series. https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series

Pampel, S. M., Jamson, S. L., Hibberd, D., & Barnard, Y. (2017). The activation of eco-driving mental models: Can text messages prime drivers to use their existing knowledge and skills? *Cognition, Technology & Work*, *19*(4), 743–758. https://doi.org/10.1007/s10111-017-0441-3

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2008). Situation awareness, mental workload, and trust in automation: Viable, empirically supported cognitive engineering constructs. *Journal of Cognitive Engineering and Decision Making*, *2*(2), 140–160. https://doi.org/10.1518/155534308X284417

Pauzié, A. (2008). A method to assess the driver mental workload: The driving activity load index (DALI). *IET Intelligent Transport Systems*, *2*(4), 315. https://doi.org/10.1049/iet-its:20080023

Paxion, J., Galy, E., & Berthelon, C. (2014). Mental workload and driving. *Frontiers in Psychology*, *5*, 1344. https://doi.org/10.3389/fpsyg.2014.01344

Powers, W. T., Abbott, B., Carey, T. A., Goldstein, D. M., Mansell, W., Marken, R. S., Nevin, B., Robertson, R., & Taylor, M. (2011). Perceptual control theory a model for understanding the mechanisms and phenomena of control. Retrieved April 15, 2025, from https://www.iapct.org/pct/perceptual-control-theorya-model-for-understanding-themechanisms-and-phenomena-of-control/

Powers, W. T., Clark, R. K., & McFarland, R. L. (1960a). A general feedback theory of human behavior: Part I. *Perceptual and Motor Skills*, *11*(1), 71–88. https://doi.org/10.2466/pms.1960.11.1.71

Powers, W. T., Clark, R. K., & McFarland, R. L. (1960b). A general feedback theory of human behavior: Part II. *Perceptual and Motor Skills*, *11*(3), 309–323. https://doi.org/10.2466/pms.1960.11.3.309

Ranney, T. A. (1994). Models of driving behavior: A review of their evolution. *Accident Analysis & Prevention*, *26*(6), 733–750. https://doi.org/10.1016/0001-4575(94)90051-5

Rasmussen, H. B., Lützen, M., & Jensen, S. (2018). Energy efficiency at sea: Knowledge, communication, and situational awareness at offshore oil supply and wind turbine vessels. *Energy Research & Social Science*, *44*, 50–60. https://doi.org/https://doi.org/10.1016/j.erss.2018.04.039

Rasmussen, J. (1983). Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models. *IEEE Transactions on Systems, Man, and Cybernetics*, *SMC-13*(3), 257–266. https://doi.org/10.1109/TSMC.1983.6313160

Ren, G., Hourizi, R., & O'Neill, E. (2015). Situation awareness and home energy reduction: A study. *Situation Awareness and Home Energy Reduction*.

Salmon, P. M., Stanton, N. A., & Young, K. L. (2012). Situation awareness on the road: Review, theoretical and methodological issues, and future directions. *Theoretical Issues in Ergonomics Science*, *13*(4), 472–492. https://doi.org/10.1080/1463922X.2010.539289

Sanguinetti, A., Dombrovski, K., & Sikand, S. (2018). Information, timing, and display: A design-behavior framework for improving the effectiveness of eco-feedback. *Energy Research & Social Science*, *39*, 55–68. https://doi.org/10.1016/j.erss.2017.10.001

Sanguinetti, A., Park, H., Sikand, S., & Kurani, K. (2017). A typology of in-vehicle eco-driving feedback. In N. A. Stanton, S. Landry, G. Di Bucchianico, & A. Vallicelli (Eds.), *Advances in human aspects of transportation* (pp. 979–992, Vol. 484). Springer International Publishing.

Sanguinetti, A., Queen, E., Yee, C., & Akanesuvan, K. (2020). Average impact and important features of onboard eco-driving feedback: A meta-analysis. *Transportation Research Part F: Traffic Psychology and Behaviour*, *70*, 1–14. https://doi.org/10.1016/j.trf.2020.02.010

Schmidt, R. A., & Wulf, G. (1997). Continuous concurrent feedback degrades skill learning: Implications for training and simulation. *Human Factors*, *39*(4), 509–525.

Seitz, D. (2022). Mentale arbeitsbelastung. In *Dorsch lexikon der psychologie*. https://dorsch.hogrefe.com/stichwort/mentale-arbeitsbelastung

Sivak, M., & Schoettle, B. (2012). Eco-driving: Strategic, tactical, and operational decisions of the driver that influence vehicle fuel economy. *Transport Policy*, *22*, 96–99. https://doi.org/10.1016/j.tranpol.2012.05.010

Sivak, M., & Schoettle, B. (2018). *Relative costs of driving electric and gasoline vehicles in the individual U.S. states* (tech. rep. No. SWT-2018-1). University of Michigan. Michigan, USA.

Steg, L., Perlaviciute, G., & Werff, E. v. d. (2015). Understanding the human dimensions of a sustainable energy transition. *Frontiers in Psychology*, *6*, 805. https://doi.org/10.3389/fpsyg.2015.00805

Stillwater, T., & Kurani, K. S. (2013). Drivers discuss ecodriving feedback: Goal setting, framing, and anchoring motivate new behaviors. *Transportation Research Part F: Traffic Psychology and Behaviour*, *19*, 85–96. https://doi.org/10.1016/j.trf.2013.03.007

Summala, H. (2007). Towards understanding motivational and emotional factors in driver behaviour: Comfort through satisficing. In P. C. Cacciabue (Ed.), *Modelling driver behaviour in automotive environments* (pp. 189–207). Springer. https://doi.org/10.1007/978-1-84628-618-6_11

Sureth, A., Moll, V., Nachtwei, J., & Franke, T. (2019). The golden rules of ecodriving? The effect of providing hybrid electric vehicle (HEV) drivers with a newly developed set of ecodriving-tips. *Transportation Research Part F: Traffic Psychology and Behaviour*, *64*, 565–581. https://doi.org/10.1016/j.trf.2019.07.003

Taylor, J. A., & Ivry, R. B. (2012). The role of strategies in motor learning. *Annals of the New York Academy of Sciences*, *1251*(1), 1–12. https://doi.org/10.1111/j.1749-6632.2011.06430.x

Thatcher, A. (2013). Green ergonomics: Definition and scope. *Ergonomics*, *56*(3), 389–398. https://doi.org/10.1080/00140139.2012.718371

Thill, S., & Riveiro, M. (2015). Situation awareness in eco-driving. *2015 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision*, 125–131. https://doi.org/10.1109/COGSIMA.2015.7108186
EcoDriving & Situation Awareness Paper.

Trope, Y., & Liberman, N. (2010). Construal-level theory of psychological distance. *Psychological Review*, *117*(2), 440–463. https://doi.org/10.1037/a0018963

Tu, R., Xu, J., Li, T., & Chen, H. (2022). Effective and acceptable eco-driving guidance for human-driving vehicles: A review. *International Journal of Environmental Research and Public Health*, *19*(12), 7310. https://doi.org/10.3390/ijerph19127310

Umweltbundesamt. (2024, January). Treibhausgase ausgewählter Verkehrsmittel in den Jahren 2021 und 2022 in Deutschland (in Gramm pro Personenkilometer). Retrieved January 23, 2025, from https://de.statista.com/statistik/daten/studie/1411850/umfrage/co2-emissionen-ausgewaehlter-verkehrsmittel/

Umweltbundesamt. (2025, March). Entwicklung und Zielerreichung der Treibhausgasemissionen in Deutschland. Retrieved March 31, 2025, from https://www.umweltbundesamt.de/themen/klima-energie/treibhausgas-emissionen

United Nations Environment Programme, Olhoff, A., Bataille, C., Christensen, J., Den Elzen, M., Fransen, T., Grant, N., Blok, K., Kejun, J., Soubeyran, E., Lamb, W., Levin, K., Portugal-Pereira, J., Pathak, M., Kuramochi, T., Strinati, C., Roe, S., & Rogelj, J. (2024, October). *Emissions Gap Report 2024: No more hot air … please! With a massive gap between rhetoric and reality, countries draft new climate commitments*. https://doi.org/10.59117/20.500.11822/46404

von Janczewski, N., Kraus, J., Engeln, A., & Baumann, M. (2022). A subjective one-item measure based on NASA-TLX to assess cognitive workload in driver-vehicle interaction. *Transportation Research Part F: Traffic Psychology and Behaviour*, *86*, 210–225. https://doi.org/10.1016/j.trf.2022.02.012

Wang, G., Makino, K., Harmandayan, A., & Wu, X. (2020). Eco-driving behaviors of electric vehicle users: A survey study. *Transportation Research Part D: Transport and Environment*, *78*, 102188. https://doi.org/10.1016/j.trd.2019.11.017

Wang, Y., & Boggio-Marzet, A. (2018). Evaluation of eco-driving training for fuel efficiency and emissions reduction according to road type. *Sustainability*, *10*(11), 3891. https://doi.org/10.3390/su10113891

Wickens, C. D. (2015). Situation awareness: Its applications value and its fuzzy dichotomies. *Journal of Cognitive Engineering and Decision Making*, *9*(1), 90–94. https://doi.org/10.1177/1555343414564571

Wickens, C. D., & Carswell, C. M. (2021). Information processing. In G. Salvendy & W. Karwowski (Eds.), *Handbook of human factors and ergonomics* (1st ed., pp. 114–158). Wiley. https://doi.org/10.1002/9781119636113.ch5

Wickens, C. D., Helton, W. S., Hollands, J. G., & Banbury, S. (2021). *Engineering psychology and human performance* (5th ed.). Routledge. https://doi.org/10.4324/9781003177616

Wolfe, B., Sawyer, B. D., Kosovicheva, A., Reimer, B., & Rosenholtz, R. (2019). Detection of brake lights while distracted: Separating peripheral vision from cognitive load. *Attention, Perception, & Psychophysics*, *81*(8), 2798–2813. https://doi.org/10.3758/s13414-019-01795-4

Xu, N., Li, X., Liu, Q., & Zhao, D. (2021). An overview of eco-driving theory, capability evaluation, and training applications. *Sensors*, *21*(19), 6547. https://doi.org/10.3390/s21196547

Yan, X., Allison, C., Fleming, J., Stanton, N., & Lot, R. (2021). The benefit of assisted and unassisted eco-driving for electrified powertrains. *IEEE Transactions on Human-Machine Systems*, *51*(4), 403–407. https://doi.org/10.1109/THMS.2021.3086057

Yasaka, Y., Shobatake, K., & Itsubo, N. (2017). Meta analysis of life cycle greenhouse gas of automobiles. *Journal of Life Cycle Assessment, Japan*, *13*(2), 164–171. https://doi.org/10.3370/lca.13.164

Zacher, H., & Frese, M. (2018). Action regulation theory: Foundations, current knowledge and future directions. In D. S. Ones, N. Anderson, C. Viswesvaran, & H. K. Sinangil (Eds.), *The SAGE handbook of industrial, work & organizational psychology* (pp. 122–143). SAGE Publications. https://doi.org/10.4135/9781473914957.n7

Zhang, W., Li, Y., Li, H., Liu, S., Zhang, J., & Kong, Y. (2024). Systematic review of life cycle assessments on carbon emissions in the transportation system. *Environmental Impact Assessment Review*, *109*, 107618. https://doi.org/10.1016/j.eiar.2024.107618

Article 1: Examining Differential Effects of Energy Interfaces on Energy Dynamics Awareness and Consumption Estimation in Electric Vehicles

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Energy Consumption Displays in Electric Vehicles: Differential Effects on Estimating Consumption and Experienced Energy Dynamics Awareness

Markus Gödker[1], Vivien E. Moll[1], and Thomas Franke[1]

Abstract

Objective: The effects of three prototypical designs of energy consumption displays on energy-specific situation awareness were examined.

Background: Energy efficiency is crucial for the sustainability of technical systems. However, without accurate situation awareness of energy dynamics (energy dynamics awareness, EDA) it can be challenging for humans to optimize the use of energy resources of electric vehicles (EVs) through their behavior.

Method: We examined three prototypical energy display designs that varied by their informational value to support EDA. Furthermore, we investigated the differential effects on EDA measured by (1) a newly constructed scale (experienced EDA), (2) estimating energy consumption, and (3) identifying efficient trips in an online experiment. Participants (N = 82) watched standardized driving scenes (videos) of EV trips presenting the energy displays.

Results: We found a strong effect of display type on experienced EDA, with the trace display being the most supportive. The EDA scale showed excellent internal consistency. The consumption estimation and efficient trip identification indicators were not affected by the display type.

Conclusion: The study indicates that experienced EDA is immediately affected by displays with higher information value, but performance might need more time and training. More research is needed to investigate the cognitive processes related to EDA and to examine how distinct display elements enhance EDA.

Application: Results from this research can be used as guidance for the design of energy displays, especially in EVs. The EDA scale can be used as an evaluation measure in the human-centered design process of energy displays.

Keywords

energy, interface evaluation, situation awareness, vehicle design, sustainability

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Introduction

To achieve climate goals in the transport sector, optimizing the energy efficiency of vehicles is key (Axsen et al., 2020; Williams et al., 2012). In electric vehicles (EVs), driver behavior is a relevant factor for energy efficiency (optimizing driving maneuvers, i.e., ecodriving; Barkenbus, 2010; Bingham et al., 2012). Psychologically, driving can be described as an action regulation control loop (Fuller, 2011): Drivers continuously observe relevant information from the environment and then act based on this information and existing knowledge to achieve their driving goals (e.g., security, time, and efficiency). Yet, due to the invisibility and high volatility of energy dynamics (e.g., transformation processes) in driving, it is demanding for EV drivers to fully comprehend the efficiency of their actions in a given situation, hindering optimal energy-related action regulation. This highlights the potential of green ergonomics, specifically display designs that support humans in preserving valuable energy resources (Thatcher, 2013).

Situation awareness (SA) is key for situation comprehension in dynamic contexts (Endsley, 1995b, 2015) and is (among other factors) supported by human–machine interfaces (HMIs; Endsley et al., 2003). Previous studies have explored the use of HMIs in assisting drivers with energy-related action regulation, including motivation, ecodriving tips, and energy consumption and range information displays (Dahlinger et al., 2018; Di Lena et al., 2017; Franke et al., 2019b; Lundström, 2014; Moll & Franke, 2021; Strömberg et al., 2011).

Energy displays that visualize energy transformations and consumption to improve awareness of energy dynamics address the challenge of enabling an accurate understanding of energy efficiency and supporting energy-related action regulation. We adapt the concept of SA to the specific application of energy dynamics and refer to this domain-specific SA as *energy dynamics awareness* (EDA). The objective of the present research is to examine the effects of prototypical energy consumption displays on drivers' EDA.

Energy Perception and Understanding

Accurately determining the energy consumption of technical systems requires technological support (e.g., displays and energy meters, Attari et al., 2010; Baird & Brier, 1981). Reasons for this lie in the inaccessibility of energy consumption information to our direct perception (Steg et al., 2015) and generally bounded rationality in interpreting given information (Gigerenzer & Gaissmaier, 2011; Simon, 1955), which has also been demonstrated in the context of ecodriving (Larrick & Soll, 2008; Moll & Franke, 2021). Additionally, inter-individual differences seem to play a role in understanding energy consumption, for example, competencies (energy literacy; DeWaters & Powers, 2013; DeWaters et al., 2013), habits (energy-efficient behavior; Stragier et al., 2012), or general cognitive styles of interaction with technology (affinity for technology interaction, ATI; Moll & Franke, 2021).

Energy-Specific Situation Awareness

Situation awareness serves as a basis for adequate decisions and actions and is defined as " […] the perception of the elements in the environment […], the comprehension of their meaning, and the projection of their status in the near future" (i.e., the three levels of SA; Endsley, 1995b, p. 36). While SA has been predominantly examined with safety in action regulation (e.g., driving safety, Baumann & Krems, 2007; Ma & Kaber, 2005), it has also been applied to the regulation of energy/range resources of EVs in first studies (Franke & Krems, 2013), including ecodriving (Endsley & Kiris, 1995; Nienhüser et al., 2012).

Training, individual factors, and system factors influence SA (e.g., automatization and interface design; Endsley et al., 2003). In a driving situation, traffic, road characteristics, and maneuvers are important for energy-related action regulation. These elements must be (1) perceived, (2) comprehended, and (3) projected to understand the current energy efficiency of the vehicle and its influencing factors, and therefore, to build EDA.

SA measurement instruments can be categorized as indirect or direct and objective or subjective measurements (Endsley, 1995a). For the present research, we applied two assessment methods for EDA (cf., section Outcome Measures): performance measurements (indirect and objective) and a self-rating scale (EDA scale; direct and subjective). In general, self-rating scales are versatile but may be inaccurate due to a lack of introspection or misinterpretation of confidence and workload. Objective performance measures circumvent the limitations of introspection, but quantifying performance or decisions derived from EDA results in EDA being measured only indirectly. Moreover, they are task-specific and do not measure the three EDA levels individually.

In line with recent discussions about the calibration of subjective and objective measures of SA (Endsley, 2020), our terminology distinguishes between EDA as measured by objective methods (referring to actual EDA) and EDA as measured by subjective measures (e.g., a self-rating scale). We refer to the latter as "experienced EDA" to point out that participants experience the displays' supporting effect when using them. Subjective SA is generally considered to indicate how a person chooses to act based on their SA and to influence performance equally to objective SA (Sulistyawati et al., 2011). We conclude that EDA, especially well-calibrated experienced and actual EDA, enables energy-efficient decisions.

EV Energy Displays

Energy displays are helpful in EVs due to the volatile and bi-directional nature of energy flow (e.g., regenerative braking, the conversion of kinetic energy into electric energy during deceleration; Cocron et al., 2013). However, the influence of energy displays on accurate perception and understanding of energy depends on distinct display elements (Sanguinetti et al., 2018).

Instantaneous consumption displays (ICDs) cpresent real-time energy consumption, hence, the most disaggregated, latency-free, dynamic energy information. This allows drivers to assess consumption during individual route sections or driving maneuvers and enables drivers to understand the influence of situational factors (e.g., terrain) or actions (e.g., strong acceleration) on consumption. Compared to other feedbacks, ICDs can be useful to understand energy dynamics and ultimately learn ecodriving (cf., Sanguinetti et al., 2017). However, the use of ICDs may lead to increased mental workload, as drivers must memorize and integrate volatile consumption data relevant to the maneuver of interest (Franke et al., 2019b). Moreover, drivers seem to process the provided information inaccurately (Moll & Franke, 2021), perceiving dynamic data as simplified, salient *snapshots* of information (so-called *peak bias*).

A major challenge in interface design to support SA is the *information gap* (Endsley, 2000), that is, that users only need a small yet relevant subsection of information provided by the environment to achieve their task goals. A display must therefore provide as much required information as possible in a usable way without transmitting irrelevant information. This *informational value* constitutes the independent variable for our study (cf., section Energy Displays). In our context, the ultimate task goal is energy-related action regulation (ecodriving) by identifying (in)efficient driving behavior.

Present Research

In the present research, we examine the research question: What are the effects of displays with different energy feedback design approaches on EDA? We conducted a video-based online experiment, preceded by a pilot study. We jointly evaluate the statistics and internal structure of the EDA scale using both studies. The pilot study assessed the feasibility of the method and obtained effect sizes for power analyses, which resulted in slight modifications in the method. The main study, involving a larger sample size, was conducted to test the hypotheses expected by the theoretical assumptions drawn from SA literature presented in Table 1. Alongside our main dependent (experienced and actual EDA) and independent variables (informational value), the hypotheses include performance confidence as a parallel subjective measure to experienced EDA for validation.

Method

In our online experiment, participants viewed driving scenes (videos) of EV trips from the driver's field of view, along with one of three different energy displays. We used this highly controlled setup, showing the same trip to every participant, to reduce situational disturbances inherent in field studies.

Pilot Study

Pilot study participants were recruited via the University of Lübeck's online platform and on Facebook and compensated by participation in a

Table 1. Hypotheses.

Number	Hypothesis
H1	If a high-supporting display (trace display) is available, the EDA scale scores are higher than with a medium-supporting display (bar display) or a low-supporting display (flow display).
H2	If an high-supporting display (trace display) is available, the energy consumption can be better estimated than with a medium-supporting display (bar display) or a low-supporting display (flow display) regarding the identification of efficient trips (H2.1), the estimation of the absolute consumption (H2.2), and the confidence (H2.3) in the correct identification (H2.3a) and in the absolute estimation (H2.3b).
H3	There is a positive correlation between the EDA scale scores and the energy efficiency estimate accuracy.
H3.1	The EDA scale scores show a positive correlation with the correct identification of inefficient and efficient trips.
H3.2	The EDA scale scores show a negative correlation with the deviation of the absolute consumption estimations from the correct value.
H3.3	The EDA scale scores show a positive correlation with the confidence in one's own energy efficiency estimates (H3.3a and H3.3.b).

raffle or study participation certificates for course credit. The final sample (N = 30; age: M = 24.6 years, SD = 3.6; 10 male, 20 female) had an average driving experience in total kilometers with any vehicle of M = 26,695 km (SD = 51,507 km; median = 3250 km), and a weekly driving distance of M = 43 km (SD = 88 km; median = 2 km).

Participants

An a-priori power analysis (Faul et al., 2007), based on the pilot study, determined a required sample size N = 62 (parameters: power = .8, α-error = .05, η_p^2 = 0.38 for H1, and η_p^2 = 0.08 for H2.2). Main study participants were recruited via online recruitment tools (*surveycircle*, *pollpool*) and compensated by participation in a raffle of 3 × 30€. The online study was completed 98 times. We excluded all participants with a computer screen too small for the videos (5), no driving experience (5), noncompliant response behavior (2), and corrupted data sets due to a technical issue in LimeSurvey (4). The final sample consisted of N = 82 participants (38 male, 42 female, 2 not stated) with an average age of M = 30.5 years (SD = 12.7). Average total driving experience with any vehicle was M = 209,642 km (SD = 603,139 km; median = 38,000 km), and weekly driving distance M = 293 km (SD = 948 km; median = 74 km).

Material

Driving Scenes. We collected OBD-II data and dashcam footage of the driver's view in a Renault ZOE EV in urban conditions. The recorded six driving scenes represented three pairs of driving scenes. Two driving scenes of each pair shared the same route ("Route A," "Route B," or "Route C") but differed in consumption due to the driver using two different driving strategies: (1) *driving-to-keep-distance* (constant distance to vehicle ahead) = inefficient or (2) *driving-to-keep-inertia* (constant speed) = efficient (adapted from Blanch Micó et al., 2018). The practice trial driving scene was a reversed section of Route B with moderate efficiency (134.5 Wh/km). Trips distance ranged between 0.70 and 1.10 km, duration from 141 to 282 seconds, and average energy consumption from 51.5 Wh/km to 180.9 Wh/km. To produce the final video material for the study, the driving data was processed, imported into a web app, and synchronized with the dashcam recordings. Additionally, speed, trip kilometers, and the positions of the throttle and the brake pedal were displayed. In our vehicle, pressing the braking pedal led to regenerative braking.

Energy Displays. Referring to common approaches to present instantaneous energy dynamics, we implemented three prototypical display designs for the present study: (1) *flow display*, (2) *bar display*, and (3) *trace display* (see all Figure 1). All displays are inspired by real EV displays and aligned with each other (i.e., same colors, consumption formula, and calculation). As the energy consumption metric, we used watt-hours per km (Wh/km). Despite being less familiar to experienced EV drivers, we believe that instantaneous consumption values

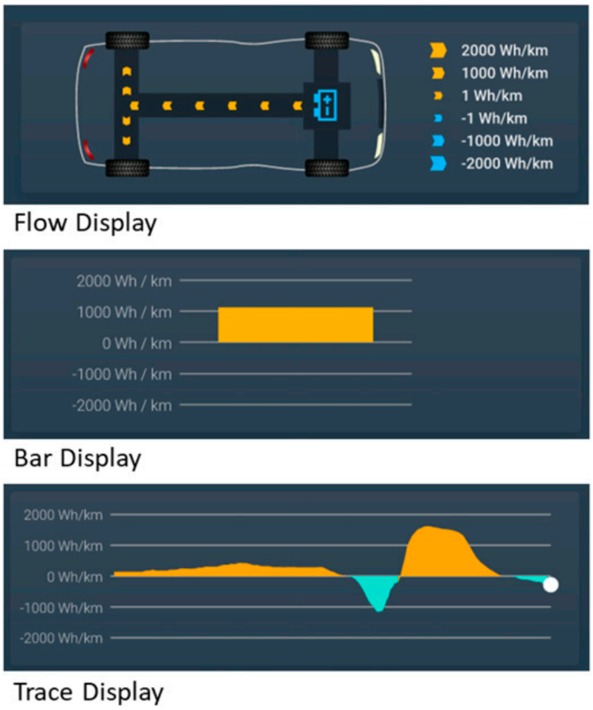


Figure 1. Three prototypical displays to visualize instantaneous consumption. All displays are adapted from existing concepts and literature (e.g., Franke et al., 2019b; Moll & Franke, 2021; Schwarze et al., 2019).

between 0 and approximately 2000 Wh/km and average consumption values between 51.5 and 180.9 Wh/km are easier to process for inexperienced drivers than the decimals in kWh/km. Almost all existing ICDs fit one of these three display prototypes, but major differences exist between them.

Flow Display. The flow display visualizes the bi-directionality of energy flows by providing arrow indicators and directional movement inside a schematic EV. While energy is consumed, orange arrows move from the motor to the tires. When energy is regained through regenerative braking, blue arrows move in the opposite direction. The thickness of the arrows represents the amount of energy consumed/regained. This design approach may help understand energy flows by visualizing their “paths” and “directions” in a meaningful way.

Bar Display. The bar display presents instantaneous consumption as a bar with no distraction from other information. Its height indicates the amount of energy while the width of the bar is constant and carries no additional information. An orange bar in the positive range means that energy is consumed, a blue bar in the negative range that energy is regained.

Trace Display. The point of trace display on the right side of the chart shows the same behavior as the bar of the bar display. The display visualizes the instantaneous consumption as a trace line continuously moving from right to left. The *x*-axis represents the last 100 m traveled. Hence, the trace stops moving when the vehicle stops.

In comparison, the flow display provides less task goal-oriented information but additional irrelevant information (low information value) as the path of the energy flow does not help in accurately perceiving consumption. The instantaneous consumption is even harder to accurately perceive: First, the energy flow design implies less space to indicate changes in consumption magnitude compared to the other displays (i.e., arrow size vs. bar height). Second, the arrows only have the scale legend on the right but miss a visual comparison scale like the inner lines in the bar and trace display (Diaz et al., 2018). The bar display provides task goal-oriented information and no irrelevant information (medium information value). The trace display provides a large amount of task goal-oriented information and no irrelevant information (high information value) because it addresses the volatility of the energy consumption data by providing additional visual persistence of the data. The distance provides a reference period, which may help to reduce bias (e.g., peak bias) in human perception and concatenates consumption magnitude with duration, as suggested by Franke et al., 2019b; Moll & Franke, 2021. As a result, the display visualizes colored areas that correspond to the consumed/regenerated energy amount to support the comprehension of the data. In summary, for EDA, the trace display is high-supporting, the flow display low-supporting, and the bar display medium-supporting (see Figure 2 for a comparison of their dynamic behavior).

Outcome Measures. We used the self-constructed *energy dynamics awareness scale (EDA scale)* as a direct and subjective method to measure EDA (experienced EDA). Based on findings in a previous study (Gödker et al., 2019), we refined the EDA scale to six items, deleting one and revising three items.

Figure 2. Comparison of the dynamic behavior of the three displays. The figure presents screenshots from the three displays, captured at four sequential maneuvers during a single trip sequence. These were taken starting 9 seconds into the low-efficiency trip on route B and continued for 12 seconds. The *x*-axis of the trace display represents the previous 100 m traveled; therefore, the time does not correspond with the position of the *x*-axis. Refer to the supplementary material for the original videos.

An English translation of the EDA scale is depicted in Table 2 (for original German items, see Appendix A). The scale aims to evaluate the subjective experience of how well the displays help to develop EDA across the three levels, that is, the correct perception (level 1) of all elements relevant to the energy situation (item 1), the comprehension (level 2) of these elements and their relationships (items 2 and 3), and the ability to make accurate projections (level 3) about the energy situation (items 4 and 5) and to control the energy situation according to one's will (action regulation capability, item 6).

As a prerequisite to interpreting the EDA scale mean, we conducted a joint scale analysis including both samples (pilot and main study, N = 112), analyzing the three display conditions separately to account for the assumed display's effect on EDA. The scale items, displays, and driving scenes were the same in both studies, and we used different recruiting strategies to prevent double participation. We assessed the scale's internal consistency with Cronbach's alpha (Cronbach, 1951), used parallel analysis (Horn, 1965) for factor number extraction as an indication for one-dimensionality, and conducted an exploratory factor analysis (principal axis factoring extraction method; PAF; Costello & Osborne, 2005).

In all conditions, EDA scale scores were distributed normally. Skewness and kurtosis were within the range of ±1. Cronbach's alphas indicated high internal consistency ($\alpha_{flowdisplay}$ = .893, $\alpha_{bardisplay}$ = .864, $\alpha_{tracedisplay}$ = .923). Parallel analyses suggested one factor in the flow and trace display condition and two factors in the bar display condition (scree plot and eigenvalues were borderline to one factor). In the factor analyses, we specified the number of factors to one for consistency. The explained variance of the factor was 58% (flow), 52% (bar), and 67% (trace). All items showed similar statistics, with rather strong factor loadings and an $\alpha_{ifitemdeleted}$ value below the corresponding scale value.

As performance measurements (indirect and objective EDA measurement), we queried participants' average energy consumption estimates of a trip in Wh/km (*ConsEst*) because an accurate EDA should be associated with a more accurate estimation of the consumed energy. To answer, participants moved a slider to values between 0 and 250 Wh/km with an accuracy of 1 Wh/km. To obtain the score, we calculated the absolute difference to the correct value. Additionally, to avoid an explicit number answering format as in the consumption estimates, after both trips on the same route, participants tried to identify the inefficient one (efficient trip identification; *EffIdent*). Confidence in performance for both measures was rated on a 6-point Likert scale, ranging from 1 = *not sure at all* to 6 = *completely sure*. As

Table 2. The EDA Scale.

Item	Text
1	With the help of this display, I get a very good overview of the energy dynamics of the system.
2	With the help of this display, I can precisely estimate the influence of various factors on energy consumption.
3	With the help of this display, I understand which of my actions influence the energy dynamics.
4	This display allows me to correctly predict energy consumption in future situations.
5	With the help of this display, I know exactly what can influence the flow of energy.
6	With the help of this display, I feel very able to increase energy efficiency.

Note. The instruction of the scale indicated the supporting object (e.g., "How do you rate the display in the last driving scenes [trace display]?"), followed by an explanation of the rating scheme ("Please indicate your level of agreement with the following statements."). The agreement to the 6 items had to be indicated on a 6-point Likert scale reading: completely disagree, largely disagree, slightly disagree, slightly agree, largely agree, completely agree, coded as 1–6 for data analysis. The mean value of all ratings (no reversed item) gives the EDA score.

ecodriving knowledge and behavior have been shown to be related (McIlroy & Stanton, 2017; Pampel et al., 2018), control variables included 7 items of the Energy Literacy Questionnaire (DeWaters et al., 2013; DeWaters & Powers, 2013), energy-efficient behavior (Stragier et al., 2012), ATI (Franke, Attig, & Wessel, 2019), technical system knowledge (adapted from Franke et al., 2016), and demographic information. Measurement methods are detailed in the Appendix.

Design and Procedure

The study utilized the online survey tool LimeSurvey and employed a within-subjects design. Participants were randomly assigned to one of three groups, each with a different combination of display and route to mitigate route-specific effects. The order of the display blocks (each containing the two efficiency conditions) was randomized. Participants saw an instructional video with a practice trial driving scene. Then they watched six driving scenes—two scenes with different energy consumptions (inefficient or efficient) for each of the three energy feedback displays (flow, bar, and trace). Each display block had a different route. After watching the first driving scene, participants responded to the ConsEst question and the corresponding confidence rating. After the second driving scene, participants responded again to ConsEst (including confidence rating), stated their EffIdent (including confidence rating), and completed the EDA scale. Control variables were completed after all driving scenes. In the end, participants were directed to the raffle and participation certification. The average duration of the main study was M = 43 min (SD = 8 min; median = 42 min). To address fatigue-related decreasing motivation, we (1) counterbalanced the order of the scenes to avoid position effects in the data and (2) implemented a timer that disabled the "next" button in LimeSurvey for the duration of the scene, preventing participants from skipping scenes. This research complied with the American Psychological Association Code of Ethics and was approved by the ethical committee of the University of Lübeck (no. 21–142). Informed consent was obtained from each participant.

Data Analysis

For H1, H2.2, and H2.3, we used a one-way repeated measures ANOVA (Leonhart, 2017), for H2.1, we used Cochran's Q test (Cochran, 1950) and its chance-corrected effect size measure R (Berry et al., 2007), and for H3, we used a repeated measures correlation (Bakdash & Marusich, 2017) to estimate the within-individual correlation between two variables on several occasions (i.e., test whether individuals score higher on two paired variables in one display condition compared to another display condition). For all analyses, the threshold of α was set to .05, and effect sizes for correlations (H3) were interpreted as small (r = .10), medium (r = .30), and large (r = .50) according to Cohen (1988). Following Bakeman (2005) and Cohen (1988), we calculated generalized η^2 (η^2_g) for the repeated measure ANOVAs (H1, H2.2, H2.3) and interpreted η^2_g = .02 being a small, η_g^2 = .13 a medium, and η_g^2 = .26 a large effect. R-Studio was used for all computations.

Results

The sample was unevenly distributed into the groups with different display-route combinations: group 1: 34 (41.5%), group 2: 24 (29.3%), and group 3: 24 (29.3%). Table 3 depicts the descriptive data for all display conditions. Additionally, we analyzed dependent variable differences across routes to assess route-related effects. Only the absolute difference of the consumption estimate (ConsEst) was higher for Route C compared to Route A and B. For clarity, we primarily report display-specific differences.

The EDA scale scores were significantly different at the different display conditions (H1, F (1.88, 152.35) = 36.22, $p < .001$, $\eta_g^2 = 0.21$, Huynh-Feldt corrected degrees of freedom). Post-hoc paired t-tests revealed strong and statistically significant differences in all three display comparisons: flow versus bar (t (81) = −4.20, $p < .001$, r = .42), flow versus trace (t (81) = −7.64, $p < .001$, r = .65), and bar versus trace (t (81) = −4.97, $p <$ .001, r = .48, all p-values Bonferroni-adjusted, see Figure 3).

Cochran's Q test indicated no significant differences between the correct efficient trip identifications in the three display conditions (H2.1, χ^2 (2) = 3.44, p = .179) and a very weak effect size (R = .01) of the display. Also, absolute deviations of the consumption estimate from the correct value were not significantly different in the display conditions (H2.2, F (2, 162) = 0.29, p = .746, η_g^2 = 0.002). Furthermore, the *relative* deviations of the consumption estimate indicate an overestimation in all display conditions (Flow: M = 19.5, SD = 36.3; Bar: M = 23.8, SD = 32.6; Trace: M = 28.2, SD = 36.2; all in Wh/km). Also here, no significant difference was observed (F (2, 162) = 1.781, p = .172, η_g^2 = 0.01).

In contrast, the efficient trip identification confidence ratings were significantly different in the display conditions (H2.3a, F (2, 162) = 4.73, p = .010, η_g^2 = 0.022). Post-hoc paired t-tests revealed a significant difference between the flow and the trace display conditions (t (81) = −3.06, p = .009, r = .32), but no difference between the flow and bar display conditions (t (81) = −1.46, p = .447, r = .16) nor between the bar and trace display conditions (t (81) = −1.63, p = .321, r = .18, all p-values Bonferroni-adjusted). The consumption estimation confidence ratings were significantly different in the display conditions (H2.3b, F (1.89, 153.43) = 14.29, $p < .001$, η_g^2 = 0.045, Huynh-Feldt corrected degrees of freedom). Post-hoc paired t-tests revealed significant differences in all pairwise comparisons: flow versus bar (t (81) = −3.20, p = .006, r = .33), flow versus trace (t (81) = −4.72, $p < .001$, r = .46), and bar versus trace (t (81) = −2.51, p = .042, r = .27, all p-values Bonferroni-adjusted).

Table 3. Descriptive Statistics of all Dependent Variables Sorted for Each Display and Route.

			Grouped by Display Condition		
Variable	Statistic	Unit	Flow	Bar	Trace
Experienced EDA Scale					
	M (*SD*)	1–6	3.0 (1.1)	3.6 (0.9)	4.2 (1.0)
Absolute difference of the consumption estimate to the correct value (*ConsEst*)					
	M (*SD*)	Wh/km	48.0 (22.2)	45.6 (21.2)	47.4 (23.8)
Correct identification of the efficient trip (*EffIdent*)					
	% correct		72.0	80.5	82.9
Confidence in one's consumption estimate (*ConsEstConf*)					
	M (*SD*)	1–6	2.3 (1.1)	2.7 (1.0)	2.9 (1.0)
Confidence in one's efficient trip identification (*EffIdentConf*)					
	M (*SD*)	1–6	3.3 (1.5)	3.6 (1.4)	3.9 (1.5)

Note. N = 82.

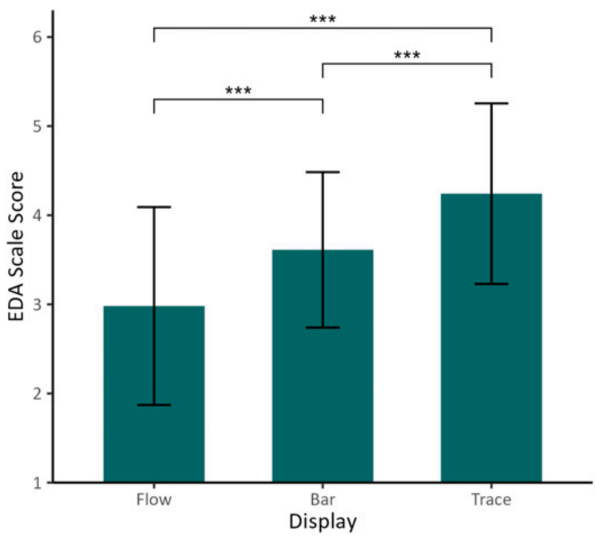


Figure 3. Result of the repeated measures ANOVA of the EDA scale scores (H1). $N = 82$, ***$p < .001$, error bars represent standard deviations.

The EDA scale showed a positive correlation with the correct efficient trip identification (H3.1, $r_{rm} = .17$, $p = .033$) but no correlation with the deviation of the consumption estimation from the correct value (H3.2, $r_{rm} = .02$, $p = .784$). Also, the EDA scale showed a positive correlation with the identification confidence ratings (H3.3a, $r_{rm} = .39$, $p < .001$) and the estimation confidence ratings (H3.3b, $r_{rm} = .55$, $p < .001$).

Exploratory Analyses

To examine the influence of individual characteristics on the performance measures, we calculated Pearson correlation coefficients between the mean EDA measures (across all three conditions) with the personality and knowledge control variables. Significant correlations were found between energy literacy and the consumption estimate score ($r = -.26$, $p = .020$, indicating more accurate estimates with higher literacy scores) and between self-rated technical knowledge and the consumption estimate score ($r = -.23$, $p = .042$).

Discussion

Summary of the Findings and Implications

The objective of the present study was to examine the effects of three prototypical energy consumption displays on EDA measured by self-ratings, estimating energy consumption, and identifying efficient trips. We found that the energy display type influenced the experienced EDA (H1) and estimation confidence (H2.3). The 6-item EDA scale showed very good internal structure statistics and a relationship with the efficient trip identification (H3.1) and the confidence ratings (H3.3). This is a first indicator of the conceptual relevance of the EDA scale and implies a consideration in the design process of energy displays in technical systems. Also, this relationship supports the theoretical assumptions of Endsley (2020) that subjective SA and confidence relate. We used repeated measures correlation analysis to calculate correlations across conditions (controlling for inter-individual variance) for H3. As multiple statistical approaches exist, which may yield different findings, these results should be interpreted cautiously.

Contrary to the hypotheses, performance in efficient trip identification (H2.1) and consumption estimation (H2.2) were not affected by the type of energy display. The present research uncovers considerable challenges to measure the effect of displays to accurately understand energy consumption. Across all displays, participants were unable to accurately estimate the energy consumption (which is in line with other empirical findings, e.g., Moll & Franke, 2021) but the share of correct answers in identifying the efficient trip was high for all displays. This could mean that participants had a generally correct but abstract understanding of energy consumption, enabling them to perform well in discriminating between very high and low consumption (as in our driving scenes). Participants might need more feedback and training to refine this abstract understanding to perform better in estimating consumption. The efficient trip identification task seems already promising to assess EDA, but the data is very rough. To compare displays, many participants and driving scenes would be necessary to detect differences. For this, shortening the scene length would be necessary and probably increase the task difficulty (due to less information). Additionally, a more structured approach to selecting the scenes could be beneficial and increase test economy. This would mean that future research should prioritize scenes that are critical for energy consumption and where human action regulation (ecodriving) is possible.

The correlation of experienced EDA and efficiency identification (H3.1) implies that displays facilitating correct efficiency identifications, also enhance experienced EDA. This could be interpreted as a first hint towards the assumption that the independent variable leads to a good calibration of experienced and actual EDA. Yet, the lack of a correlation between the consumption estimation accuracy and experienced EDA (H3.2) and the lack of objective performance differences due to the display condition (H2.1 and H2.2) leave room for alternative interpretations, for example, that participants were unaware of insufficient EDA due to the lack of adequate performance feedback (cf., Endsley, 2020). But, considering the observed correlations and the methodological issues, we conclude that the energy displays *first* influence the experienced EDA and *then* the performance associated with EDA, although we were not yet able to observe this in the current study.

Furthermore, the results imply that experienced EDA and actual EDA should be theoretically understood as individual concepts within a common theoretical model of energy-specific SA. In summary, the results contribute to the discussion concerning the conceptual distinction of experienced (subjective) and actual (objective) SA and their combined influence on task performance (see also Edgar et al., 2018; Schrills & Franke, 2023).

Limitations and Future Research

Important situational information (e.g., g-forces and peripheral visual information) that could help estimate efficiency is missing in this video-based method. Yet, statistical differences between the displays can be assumed to be largely unaffected by the shortcomings of the video-based method as they apply to all displays. Furthermore, the lengthy duration of the online study (43 minutes on average) may decrease motivation and cognitive performance, particularly affecting the EDA performance measures.

We ranked existing energy display design approaches by their informational value (independent variable). Yet, additional properties of the displays might also have an impact on the dependent variables. The development of custom energy displays that operationalize the independent variable more precisely while keeping all other properties constant would be more standardized and allow more conclusions about the display elements, but may be difficult to construct while keeping meaningful display visualizations.

The absence of distinct performance data between display conditions is a study limitation. However, the correlation between experienced EDA and efficiency identification is a first indication for the conceptual relevance of performance data. Future research could reveal clearer distinctions with more diverging display conditions (e.g., addressing different information processing stages) and well-calibrated performance tasks (e.g., more identification tasks or estimation training). Overall, empirical research on quantitatively estimating energy consumption is limited. The findings from this study can contribute to establishing basic energy display design principles (e.g., types of indicator, included dimensions) and their link to variables of human-energy interaction (Dahlinger et al., 2018; Sanguinetti et al., 2018).

It is important to note that this research focuses specifically on information perception and processing (i.e., the facets more closely linked to SA). Compared to real-vehicle or driving simulator studies, an online study is not able to capture the impact of different energy displays or improved EDA on energy-efficient driving behavior. By shedding light on the differential effects of energy displays on EDA, we aim to pave the way for future studies, ultimately providing more insights into which energy feedback display supports ecodriving in electric vehicles.

Conclusion

The objective of the present study was to examine the effects of energy consumption displays on EDA in an online study using driving scenes. We used prototypical display approaches and classified them regarding their informational value to support EDA. The EDA scale showed very good scale statistics, significant differences due to the energy displays, and correlated with the performance to identify an efficient trip out of two. The type of display did not influence the performance measurements but the subjective ratings, which implicates the potential of the EDA concept and scale for further studies examining the psychological benefits of energy displays in technical systems. The research's novel contribution to the field of human-energy interaction is a new concept (EDA) including its measurement and empirical results from a new online experiment paradigm. Further research that includes the concept of EDA seems promising, especially research that links EDA with distinct energy display elements and with energy-related action regulation.

Appendix

A. Experienced EDA Self-Rating Scale in German (Original Version)

Table A1. The EDA Scale in German (Original Version).

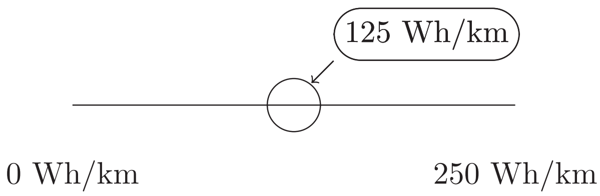
Item	Text
1	Durch diese Anzeige bekomme ich einen sehr guten Überblick über die Energiedynamik des Systems.
2	Mithilfe dieser Anzeige kann ich den Einfluss verschiedener Faktoren auf den Energieverbrauch präzise einschätzen.
3	Es ist für mich durch diese Anzeige verständlich, welche meiner Handlungen die Energiedynamik beeinflussen.
4	Diese Anzeige erlaubt mir, den Energieverbrauch in zukünftigen Situationen korrekt vorherzusehen.
5	Durch diese Anzeige weiß ich genau, durch was die Energieflüsse beeinflusst werden können.
6	Durch diese Anzeige fühle ich mich sehr gut dazu imstande, die Energieeffizienz zu erhöhen.

Note. The instruction of the scale indicated the supporting object (e.g., "Wie bewerten Sie die Anzeige aus den letzen Videos [Energiefluss-Display]?"), followed by an explanation of the rating scheme ("Bitte geben Sie den Grad Ihrer Zustimmung zu folgenden Aussagen an"). The agreement to the 6 items had to be indicated on a 6-point Likert scale reading: stimmt gar nicht, stimmt weitgehend nicht, stimmt eher nicht, stimmt eher, stimmt weitgehend, stimmt völlig, coded as 1–6 for data analysis. The mean value of all ratings (no reversed item) gives the EDA score.

B. EDA Performance Measurements Prompts

Table B1. Consumption Estimate Prompt in English (Translated From Original Language German).

Please Estimate as Accurately as Possible:
How many watt-hours per km were consumed on average during this trip?



Participants were supposed to indicate their consumption estimate on a vertical slider ranging from 0 to 250 Wh/km by moving a slider handle.

Table B2. Consumption Estimate Confidence Prompt in English (Translated From Original Language German).

Regarding Your Estimate in the Preceding Question on Average Consumption:						
How Confident Are You in Your Estimate?						
	1 Not at all confident	2	3	4	5	6 Fully confident
Regarding this estimate, I am …	○	○	○	○	○	○

Table B3. Efficient Trip Identification Prompt in English (Translated From Original Language German).

	1st Video	2nd Video
When comparing the trips in the two videos of the same route just shown, during which trip was more energy used overall?	○	○

Table B4. Efficient Trip Identification Confidence Prompt in English (Translated From Original Language German).

Regarding Your Estimate in the Preceding Question on in which Video More Energy was Consumed:						
How Confident Are You in Your Estimate?						
	1 Not at all confident	2	3	4	5	6 Fully confident
Regarding this estimate, I am …	x̂	○	○	○	○	○

C. Control Variable Measurements Included in the Study

Table C1. Control Variable Measurements Included in the Study.

Name (Origin)	Description
Energy knowledge (DeWaters et al., 2013; DeWaters & Powers, 2013)	Measured by a selection of 7 questions with good item statistics and different item difficulty (α_{cron} = .637) of the original energy literacy questionnaire. Knowledge about the context of energy might facilitate awareness about the current energy-related situation (DeWaters & Powers, 2011).
Energy-efficient behavior (Stragier et al., 2012)	Individual disposition for energy-efficient behavior in everyday life at home. This behavior is assessed via self-ratings (α_{cron} = .768).
Affinity for technology interaction (Franke, Attig, & Wessel, 2019)	Considered as a personal resource for interaction with technology and might also influence the effective usage of human–machine interfaces, that is, energy displays (α_{cron} = .958).
Technical system knowledge (adapted and edited from Franke et al., 2016)	Various self-constructed questions capturing the technical knowledge about EVs, energy, and ecodriving (α_{cron} = .771).
Demographic information (self-created)	Age, gender, education, and EV driving experience.

Key Points

- Three prototypical energy consumption displays were examined for their effects on energy dynamic awareness (EDA) and estimates of energy usage (performance) during electric vehicle driving in an online study.
- Experienced EDA, measured by a new self-rating scale, was strongly affected by display type.
- Display type did not affect the ability of drivers to distinguish between efficient and inefficient driving behavior, nor did it affect the accuracy of driver estimates of performance.
- However, EDA was correlated with the ability to distinguish between efficient and inefficient driving behavior.
- The new contribution to the field of human-energy interaction—EDA—can be considered in the evaluation process of energy displays in technical systems.

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Supplemental Material

Supplemental material for this article is available online.

References

Attari, S. Z., DeKay, M. L., Davidson, C. I., & Bruine de Bruin, W. (2010). Public perceptions of energy consumption and savings. *Proceedings of the National Academy of Sciences of the United States of America*, *107*(37), 16054–16059. https://doi.org/10.1073/pnas.1001509107

Axsen, J., Plötz, P., & Wolinetz, M. (2020). Crafting strong, integrated policy mixes for deep CO2 mitigation in road transport. *Nature Climate Change*, *10*(9), 809–818. https://doi.org/10.1038/s41558-020-0877-y

Baird, J. C. & Brier, J. M. (1981). Perceptual awareness of energy requirements of familiar objects. *Journal of Applied Psychology*, *66*(1), 90–96. https://doi.org/10.1037/0021-9010.66.1.90

Bakdash, J. Z. & Marusich, L. R. (2017). Repeated measures correlation. *Frontiers in Psychology*, *8*(456). https://doi.org/10.3389/fpsyg.2017.00456.

Bakeman, R. (2005). Recommended effect size statistics for repeated measures designs. *Behavior Research Methods*, *37*(3), 379–384. https://doi.org/10.3758/BF03192707

Barkenbus, J. N. (2010). Eco-driving: An overlooked climate change initiative. *Energy Policy*, *38*(2), 762–769. https://doi.org/10.1016/j.enpol.2009.10.021

Baumann, M. & Krems, J. F. (2007). Situation awareness and driving: A cognitive model. In P. C. Cacciabue (Ed.), *Modelling driver behaviour in automotive environments* (pp. 253–265). Springer. https://doi.org/10.1007/978-1-84628-618-614

Berry, K. J., Johnston, J. E., & Mielke, P. W. (2007). An alternative measure of effect size for Cochran's Q test for related proportions. *Perceptual and Motor Skills*, *104*(3 Pt 2), 1236–1242. https://doi.org/10.2466/pms.104.4.1236-1242

Bingham, C., Walsh, C., & Carroll, S. (2012). Impact of driving characteristics on electric vehicle energy consumption and range. *IET Intelligent Transport Systems*, *6*(1), 29. https://doi.org/10.1049/iet-its.2010.0137

Blanch Micó, M. T., Lucas Alba, A., Bellés Rivera, T., Ferruz Gracia, A. M., Melchor Galán, Ó. M., Delgado Pastor, L. C., Ruíz Jiménez, F., & Chóliz Montañés, M. (2018). Car following: Comparing distance-oriented vs. inertia-oriented driving techniques. *Transport Policy*, *67*, 13–22. https://doi.org/10.1016/j.tranpol.2017.05.008.

Cochran, W. G. (1950). The comparison of percentages in matched samples. *Biometrika*, *37*(3/4), 256–266. https://doi.org/10.2307/2332378

Cocron, P., Bühler, F., Franke, T., Neumann, I., Dielmann, B., & Krems, J. F. (2013). Energy recapture through deceleration – regenerative braking in electric vehicles from a user perspective. *Ergonomics*, *56*(8), 1203–1215. https://doi.org/10.1080/00140139.2013.803160

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates Publishers. https://doi.org/10.4324/9780203771587

Costello, A. B. & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research and Evaluation*, *10*(7), 1–9. https://doi.org/10.7275/JYJ1-4868

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297–334. https://doi.org/10.1007/BF02310555

DeWaters, J. E. & Powers, S. (2013). Establishing measurement criteria for an energy literacy questionnaire. *The Journal of Environmental Education*, *44*(1), 38–55. https://doi.org/10.1080/00958964.2012.711378

Dahlinger, A., Wortmann, F., Ryder, B., & Gahr, B. (2018, April, 21-26). The impact of abstract vs. concrete feedback design on behavior insights from a large eco-driving field experiment. Proceedings of the 2018 CHI conference on human factors in computing systems (pp. 1–11), Montréal QC, Canada. https://doi.org/10.1145/3173574.3173953

DeWaters, J. E. & Powers, S. E. (2011). Energy literacy of secondary students in New York State (USA): A measure of knowledge, affect, and behavior. *Energy Policy*, *39*(3), 1699–1710. https://doi.org/10.1016/j.enpol.2010.12.049

DeWaters, J. E., Qaqish, B., Graham, M., & Powers, S. (2013). Designing an energy literacy questionnaire for middle and high school youth. *The Journal of Environmental Education*, *44*(1), 56–78. https://doi.org/10.1080/00958964.2012.682615

Di Lena, P., Mirri, S., Prandi, C., Salomoni, P., & Delnevo, G. (2017, March, 13). Invehicle human machine interface: An approach to enhance ecodriving behaviors. Proceedings of the 2017 ACM workshop on interacting with smart objects (pp. 7–12), Limassol, Cyprus. https://doi.org/10.1145/3038450.3038455

Diaz, J., Meruvia-Pastor, O., & Vazquez, P.-P. (2018). Improving perception accuracy in bar charts with internal contrast and framing enhancements. 2018 22nd international conference information visualisation (IV) (pp. 159–168), Fisciano, Italy, 10–13 July 2018. https://doi.org/10.1109/iV.2018.00037

Edgar, G. K., Catherwood, D., Baker, S., Sallis, G., Bertels, M., Edgar, H. E., Nikolla, D., Buckle, S., Goodwin, C., & Whelan, A. (2018). Quantitative Analysis of Situation Awareness (QASA): Modelling and measuring situation awareness using signal detection theory. *Ergonomics*, *61*(6), 762–777. https://doi.org/10.1080/00140139.2017.1420238

Endsley, M. R. (1995a). Measurement of situation awareness in dynamic systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *37*(1), 65–84. https://doi.org/10.1518/001872095779049499

Endsley, M. R. (1995b). Toward a theory of situation awareness in dynamic systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *37*(1), 32–64. https://doi.org/10.1518/001872095779049543

Endsley, M. R. (2000). Theoretical underpinnings of situation awareness: A critical review. In M. R. Endsley, & D. J. Garland (Eds.), *Situation awareness analysis and measurement* (pp. 3–32). Lawrence Erlbaum Associates Publishers.

Endsley, M. R. (2015). Situation awareness misconceptions and misunderstandings. *Journal of Cognitive Engineering and Decision Making*, *9*(1), 4–32. https://doi.org/10.1177/1555343415572631

Endsley, M. R. (2020). The divergence of objective and subjective situation awareness: A meta-analysis. *Journal of Cognitive Engineering and Decision Making*, *14*(1), 34–53. https://doi.org/10.1177/1555343419874248

Endsley, M. R., Bolté, B., & Jones, D. G. (2003). *Designing for situation awareness: An approach to user-centered design*. Taylor & Francis. https://doi.org/10.1201/9780203485088

Endsley, M. R. & Kiris, E. O. (1995). The out-of-the-loop performance problem and level of control in automation. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *37*(2), 381–394. https://doi.org/10.1518/001872095779064555

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Franke, T., Arend, M. G., McIlroy, R. C., & Stanton, N. A. (2016). Ecodriving in hybrid electric vehicles – exploring challenges for user-energy interaction. *Applied Ergonomics*, *55*, 33–45. https://doi.org/10.1016/j.apergo.2016.01.007

Franke, T., Attig, C., & Wessel, D. (2019a). A personal resource for technology interaction: Development and validation of the affinity for technology interaction (ATI) scale. *International Journal of Human-Computer Interaction*, *35*(6), 456–467. https://doi.org/10.1080/10447318.2018.1456150

Franke, T., Görges, D., & Arend, M. G. (2019b, September, 21-25). The energy interface challenge. towards designing effective energy efficiency interfaces for electric vehicles. Proceedings of the 11thInternational Conference on Automotive User Interfaces and Interactive Vehicular Applications (pp. 35–48), Utrecht, Netherlands. https://doi.org/10.1145/3342197.3344526

Franke, T. & Krems, J. F. (2013). Understanding charging behaviour of electric vehicle users. *Transportation Research Part F: Traffic Psychology and Behaviour*, *21*, 75–89. https://doi.org/10.1016/j.trf.2013.09.002

Fuller, R. (2011). Driver control theory. In *Handbook of traffic psychology* (pp. 13–26). Elsevier. https://doi.org/10.1016/B978-0-12-381984-0.10002-5

Gigerenzer, G. & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, *62*(1), 451–482. https://doi.org/10.1146/annurev-psych-120709-145346

Gödker, M., Dresel, M., & Franke, T. (2019). EDA scale - assessing awareness for energy dynamics. In F. Alt, A. Bulling, & T. Döring (Eds.), *Mensch und computer 2019 - tagungsband*. ACM. https://doi.org/10.1145/3340764.3344891

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179–185. https://doi.org/10.1007/BF02289447

Larrick, R. P. & Soll, J. B. (2008). Economics. The MPG illusion. *Science*, *320*(5883), 1593–1594. https://doi.org/10.1126/science.1154983

Leonhart, R. (2017). *Lehrbuch statistik: Einstieg und vertiefung* (4th ed.). Hogrefe.

Lundström, A. (2014, September, 17-19). Differentiated driving range: Exploring a solution to the problems with the "Guess-O-Meter" in electric cars. Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (pp. 1–8), Seattle WA, USA. https://doi.org/10.1145/2667317.2667347

Ma, R. & Kaber, D. B. (2005). Situation awareness and workload in driving while using adaptive cruise control and a cell phone. *International Journal of Industrial Ergonomics*, *35*(10), 939–953. https://doi.org/10.1016/j.ergon.2005.04.002

McIlroy, R. C. & Stanton, N. A. (2017). What do people know about eco-driving? *Ergonomics*, *60*(6), 754–769. https://doi.org/10.1080/00140139.2016.1227092

Moll, V. E. & Franke, T. (2021). Biased energy efficiency perception based on instantaneous consumption displays – indication for heuristic energy information processing. *Applied Ergonomics*, *94*, 103399. https://doi.org/10.1016/j.apergo.2021.103399.

Nienhüser, D., Bär, T., Kohlhaas, R., Schamm, T., Zimmermann, J., Gumpp, T., Strand, M., Bringmann, O., & Zöllner, J. M. (2012). Energy efficient driving and operation strategies based on situation awareness and reasoning. *IT-Information Technology*, *54*(1), 5–16. https://doi.org/10.1524/itit.2012.0658

Pampel, S. M., Jamson, S. L., Hibberd, D. L., & Barnard, Y. (2018). Old habits die hard? The fragility of eco-driving mental models and why green driving behaviour is difficult to sustain. *Transportation Research Part F: Traffic Psychology and Behaviour*, *57*, 139–150. https://doi.org/10.1016/j.trf.2018.01.005.

Sanguinetti, A., Dombrovski, K., & Sikand, S. (2018). Information, timing, and display: A design-behavior framework for improving the effectiveness of eco-feedback. *Energy Research and Social Science*, *39*, 55–68. https://doi.org/10.1016/j.erss.2017.10.001.

Sanguinetti, A., Park, H., Sikand, S., & Kurani, K. (2017). A typology of in-vehicle eco-driving feedback. In N. A. Stanton, S. Landry, G. Di Bucchianico, & A. Vallicelli (Eds.), *Advances in Human Aspects of Transportation* (Vol. 484, pp. 979–992). Springer International Publishing. https://doi.org/10.1007/978-3-319-41682-380

Schrills, T. P. P. & Franke, T. (2023). How do users experience traceability of AI systems? Examining subjective information processing awareness in automated insulin delivery (AID) systems. *ACM Transactions on Interactive Intelligent Systems*, *13*(4), 1–34. https://doi.org/10.1145/3588594.

Schwarze, D., Arend, M. G., & Franke, T. (2019). The effect of displaying kinetic energy on hybrid electric vehicle drivers' evaluation of regenerative braking. In S. Bagnara, R. Tartaglia, S. Albolino, T. Alexander, & Y. Fujita (Eds.), *Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018* (Vol. 825, pp. 727–736). Springer International Publishing. https://doi.org/10.1007/978-3-319-96068-578

Simon, H. A. (1955). A behavioral model of rational choice. *Quarterly Journal of Economics*, *69*(1), 99. https://doi.org/10.2307/1884852

Steg, L., Perlaviciute, G., & van der Werff, E. (2015). Understanding the human dimensions of a sustainable energy transition. *Frontiers in Psychology*, *6*(805). https://doi.org/10.3389/fpsyg.2015.00805.

Stragier, J., Hauttekeete, L., De Marez, L., & Brondeel, R. (2012). Measuring energy-efficient behavior in households: The development of a standardized scale. *Ecopsychology*, *4*(1), 64–71. https://doi.org/10.1089/eco.2012.0026

Strömberg, H., Andersson, P., Almgren, S., Ericsson, J., Karlsson, M., & Nåbo, A. (2011). Driver interfaces for electric vehicles. *Proceedings of the 3rd International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, *11*, 177. https://doi.org/10.1145/2381416.2381445.

Sulistyawati, K., Wickens, C. D., & Chui, Y. P. (2011). Prediction in situation awareness: Confidence bias and underlying cognitive abilities. *The International Journal of Aviation Psychology*, *21*(2), 153–174. https://doi.org/10.1080/10508414.2011.556492

Thatcher, A. (2013). Green ergonomics: Definition and scope. *Ergonomics*, *56*(3), 389–398. https://doi.org/10.1080/00140139.2012.718371

Williams, J. H., DeBenedictis, A., Ghanadan, R., Mahone, A., Moore, J., Morrow, W. R. III, Price, S., & Torn, M. S. (2012). The technology path to deep greenhouse gas emissions cuts by 2050: The pivotal role of electricity. *Science*, *335*(6064), 53–59. https://doi.org/10.1126/science.1208365

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Article 2: Assessing Energy-Related Situation Awareness Using Self-Controlled Occlusion During Electric Vehicle Driving Scenes

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Assessing Energy-Related Situation Awareness Using Self-Controlled Occlusion During Electric Vehicle Driving Scenes

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ABSTRACT

Optimal eco-driving in electric vehicles (EVs) can be challenging due to volatile, bidirectional energy flows and the difficulty of directly sensing energy flows. The present research investigates energy-related situation awareness (Energy Dynamics Awareness, EDA) as a pilot study. EDA is a theoretical concept that helps to describe and understand how visual energy feedback displays inform energy-efficient vehicle control decisions. We compared three methods (estimation tasks, subjective EDA rating scale, and gaze behavior metric) to assess EDA under two different workload conditions, using a video-based online study displaying EV driving scenes ($N = 29$). We developed a novel approach to collect gaze behavior indicators using self-controlled (i.e., manually directed) occlusion through keyboard input. Participants were asked to estimate and compare the energy consumed in EV driving scenes while performing a parallel visuospatial n-back task to induce cognitive load. Based on our findings, the n-back task successfully induced cognitive load and self-directed occlusion showed to be a promising method for energy display evaluation studies. The performance of the consumption estimation task and display fixations were influenced by cognitive workload, which has important implications for ecodriving interface design. As the subjective and performance-related measures of EDA did not correlate, the results contribute to the discussion on the divergence between subjective and objective measures of situation awareness. This pilot study encourages further research with a larger sample and adapted methods.

Keywords: Electric vehicles, Situation awareness, Ecodriving, Self-controlled occlusion, Workload, Instantaneous consumption display

INTRODUCTION

Electric vehicles (EVs) offer sustainable transportation, with drivers playing a crucial role in determining the ultimate actual energy efficiency of EVs while driving through their individual ecodriving behavior (Galvin, 2017; Sureth *et al.*, 2019). Ecodriving has a utility on a social (e.g., reduction of CO2 emission) and individual level (e.g., reduction in energy costs, potential coping skill for situations facing limited remaining range; Rauh, Franke and Krems, 2017) but can be challenging due to volatile, bidirectional energy flows (i.e., regenerative braking; Arend and Franke, 2017) and the difficulties

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for humans to directly sense energy dynamics (in contrast to other physical phenomena such as light or sound with dedicated human sensory capabilities). Therefore, to support drivers, energy displays that provide access to energy information are a standard built-in feature and have already been the subject of scientific debate and empirical research in the field of human factors (Dahlinger *et al.*, 2018; Sanguinetti *et al.*, 2020; Moll and Franke, 2021).

The human-machine interaction context of drivers executing ecodriving behavior inside the vehicle based on available information can psychologically be conceptualized as an action regulation control loop, similar to other control-theoretic models of facets of driving behavior (Fuller, 2011) or self-regulation in general (Carver and Scheier, 1982), in which drivers continuously perceive the vehicle and the environment, and act accordingly to perceived information and current driving goals (Franke *et al.*, 2016). We assume that in this context of ecodriving an energy-specific situation awareness (Endsley, 1995, 2015), which we refer to as Energy Dynamics Awareness (EDA; Gödker, Dresel and Franke, 2019; Gödker, Moll and Franke, 2024), supports energy-efficient decisions and actions in electric vehicles and that visual energy feedback interfaces can support EDA by providing information to perceive, understand, or predict energy dynamics.

Here, workload plays a significant role as a limiting factor in conscious cognitive and attentional processes. The closed-loop model of Johnson *et al.* (2017) is an adaptation of the SEEV model (Wickens *et al.*, 2003), and has been designed to help understand and predict visual attention, cognitive load, and situation awareness. Following this model, a lack of knowledge about current system states (e.g., energy consumption) leads to uncertainty, prompting operators to seek information from interfaces to clarify the state of relevant elements (e.g., speed) and improve awareness. The longer operators refrain from looking at the interface, the more uncertainty grows until it reaches a limit, which is the *maximum desired uncertainty*. Beyond this limit, the situation awareness decreases significantly, and ultimately, performance.

Therefore, EDA and cognitive load in energy information processing are central elements in the supporting effects of energy displays on ecodriving and important to examine. In the present work, we focus on video-based online studies. They are highly controllable, as they offer identical stimuli for all participants (as opposed to field studies). In addition, they are a safe and economical way to evaluate energy displays in early development stages. However, gaze-based metrics such as *uncertainty* are difficult to measure when eye tracking technology is unavailable.

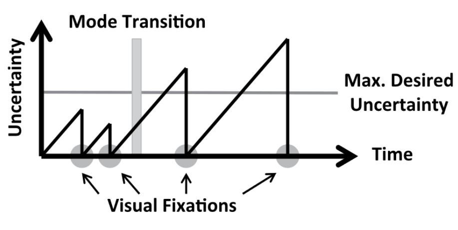


Figure 1: Schematic representation of the relationship between visual fixations and uncertainty from Johnson et al. (2017, p. 231).

We adapted occlusion to assess indicators of gaze behavior, which is an established method in information processing demand experiments with in-vehicle displays (Krems *et al.*, 2000; Baumann *et al.*, 2004). Occlusion is the temporary covering of information or visualizations to control the visual attention on displays or on the traffic. Normally, occlusion is manipulated and introduced by the experimenter, and participants do not control what is occluded and when. But when participants can control when the occlusion occurs, it is possible to infer with some accuracy the visual attention foci of participants (i.e., self-controlled occlusion).

To sum up, since energy-related situation awareness can be assumed to be influenced by workload and related to visual attention and behavior, we tested whether we could link uncertainty as a gaze behavior metric during the use of energy displays under different workload conditions to different EDA measures in a pilot study.

Therefore, the present research had three research objectives:

RO1. To build and test an experimental setting to examine EDA under different workload conditions.
RO2. To integrate and test self-controlled occlusion as a gaze data collection method to quantify drivers' energy information acquisition.
RO3. To examine any empirical link between visual attention towards the energy information and (self-assessed) EDA.

METHOD

Sample

We recruited participants through the online learning platform of the University of Lübeck and by personally approaching colleagues and acquaintances. Of the 43 full participations, we had to exclude 14 because the self-controlled occlusion data could not be obtained or validated correctly due to technical reasons. The final sample ($N = 29$, 16 female, 12 male, 1 not stated) had an average age of $M = 29.9$ years ($SD = 14.1$) and an average affinity for technology interaction (ATI) of $M = 3.58$ ($SD = 1.32$), which was almost exactly equal to the distribution of a quota sample assumed to represent the general population in Germany ($M = 3.61$; Franke, Attig and Wessel, 2019).

Driving Scenes

In this online experiment, participants viewed driving scenes (videos) of EV trips from the driver's field of view, along with an instantaneous consumption display that has been designed for a previous study (for more details, see Gödker, Moll and Franke, 2024). In addition, current speed as well as brake and throttle pedal position were presented (Figure 2). For the driving scenes, we collected OBD-II data and dashcam footage of the driver's view in a Renault ZOE EV in urban conditions. Participants had to watch five driving scenes: one test driving scene to introduce the setting and task, then four experimental driving scenes to measure the dependent variables. Of these, two driving scenes each shared the same route ("Route A" or "Route B") but differed in consumption due to the driver using two different driving strategies: (1) *driving-to-keep-distance* (constant distance to vehicle ahead), that is, inefficient or (2) *driving-to-keep-inertia* (constant speed), that is, efficient (adapted from Blanch Micó *et al.*, 2018; Lucas-Alba *et al.*, 2020).

To produce the final videos, driving data was imported into a Web app that displayed velocity, trip distance, pedal positions, and an energy display along with a synchronized video of the dashcam recordings. The trips lasted between 142 and 282 seconds, and the average energy consumption was between 5.14 and 18.09 kWh/100km.

Figure 2: Screenshot of the video of the electric vehicle driving scene..

Measurement

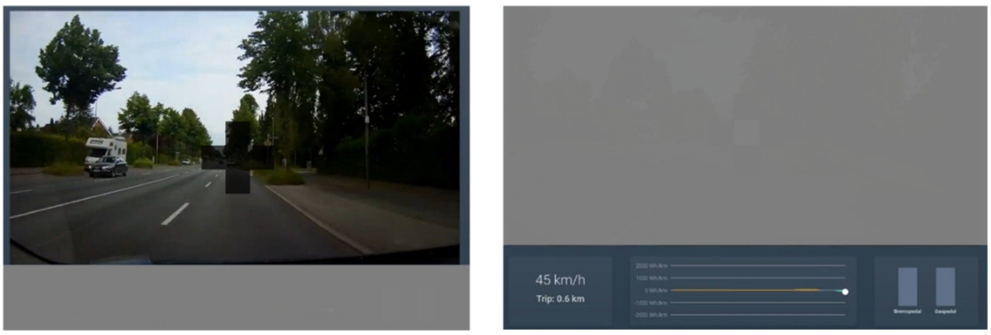
We first assessed EDA using two performance-related energy consumption estimation tasks. First, after each driving scene, participants had to estimate as accurately as possible how many watt hours per kilometer were consumed on average during this trip (*ConsEst*). Then, after the second driving scene of the same route, participants were additionally asked to indicate on which of the two trips of the same route more energy was consumed (*EffIdent*). The second method to assess EDA was an adaptation of the *EDA scale* (Gödker, Moll and Franke, 2024) as a subjective self-rating scale assumed to assess experienced EDA (Table 1). The internal consistency of this scale was overall good (Cronbach's α =.881). The six items had an α-if-item-deleted value below 0.881, which means that no item should be excluded from the analysis.

As a third method to assess EDA, we used the *sampling period* and the uncertainty metric by Johnson *et al.* (2017). The sampling period is defined as the average duration between two fixations on the display. The *uncertainty* is determined by the extent to which the sampling period exceeds the baseline sampling period. We defined the latter as the sampling period under normal circumstances without additional workload. The uncertainty metric was calculated by dividing the sampling period by the baseline sampling period. Following the assumptions of Johnson *et al.* (2017), if the sampling period exceeds the baseline (uncertainty > 1), important information cannot be perceived and situation awareness decreases.

Table 1. EDA scale items used in the present study, adapted item wording based on (Gödker, Moll and Franke, 2024).

Item	Text (translated from German)
1	By using the display during the previous two trips, I got a very good overview of the energy dynamics of the system.
2	By using the display during the previous two trips, I was able to precisely estimate the influence of various factors on the energy consumption.
3	By using the display during the previous two trips, I understood which of my actions influence the energy dynamics.
4	Using the display during the previous two trips allowed me to correctly predict the energy consumption in future situations.
5	By using the display during the previous two trips, I knew exactly what can influence the flow of energy.
6	By using the display during the previous two trips, I felt very able to increase energy efficiency if I had the opportunity.

We implemented self-controlled occlusion so that at any time either the entire view from the windshield was obscured by a gray box or the displays in the lower area. By pressing the space bar, participants could decide which area was covered and could change this as often as they wished and at any time. The sampling period was then calculated by averaging the time between two space bar presses, which indicated an active removal of the display occlusion (see both occlusion states in Figure 3).



Space bar *not* pressed   Space bar pressed

Figure 3: Screenshots of the two occlusion states that could be changed by pressing the space bar.

N-Back Task

During each driving scene, participants had to perform a parallel visuo-manual n-back task in two variations to induce two workload conditions as independent variable (0-back = low workload and 1-back = high workload).

The n-back task was to press the keys W, A, S, or D according to a visual signal. The visual signal was a gray cross, semi-transparent in the view from the windshield. At variable time intervals (between 3 and 10 seconds), one side of the cross was highlighted white for 1.5 seconds. In the 0-back condition, the response was to be given directly via W (up), A (left), S (down), D (right); in the 1-back condition, the first visual stimulus was not responded to at all, and from the second stimulus onward, the correct reaction had to be given to the previously seen stimulus. A correct response was indicated with a green square surrounding the cross, and a false response was indicated with a red square. Giving no response at all was counted as false. If the windshield view was occluded during a stimulus, the stimulus was indicated by highlighting the middle of the cross to give participants the opportunity to change the occlusion for the n-back task (right screenshot in Figure 3).

Procedure

Participants began by providing demographic information. The experiment proceeded in two blocks, each presenting a different workload condition (low or high). In each block, participants watched the two driving scenes (high and low efficiency) while performing the n-back task with self-controlled occlusion. Consumption estimation accuracy (ConsEst and EffIdent), self-assessed EDA (EDA scale), and the NASA-TLX scale (Hart and Staveland, 1988) were queried in each block. After completing both workload conditions, the participants' affinity for technology interaction (ATI) and technical knowledge were queried.

Manipulation Check

Regarding RO1, we checked whether the manipulation of different workload conditions was successful in this setup. The accuracy of the responses to the n-back task was significantly higher in the low workload condition ($Mdn = 92.9\%$) than in the high condition ($Mdn = 87.6\%$, $p = .004$, $r = .52$). Furthermore, although the NASA-TLX total score does not differ as indicated by a Wilcoxon signed-rank test ($p = .176$, $r = .25$), the mental load item was significantly higher in the high workload condition ($M = 11.59$, $SD = 3.86$) than in the low condition ($M = 10.24$, $SD = 4.00$, $t(28) = -2.11$, $p = .044$, $d = -0.39$). Both results implied a successful workload manipulation by the n-back task.

RESULTS

Our first research objective (RO1) was to assess EDA under different workload conditions. Neither the average EDA scale mean score ($M_{\text{low}} = 4.09$, $SD_{\text{low}} = 0.86$, $M_{\text{high}} = 4.18$, $SD_{\text{high}} = 0.74$, $t(28) = -0.9$, $p = .824$, $d = -0.18$) nor the share of correct efficiency identifications (EffIdent, $M_{\text{low}} = 93\%$, $SD_{\text{low}} = 26\%$, $M_{\text{high}} = 93\%$, $SD_{\text{high}} = 26\%$, that is, identical) showed significant differences. But the accuracy of the absolute consumption estimation (a higher value indicates more absolute difference to the correct value, that is, less accuracy) was significantly higher in the low workload condition ($M_{\text{low}} = 38.9$, $SD_{\text{low}} = 19.9$) than in the high workload condition

($M_{high} = 61.8$, $SD_{high} = 24.6$, $t(28) = -3.62$, $p = .001$, $d = -0.67$). This implies a reduced understanding of energy dynamics with higher cognitive workload.

Regarding RO2, the sampling period (showing a non-normal distribution, hence, we used non-parametric analysis methods) was significantly different ($Mdn_{low} = 5.35$, $IQR_{low} = 5.0$ $Mdn_{high} = 7.63$, $IQR_{high} = 5.0$) in the two workload conditions, tested using a Wilcoxon signed-rank test ($p = .001$, $r = .58$) and indicating a negative effect of workload on visual attention to energy-relevant information. This is remarkable, as the demands for visual attention are identical in the two workload conditions. We also calculated the uncertainty metric for each person by dividing the sampling period for the high workload condition by the sampling period for the low workload condition. If there were no uncertainty, this value would be 1. In our sample, the median $Mdn = 1.37$ ($IQR = 0.95$) was significantly higher than 1 as indicated by a one-sample Wilcoxon test ($p <.001$, $r =.64$), which implies that the higher workload condition affected gaze behavior. This, in turn, could potentially have led to an information acquisition deficit due to the reduced visual attention allocated to the energy feedback display to obtain necessary energy information.

Regarding RO3, the three EDA measurements (ConsEst/EffIdent, EDA scale, and the uncertainty / sampling period) did not show significant correlations with each other ($-.07 < r <.19$, $.148 < p < .606$), implying no empirical relationship between the EDA measures and gaze behavior in the present study.

DISCUSSION

The results showed differences in consumption estimation and the sampling period in the two workload conditions. However, the self-assessed EDA and efficiency identification did not differ due to the workload condition. Furthermore, no correlation was found between the EDA measures. Consequently, the present study presents methodological, theoretical, and practical implications for understanding the processing of energy-related information by drivers under varying workload conditions.

Methodologically, the research successfully built and tested an experimental online setting to test human information processing in the context of understanding energy efficiency under varying workload conditions (RO1). This method can be used to evaluate energy display concepts in the early development stages. Moreover, we introduced self-controlled occlusion as a novel gaze data collection technique in an online video-based setting (RO2). This innovative approach enables the calculation of fixation-based eye-tracking metrics without any camera or sensor technology. Furthermore, the present study applied three different methods to assess and quantify energy-related situation awareness (EDA), providing insights on the properties and potential applications of these measures.

Theoretically, the lack of correlation between self-assessed EDA and performance-based EDA measures, along with the absence of a difference in self-assessed EDA between workload conditions, hints at a conceptual divergence in subjective and objective measures of EDA (RO3). This suggests that individuals' experience of their energy-related situation awareness may not accurately reflect their actual comprehension. This finding contributes to the discussion of the theoretical divergence of subjective and objective situation awareness measures (Endsley, 2020).

Practically, the findings suggest that visual attention and comprehension of energy consumption are influenced by workload, as evidenced by the differing sampling periods under the two conditions and the difference in the accuracy of consumption estimation. This indicates a dynamic interplay between task demand and information processing in the ecodriving context. In turn, this suggests the need for careful selection of displays or even the use of situation-adaptive energy displays in complex driving situations. Instead of displays supporting the understanding of energy consumption, more action-oriented displays might be favorable (e.g., indicating the optimal speed).

Limitations and Outlook

The present study served primarily as a feasibility test for self-controlled occlusion as a gaze indicator assessment method and to obtain first results on any empirical link between visual attention towards the energy information and (self-assessed) EDA. The rather small sample size ($N = 29$) limits the generalizability of our findings to some extent. Our different EDA measures did not show correlation with each other. This might signal a methodological concern, such as issues with the reliability or validity of our measures (also discussed in Gödker, Moll and Franke, 2024). Alternatively, it could reflect a conceptual divergence between subjective, objective, direct, and indirect measurements. Detailed investigations are necessary to discern and understand these nuances. Furthermore, our pilot study did not involve real driving behavior but focused solely on the acquisition and comprehension of energy-related information. While this provides valuable insights, the transferability of our findings to actual driving scenarios cannot be answered based on the present study. Additionally, the scenes used in the present study were not theoretically derived, which means they were not selected based on their energy relevance (i.e., where ecodriving makes a difference in consumption) or other characteristics of driving situations such as complexity (leading to additional cognitive workload).

Although the present pilot study only used one energy display, different displays or display variations should be incorporated into future studies. This could increase understanding of the effect of single display elements on human information processing and the resulting behavior (Sanguinetti, Dombrovski and Sikand, 2018). Additionally, the successful manipulation of cognitive workload and the sensitivity of the sampling period data provided a solid foundation for further analyses and empirical studies. In the present study, participants watched driving scenes and energy information on the computer screen. As eye movement in real vehicles is different, subsequent research should also compare the present results with eye tracking data in real or simulated driving scenarios. Transfer to driving simulator studies or field studies would not only enhance the ecological validity of the findings but would also allow for a more nuanced understanding of how EDA influences actual driving behavior and energy efficiency.

Finally, future studies should ensure that the scenarios used are carefully selected and recorded based on their energy relevance and complexity. This would ensure that the research context closely mirrors real-world driving conditions, thereby enhancing the practical applicability and impact of the research. Furthermore, the omission of irrelevant situations could further increase the diagnosticity and economy. Established catalogs of driving situation requirements should be used for such a definition and selection of driving situations (e.g., Fastenmeier and Gstalter, 2007) to inform optimal design of driving scenes to advance understanding of human-energy interaction.

In summary, the present pilot study offers a promising basis for future research. While this study represents an important first step in evaluating human energy information processing in electric vehicles, much remains to be explored to better understand and support ecodriving, energy display design, and electric vehicle use, ultimately contributing to more energy-efficient and sustainable driving behavior.

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REFERENCES

Arend, M. G. and Franke, T. (2017) ‘The Role of Interaction Patterns with Hybrid Electric Vehicle Eco-Features for Drivers’ Eco-Driving Performance’, *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 59(2), pp. 314–327. Available at: https://doi.org/10.1177/0018720816670819.

Baumann, M. *et al.* (2004) ‘Evaluation of in-vehicle HMI using occlusion techniques: experimental results and practical implications’, *Applied Ergonomics*, 35(3), pp. 197–205. Available at: https://doi.org/10.1016/j.apergo.2003.11.011.

Blanch Micó, M. T. *et al.* (2018) ‘Car following: Comparing distance-oriented vs. inertia-oriented driving techniques’, *Transport Policy*, 67, pp. 13–22. Available at: https://doi.org/10.1016/j.tranpol.2017.05.008.

Carver, C. S. and Scheier, M. F. (1982) ‘Control theory: A useful conceptual framework for personality–social, clinical, and health psychology.’, *Psychological Bulletin*, 92(1), pp. 111–135. Available at: https://doi.org/10.1037/0033-2909.92.1.111.

Dahlinger, A. *et al.* (2018) ‘The impact of abstract vs. concrete feedback design on behavior insights from a large eco-driving field experiment’, in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. CHI ‘18: CHI Conference on Human Factors in Computing Systems*, Montreal QC Canada: ACM, pp. 1–11. Available at: https://doi.org/10.1145/3173574.3173953.

Endsley, M. R. (1995) 'Toward a theory of situation awareness in dynamic systems', *Human Factors*, 37(1), pp. 32–64. Available at: https://doi.org/10.1518/001872095779049543.

Endsley, M. R. (2015) 'Situation awareness misconceptions and misunderstandings', *Journal of Cognitive Engineering and Decision Making*, 9(1), pp. 4–32. Available at: https://doi.org/10.1177/1555343415572631.

Endsley, M. R. (2020) 'The Divergence of Objective and Subjective Situation Awareness: A Meta-Analysis', *Journal of Cognitive Engineering and Decision Making*, 14(1), pp. 34–53. Available at: https://doi.org/10.1177/1555343419874248.

Fastenmeier, W. and Gstalter, H. (2007) 'Driving task analysis as a tool in traffic safety research and practice', *Safety Science*, 45(9), pp. 952–979. Available at: https://doi.org/10.1016/j.ssci.2006.08.023.

Franke, T. *et al.* (2016) 'Ecodriving in hybrid electric vehicles – Exploring challenges for user-energy interaction', *Applied Ergonomics*, 55, pp. 33–45. Available at: https://doi.org/10.1016/j.apergo.2016.01.007.

Franke, T., Attig, C. and Wessel, D. (2019) 'A personal resource for technology interaction: Development and validation of the affinity for technology interaction (ATI) scale', *International Journal of Human–Computer Interaction*, 35(6), pp. 456–467. Available at: https://doi.org/10.1080/10447318.2018.1456150.

Fuller, R. (2011) 'Driver Control Theory', in *Handbook of Traffic Psychology*. Elsevier, pp. 13–26. Available at: https://doi.org/10.1016/B978-0-12-381984-0.10002-5.

Galvin, R. (2017) 'Energy consumption effects of speed and acceleration in electric vehicles: Laboratory case studies and implications for drivers and policymakers', *Transportation Research Part D: Transport and Environment*, 53, pp. 234–248. Available at: https://doi.org/10.1016/j.trd.2017.04.020.

Gödker, M., Dresel, M. and Franke, T. (2019) 'EDA scale - Assessing awareness for energy dynamics', in F. Alt, A. Bulling, and T. Döring (eds) *Mensch und Computer 2019 - Tagungsband*. New York: ACM. Available at: https://doi.org/10.1145/3340764.3344891.

Gödker, M., Moll, V. E. and Franke, T. (2024) 'Energy Consumption Displays in Electric Vehicles: Differential Effects on Estimating Consumption and Experienced Energy Dynamics Awareness', *Human Factors: The Journal of the Human Factors and Ergonomics Society*, p. 00187208231222154. Available at: https://doi.org/10.1177/00187208231222154.

Hart, S. G. and Staveland, L. E. (1988) 'Develpoment of NASA-TLX (task load index): Results of empirical and theoretical research', *Advances in Psychology*, 52, pp. 139–183. Available at: https://doi.org/10.1016/S0166-4115(08)62386-9.

Johnson, A. W. *et al.* (2017) 'A Closed-Loop Model of Operator Visual Attention, Situation Awareness, and Performance Across Automation Mode Transitions', *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 59(2), pp. 229–241. Available at: https://doi.org/10.1177/0018720816665759.

Krems, J. F. *et al.* (2000) 'Evaluating Visual Display Designs in Vehicles: Advantages and Disadvantages of the Occlusion Technique', in L. M. Camarinha-Matos, H. Afsarmanesh, and H.-H. Erbe (eds) *Advances in Networked Enterprises*. Boston, MA: Springer US, pp. 361–368. Available at: https://doi.org/10.1007/978-0-387-35529-0_34.

Lucas-Alba, A. *et al.* (2020) 'Distressed in the queue? Psychophysiological and behavioral evidence for two alternative car-following techniques', *Transportation Research Part F: Traffic Psychology and Behaviour*, 74, pp. 418–432. Available at: https://doi.org/10.1016/j.trf.2020.09.011.

Moll, V. E. and Franke, T. (2021) 'Biased energy efficiency perception based on instantaneous consumption displays – Indication for heuristic energy information processing', *Applied Ergonomics*, 94, p. 103399. Available at: https://doi.org/10.1016/j.apergo.2021.103399.

Rauh, N., Franke, T. and Krems, J. F. (2017) 'First-time experience of critical range situations in BEV use and the positive effect of coping information', *Transportation Research Part F: Traffic Psychology and Behaviour*, 44, pp. 30–41. Available at: https://doi.org/10.1016/j.trf.2016.10.001.

Sanguinetti, A. *et al.* (2020) 'Average impact and important features of onboard eco-driving feedback: A meta-analysis', *Transportation Research Part F: Traffic Psychology and Behaviour*, 70, pp. 1–14. Available at: https://doi.org/10.1016/j.trf.2020.02.010.

Sanguinetti, A., Dombrovski, K. and Sikand, S. (2018) 'Information, timing, and display: A design-behavior framework for improving the effectiveness of eco-feedback', *Energy Research & Social Science*, 39, pp. 55–68. Available at: https://doi.org/10.1016/j.erss.2017.10.001.

Sureth, A. *et al.* (2019) 'The golden rules of ecodriving? The effect of providing hybrid electric vehicle (HEV) drivers with a newly developed set of ecodriving-tips', *Transportation Research Part F: Traffic Psychology and Behaviour*, 64, pp. 565–581. Available at: https://doi.org/10.1016/j.trf.2019.07.003.

Wickens, C. D. *et al.* (2003) 'Attentional Models of Multitask Pilot Performance Using Advanced Display Technology', *Human Factors*, p. 21.

Article 3: Improved Ecodriving Using Instantaneous Consumption Displays in an Electric Vehicle Driving Simulator: The Role of Energy Dynamics Awareness

Improved Ecodriving Using Instantaneous Consumption Displays in an Electric Vehicle Driving Simulator: The Role of Energy Dynamics Awareness

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Supporting drivers in reducing energy consumption is essential for sustainable mobility. In electric vehicles, the invisibility and volatility of energy make it difficult for drivers to understand energy dynamics, hindering optimally energy-efficient action regulation. In a driving simulator experiment with $N = 77$ participants, we investigated drivers' operational ecodriving and its improvement over eight trials using instantaneous consumption displays with different extents and qualities of energy information provision. Participants were divided into two display groups (trace, bar) and a control group (no display). We assessed their ecodriving (average consumption) and Energy Dynamics Awareness (energy-specific situation awareness, EnDynA), specifically, their experienced (self-rating scale) and actual (consumption estimate accuracy) EnDynA. Across groups, we observed improvements in experienced EnDynA, consumption estimate accuracy, and energy efficiency. The information provision affected improvements in experienced EnDynA and ecodriving but not consumption estimate accuracy. Experienced EnDynA negatively correlated with energy consumption, highlighting its relevance in ecodriving.

Keywords: electric vehicle, energy, interface, driving simulator, situation awareness, ecodriving, sustainability

1 Introduction

Supporting drivers in reducing energy consumption is central to sustainable mobility. In electric vehicles (EVs), an energy-efficient driving style (i.e., *eco-driving* or *ecodriving*) benefits individuals (e.g., cost-reduction, sustainable behavior motive, driving competence in low-battery events; Barkenbus, 2010; Bingham et al., 2012; Franke et al., 2016) as well as society (e.g., reduction of global greenhouse gas emissions, grid infrastructure demand reduction; Axsen et al., 2020; Franke, Görges, and Arend, 2019; Marmaras et al., 2017). Drivers can greatly benefit from support to enhance ecodriving, as demonstrated for internal combustion vehicles (e.g., Allison et al., 2021; Beloufa et al., 2019; Sanguinetti et al., 2020). This highlights the potential for green ergonomics (Thatcher, 2013), indicating that a human-centered driver-vehicle interaction design can promote the sustainable use of technology. Empirical studies on EV energy consumption highlight the benefits of ecodriving tips and assistive driving functions (Chada et al., 2023; Sureth et al., 2019). Regarding internal combustion vehicles, previous empirical studies have already observed an effect of consumption feedback displays on fuel efficiency (Sanguinetti et al., 2020). However, while Sanguinetti et al. (2018) introduce the design-behavior model, the specific effects of display elements on driver experience and behavior remain underexplored (e.g., motivation, understanding). Informative in-vehicle displays that provide feedback about instantaneous or average consumption (instantaneous consumption display, ICD / average consumption display, ACD) are among EVs' most common built-in consumption-related features. However, their influence on consumption has not been sufficiently investigated experimentally. ICDs provide disaggregated, latency-free, and dynamic energy information, allowing drivers to assess consumption during specific route sections or driving maneuvers and understand the influence of situational factors (e.g., terrain) or actions (e.g., strong acceleration). By enhancing the data and temporal granularity, ICDs might better help understand energy dynamics and, ultimately, learn ecodriving (Sanguinetti et al., 2018). However, the volatile data in ICDs could increase the mental workload as drivers process it in real-time. Regarding some aspects of driving behavior, (Dijksterhuis et al., 2015) showed that delayed feedback can be equally effective to ICDs; however, in an EV field study by Günther et al. (2020), an ACD alone did not lead to reduced energy consumption compared to the control group. To sum up, although ICDs are well-established displays in electric vehicles and their effectiveness is presumable, to our knowledge, no empirical study has explicitly demonstrated a reduction in energy consumption while driving an EV using an ICD in an experimental setting.

Besides external factors (Birrell et al., 2014; Donkers et al., 2020), driver behavior plays a significant role in reducing energy use. Among strategic and tactical decisions (e.g., vehicle maintenance, route choice, vehicle load; Michon, 1985; Sivak & Schoettle, 2012), operational driving maneuver decisions, including velocity selection and the execution of accelerations and decelerations, are critical determinants of energy efficiency (see also Huang et al., 2018; Wang et al., 2020). This maneuver-related, operational ecodriving can psychologically be described as an action regulation control loop like in control theoretic models of driver behavior (Fuller, 2011; Macadam, 2003; Nash et al., 2016) based on human information processing (Wickens & Carswell, 2021). Beyond automatic action regulation processes of vehicle control, drivers continuously observe the environment to perceive and understand relevant information and then decide and act based on this information and existing knowledge to achieve their driving goals (e.g., safety, time, energy efficiency). Decisions involve selecting the goal-optimal speed profiles (e.g., acceleration, deceleration), which are then implemented via vehicle controls like pedals or cruise control. The invisibility and high volatility of energy dynamics (transformation processes) make it challenging for EV drivers to perceive and comprehend efficiency-related information - like consumption - accurately (Gödker, Moll, & Franke, 2024; Moll & Franke, 2021). This makes it difficult to evaluate actions' efficiency, hindering optimal operational ecodriving action control loops. Energy information must be perceivable and useful for information processing and action regulation (Franke, Görges, & Arend, 2019).

In line with previous research on mental models and situation models in ecodriving (Arend et al., 2019; Pampel et al., 2015, 2017; Sureth et al., 2019), an informed cognitive state allows drivers to adjust their driving style and driving behavior in varying and dynamic driving situations towards ecodriving. We describe such a concept of an informed cognitive state of drivers' ability to perceive and use energy information for ecodriving, based on the theory of situation awareness (Endsley, 1995, 2015). By focusing situation awareness on energy dynamics (comparable to Nienhüser et al., 2012; Rasmussen et al., 2018), mental representations of energy consumption can be better described and examined. We call this energy-specific situation awareness *Energy Dynamics Awareness (EnDynA)*, which we have already introduced in previous publications (Gödker & Franke, 2024; Gödker, Moll, & Franke, 2024).

System design should support drivers' continuous improvement of EnDynA. Situation awareness theory suggests displayed information should be (1) goal-relevant and (2) reduce cognitive workload (Endsley et al., 2003). Hence, in energy contexts, displayed information should (1) help to understand which factors or behaviors determine energy consumption and (2) should be designed to be easily processed and integrated into mental representations of energy dynamics (see also Endsley & Connors, 2008). Consequently, in our case, the displays' support to effectively acquire, comprehend, and process task-relevant energy information might affect the improvement of EnDynA and consequently help to adjust the driving behavior towards ecodriving. Hence, the extent and quality of the displays' *provision of task-relevant energy information* (to improve ecodriving) constitutes our key independent variable.

As Endsley (2020) notes, drivers' self-assessment of situation awareness (we name *experienced EnDynA*) can differ from their actual situation awareness (in our case *actual EnDynA*). The interplay between subjective (experienced) and objective (actual) situation awareness affects performance, highlighting the need for their alignment and calibration. We assume experienced EnDynA to be essential for drivers' action regulation. When users are certain about optimal actions, they do not see the necessity of correcting their EnDynA. In contrast, if users are uncertain and report a low experienced EnDynA, they might feel compelled to improve their EnDynA (c.f., Endsley, 2020) and form intentions to do so. Specifically, higher experienced EnDynA should be negatively associated with intentions to gather information to improve EnDynA. Thus, it appears relevant to understand how the task-relevant energy information provision influences both experienced and actual EnDynA. The operationalization and measurement of experienced and actual EnDynA

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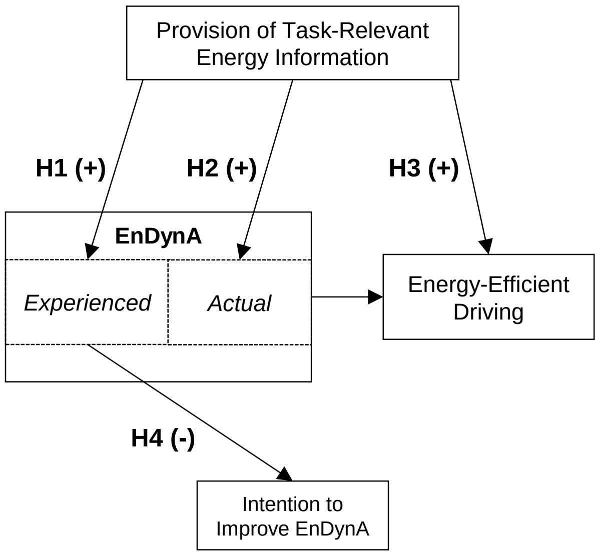
are detailed in Section 2.

Hence, the objective of the present research was to examine drivers' improvement in EV operational ecodriving using ICDs with a different task-relevant energy information provision and the role of EnDynA in this process. As shown in Figure 1, we assume that displays' provision of energy information influences EnDynA (experienced and actual) and energy-efficient driving. Additionally, we believe that experienced EnDynA motivates drivers to improve EnDynA actively.

Figure 1

Hypothesized Conceptual Relations Between the Study's Variables (Direction in Parentheses).



Present Research

In the present study, we introduced two ICDs inducing medium (*bar display*) or greater (*trace display*) information provision (i.e., energy information relevant for efficient and effective evaluation and regulation of ecodriving). The control group, without an ICD, represented the low information provision condition.

In the experiment, participants were instructed to drive as efficiently as possible, given a specific time constraint (i.e., to focus on maneuver optimization rather than time-consumption tradeoff) for a total of eight individual trials (c.f., Section 2). To approximate the accuracy of the participants' comprehension of energy consumption (that is, actual EnDynA), participants were asked to estimate changes in their energy consumption between two subsequent trials. Additionally, participants stated their current subjectively experienced EnDynA and their intention to actively search for information to correct their assumptions on energy dynamics (intention to improve EnDynA).

Hypotheses

We hypothesize that improvement in ecodriving is possible through repeated trials while having access to energy information but that the extent and quality of task-relevant energy information moderate this process. We believe that information provision influences the EnDynA (reflected by self-assessed experienced EnDynA and estimating consumption changes) and average energy consumption. Specifically, we formulate the following hypotheses:

H1: Experienced EnDynA improves over the course of trials (H1a). The improvement is strongest for the greater information provision condition and weakest for the control group (H1b).

H2: The accuracy of energy consumption estimates improves over the course of trials (H2a). The accuracy of energy consumption estimates improves most for the greater information provision condition and weakest for the control group (H2b).

H3: Participants improve energy-efficient driving over the course of trials (H3a). The improvement in energy-efficient driving is strongest for the greater information provision condition and weakest for the control group (H3b).

H4: Participants with lower experienced EnDynA express a stronger intention to use energy information for improvement.

2 Method

Participants

In total, 97 participants completed the experiment. They were recruited via mailing lists, university's learning management system forums, and social media. Participants had to be at least 18 years old, possess a driving license, and be fluent in German. Participants volunteered to participate in the study (with informed consent) and received €15 or course credit (for psychology and media informatics students). Ethics approval for this study was granted by the Ethics Committee of the University of Lübeck (tracking number: 2022-437).

We excluded data from two participants with corrupted data sets, two with display failures, one who participated twice, and 15 who aborted due to simulation sickness.

The final sample (N = 77) was between 18 and 50 years old (M = 24.0, SD = 5.6). Forty-four participants stated to identify themselves as female (57% of the sample), 32 as male (42%), and one person did not state (1%). All participants stated to have a valid driving license with M = 60270 km (SD = 186068 km) of driving experience, and 23.4% of the sample had already driven an EV at least once. We assessed user diversity in human-technology interaction using the Affinity for Technology Interaction scale (ATI; Franke, Attig, & Wessel, 2019). Our sample had an average value of M = 3.95 (SD = 0.87, ATI mean values can range between 1 and 6), being higher than the mean of a quota sample assumed to represent the general population in Germany (3.61 as in Franke, Attig, & Wessel, 2019).

Electric Vehicle Driving Simulator

The study was conducted in the EcoSimLab driving simulator of the Institute of Multimedia and Interactive Systems of the University of Lübeck (for details, see Heidinger et al., 2023). The driving simulator featured three 55″ 120 Hz monitors forming a 180° field of view and a Fanatec gaming simulation rig with a seat, wheelbase, and pedals. An original Renault Zoe steering wheel was mounted for realism. The steering wheel and pedals had force feedback. The simulation software was BeamNG.tech, a variant of the BeamNG.drive platform (BeamNG GmbH, 2022). The energy consumption was calculated using an energy model created by Heidinger et al. (2023) in the simulation software, which accounted for the vehicle's and environment's physics. The setup can be seen in Figure 2.

Figure 2

EcoSimLab Driving Simulation Setup

Energy Displays

To present the ICDs, a 10.5″ Samsung Galaxy S4 tablet was mounted on a gooseneck to the right of the steering wheel, slightly overlapping the simulator screen. In the control group, the tablet was turned off. We tested two ICDs: (1) the *trace display* (greater information provision) and (2) the *bar display* (medium information provision), alongside a control group without a display (low information provision; Figure 3). The bar display, simulating a typical built-in display, used a vertical bar to show instantaneous consumption. Orange indicated energy consumption (values above zero), and blue indicated regenerative braking (values below zero). Bar height represented the amount of energy consumed or regained.

The trace display showed current energy consumption as a white point and a trace of the last 100 meters, moving from left to right (comparable to Franke, Görges, & Arend, 2019; Gödker, Schmees, et al., 2024). A trace interval of 100 meters is sufficient to capture (in most cases) complete acceleration and deceleration maneuvers while maintaining data granularity. Orange lines in the positive range indicated energy consumption, while blue lines in the negative range showed that energy was regained. The height of the white point and the amplitude of the curve indicated the amount of energy at each moment. This enhanced the extent and quality of information provision in three ways: First, the energy information remained visible longer so that more information could be seen at a glance without information loss. Second, the additional x-axis (representing distance) visualized the amount of consumed energy as an area. This helped drivers understand the energy consumption metric Wh/km without the need to mentally represent the area themselves (as necessary with the bar display). Third, maneuvers could be better related to the consumed energy: it was easier for drivers to relate maneuvers to consumed energy and check assumptions about maneuver-specific energy dynamics by evaluating energy consumption after the maneuver.

Consequently, we expected information provision extent and quality to be greater for the trace display, resulting in energy information being acquired more easily and used to test hypotheses about maneuvers and energy dynamics. Additionally, we included a control group without display where energy-related information can only be perceived and understood indirectly via sounds or speed and their mental representation.

Note that although these types of ICDs already exist in EVs, their demand for visual attention and cognitive capacity could potentially impede safe driving when used extensively. In the present study, the displays operationalized our independent variable to investigate the impact of their deliberate use on ecodriving. Practically, this could support using these displays in safe training environments like driving simulators or controlled test tracks.

Figure 3

Instantaneous Consumption Displays (Bar Display top, Trace Display Bottom)

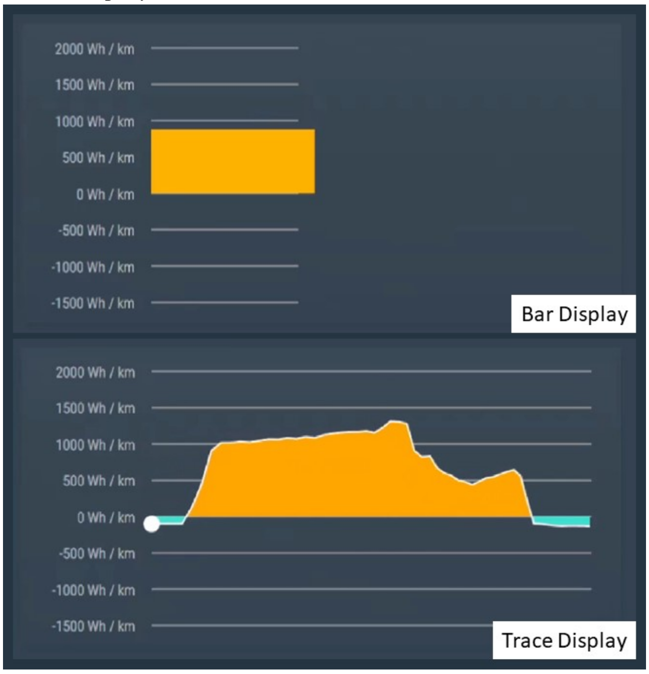
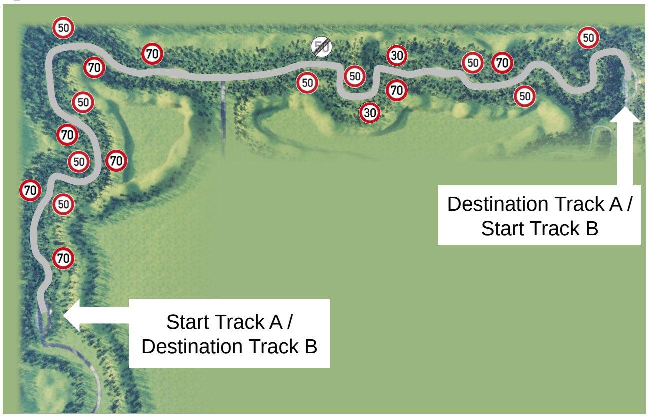


Figure 4

Bird's Eye Snapshot of the Route With the Corresponding Speed Limits



Note. Track A followed the route from left to right, Track B from right to left. The speed limits shown on the right-hand side from the direction of travel apply. See supplementary material for a video of the scenario.

Driving Scene

We designed a map with a flat rural road (see Figure 4) including curves requiring longitudinal and lateral control maneuvers. Trials began at a service station and ended by stopping at the final service station. Along the way, participants passed three lay-bys serving as checkpoints. In case of a crash, participants were reset to the last checkpoint. The road had no other users, unexpected events, traffic lights, or stop signs. On Track A, participants drove on average for a duration of $M = 246$ s ($SD = 17$ s) and a distance of $M = 3334$ m (44 m). on Track B for a duration of $M = 242$ s ($SD = 15$ s) and a distance of $M = 3358$ m ($SD = 12$ m).

Measures

Energy-Efficient Driving

Average energy consumption (Wh/km) was measured as an indicator of operational ecodriving performance, meaning energy-efficient driving. This was calculated by measuring the state of charge (SOC) in the simulated car at the start and end of the trip and then dividing the energy consumed by the distance traveled.

EnDynA-Related Measures

Experienced EnDynA. We assessed drivers' subjectively experienced EnDynA with a revised version of the EnDynA scale. The revised version was a 9-item scale with a 6-point Likert agreement rating scheme (1 = *completely disagree* to 6 = *completely agree*; Table 1). Compared to prior versions (Gödker & Franke, 2024; Gödker, Moll, & Franke, 2024), the scale now focuses on the individually experienced state rather than a display's support for EnDynA (the previous version is now referred to as *EnDynA enabling scale*, see Table 3). Items 8 and 9 were added to assess drivers' action confidence. he scale showed high internal consistency across all eight administrations (Cronbach's α ranged between .89 and .95). However, item 6 performed poorly ($\alpha_{ifitemdeleted}$ between .93 and .97, discrimination values between -.11 and .49), indicating it did not fit conceptually. Parallel analysis suggested only one principal component, indicating unidimensionality. Therefore, we omitted item 6 from our analysis. For all analyses, a mean score of all remaining items was calculated.

Actual EnDynA. From the second trial onward, participants additionally estimated the energy in Wh/km they consumed or saved compared to the previous trial (see Table A1 for the prompt). The absolute difference to the correct value (estimate deviation) was used as an indicator for actual EnDynA as it represented the inverse of the estimates' accuracy.

Intention to Improve EnDynA. Participants' intention to improve their EnDynA was measured with a 3-item self-constructed scale using a 6-point Likert rating (1 =*completely disagree* to 6= *completely agree*). Cronbach's α values ranged between .95 and .97. The scale is shown in Table 2. Mean scores of all items were used for analyses.

EnDynA Enabling Scale. We believe EnDynA arises in a situation from the use of the available energy-related in-

Table 1

All Items of the Energy Dynamics Awareness (EnDynA) Scale

Item	Text
1	I have a very good overview of the energy dynamics of the system.
2	I can precisely estimate the influence of different factors on energy consumption.
3	I understand which of my actions influence the energy dynamics.
4	I am able to correctly predict energy consumption in future situations.
5	I know exactly how to optimize energy consumption.
6	I am not sure to what extent my behavior to optimize energy consumption was correct.
7	I am sure I can notice errors in my energy-efficient behavior.
8	I feel confident in choosing energy-efficient actions.
9	I feel confident in optimizing energy consumption.

Note. The instructions explained the rating scheme ("Please indicate your level of agreement with the following statements."). The agreement to the 9 items had to be indicated on a 6-point Likert scale reading: *completely disagree*, *largely disagree*, *slightly disagree*, *slightly agree*, *largely agree*, *completely agree*, coded as 1-6 for data analysis. In the current analysis, item 6 was excluded due to its poor item statistics. For original German items, see Table B1.

formation. To specifically assess the displays' EnDynA support as experienced by participants, we used the *EnDynA enabling* scale, a parallel version of the EnDynA scale. We used this scale in previous studies (Gödker & Franke, 2024; Gödker, Moll, & Franke, 2024). In this study, the EnDynA enabling scale assessed the support participants experienced from the display after all trials rather than their self-assessment. Therefore, this scale was only administered to the participants of the display groups (N = 52), not the control group. The 9-item 6-point Likert (1 = *completely disagree* to 6 = *completely agree*) scale is depicted in Table 3. Also here, item 6 showed low item statistics and was omitted (final Cronbach's α = .94). Mean scores of the remaining items were used for analyses.

Experimental Procedure

This repeated-measures driving simulator experiment used block randomization (Kang et al., 2008, block size = 30) to assign participants to one of three information provision conditions: bar display, trace display, or no display (control). Due to drop-outs and exclusions, the final sample of 77 participants was distributed unevenly across conditions: bar display (31), trace display (21), and control (25). At the start of the experiment, participants were informed about the procedure, provided consent, and completed the first questionnaire. Then, a four-minute *familiarization trial* was performed to familiarize participants with the simulated EV by driving freely on a test track. Afterward, participants watched a video explaining the experimental procedure. Participants were asked to drive as efficiently as possible while reaching the destination within 4.30 min. The time limit was easy enough to meet to focus on energy efficiency over time efficiency. They completed two baseline trials (routes A and B) with only a speed indicator and timer, without energy displays. Following the first trial, participants completed the EnDynA and EnDynA improvement intention scales. Starting from the second trial, participants also completed the consumption estimate task. After the second trial, participants of the display groups watched a group-specific video explaining the energy display, followed by a second familiarization trial for all participants with their assigned display (or none for the control group). The trials three to six were identical and involved driving route A with their assigned energy display, along with a speed indicator and timer. Trials seven and eight followed the same procedure on route B. Weather and HVAC settings were kept consistent across all trials to control their impact on energy consumption. We used these two different routes to account for route-dependent learning effects. After the final trial, participants completed a control variable questionnaire before being compensated and thanked. The complete experimental procedure took about 105 minutes for one participant.

Table 2

All Items of the EnDynA Improvement Intention Scale

Item	Text
1	I firmly intend to use the information available for me to optimize my energy consumption next time.
2	I firmly intend to use the information available for me to correct existing errors in my understanding of energy dynamics.
3	I firmly intend to identify the relevant information from the information available to me.

Note. The instructions explained the rating scheme ("Please indicate your level of agreement with the following statements."). The agreement to the 3 items had to be indicated on a 6-point Likert scale reading: *completely disagree*, *largely disagree*, *slightly disagree*, *slightly agree*, *largely agree*, *completely agree*, coded as 1-6 for data analysis. For original German items, see Table B3.

Table 3

All Items of the EnDynA Enabling Scale

Item	Text
1.	This display gives me a very good overview of the energy dynamics of the system.
2.	With the help of this display, I can precisely estimate the influence of various factors on energy consumption.
3.	This display helps me to understand which of my actions influence the energy dynamics.
4.	This display allows me to correctly predict energy consumption in future situations.
5.	With this display, I know exactly how to optimize energy consumption
6.	The display does not help me to assess to what extent my behavior to optimize energy consumption was correct.
7.	Through the display, I am sure that I can notice the errors in my energy-efficient behavior.
8.	Through the display, I feel confident in choosing energy-efficient actions.
9.	Through the display, I feel confident in optimizing energy consumption.

Note. The instructions indicated the supporting object ("How do you rate the display in the last driving scenes [trace display]?"), followed by an explanation of the rating scheme ("Please indicate your level of agreement with the following statements."). The agreement to the 9 items had to be indicated on a 6-point Likert scale reading: *completely disagree*, *largely disagree*, *slightly disagree*, *slightly agree*, *largely agree*, *completely agree*, coded as 1-6 for data analysis. In the current analysis, item 6 was excluded due to its poor item statistics. For original German items, see Table B4

Analyses

All analyses were performed using R-Studio (R Core Team, 2023). To test hypotheses H1–H3, we used contrast analysis, which provides more precise hypothesis testing than omnibus F-tests like repeated measures ANOVA (Buckless & Ravenscroft, 1990; Wiens & Nilsson, 2017) and allows for two-factorial designs. Hypotheses H1 - H3 related to improvements in the dependent variables in repeated trials with varying effects of the display condition. Accordingly, we assigned contrast weights for each measurement based on trial number (linear trend) and display condition (group comparison of the trend), as shown in Table 4. Following (Rosenthal et al., 2000), we first calculated the linear trend across trips to obtain a score representing the linear trend and then compared this score across groups. This was calculated using the "cofad" package (Titz & Burkhardt, 2021, 2024). To test H4, we calculated mean scores for the EnDynA and EnDynA improvement intention scales across trips one to eight and performed a Pearson correlation using the 'stats' package in R.

For all analyses related to the average consumption, we excluded trips exceeding the time limit (270s) by an additional 10% (5) and with technical driving data errors (4). For the consumption estimate task, we excluded participants who misunderstood the task (5 from the control group, 1 from the trace group; e.g., by always answering around +150 Wh/km), trips with a crash (1), driving data errors (3[1]), and trips following excluded trials (4). Following Rosenthal et al. (2000), excluded values were imputed with the cell mean.

3 Results

Regarding the experienced EnDynA (EnDynA scale, H1), the contrast analysis checking the overall improvement in experienced EnDynA (within-subjects linear trend only, H1a) was significant ($t(76) = 7.62$, $p < .001$, $g_{effectsize} = 0.87$). Also, the contrast analysis examining whether this linear trend was highest for the trace display group and lowest for the control group (between-subjects, H1b) was significant ($F(1,74) = 36.24$, $p < .001$, $r_{effectsize} = .50$; Figure 5, top left).

Regarding the actual EnDynA (consumption estimate accuracy, H2; Figure 5, top right), the contrast analysis testing the linear trend of the consumption estimate deviation for all groups (within-subjects, H2a) was significant ($t(70) = 3.31$; $p < .001$; $g_{effectsize} = 0.39$), indicating a significant improvement in estimating accuracy over the course of trials. Yet, the contrast analysis checking whether this linear trend was highest for the trace display group and lowest for the control group (between-subjects, H2b) was not significant ($F(1,68) = 0.07$, $p = .795$, $r_{effectsize} = -.02$), indicating no difference in improvement between groups.

Regarding the energy consumption measured in the driving simulator (H3), the contrast analysis checking the linear trend across all groups (within-subjects, H3a) indicated a significant reduction in energy consumption over the course of trials ($t(76) = 6.04$, $p < .001$) with an effect magnitude of $g_{effectsize} = 0.69$. Additionally, the contrast analysis testing whether this linear trend was highest for the trace display group and lowest for the control group (between-subjects, H3b) also yielded significant statistics ($F(1,74) = 17.88$, $p < .001$) with an effect magnitude of $r_{effectsize} = .45$ (Figure 5, bottom left). Also, see Appendix C for detailed descriptive driving statistics.

Regarding H4, the correlation between the EnDynA improvement intention and experienced EnDynA was indeed significant, but in the opposite (positive) direction than hypothesized ($r = .67$, $p < .001$).

[1]The trials to be excluded due to driving data errors do not match for H1 and H2 because the consumption estimate task was only ad-

Table 4

Dependent Variables and Contrast Weights for each Measurement for Hypotheses 1 to 3

		Trip (Within)								Group (Between)		
Hyp.	DV	1	2	3	4	5	6	7	8	Control	Bar	Trace
1	Experienced EnDynA (EnDynA Scale)											
		3.5	2.5	1.5	0.5	-0.5	-1.5	-2.5	-3.5	-2	0.5	1.5
2	Actual EnDynA (Consumption Estimate Deviation)											
		-	3	2	1	0	-1	-2	-3	-2	0.5	1.5
3	Energy-Efficient Driving (Average Energy Consumption)											
		-3.5	-2.5	-1.5	-0.5	0.5	1.5	2.5	3.5	-2	0.5	1.5

Note. Hyp. = hypothesis; DV = dependent variable. H1-H3 (summarized): (H1) Experienced EnDynA improves over the course of trials (H1a) to different degrees between groups (H1b), (H2) the accuracy of energy consumption estimates improves over the course of trials (H2a) to different degrees between groups (H2b), (H3) participants improve energy-efficient driving over the course of trials (H3a) to different degrees between groups (H3b). Note that for H2a, we used the consumption estimate deviation as the inverse indicator of actual EnDynA accuracy. Therefore, the direction of the linear trend shown represents an improvement in accuracy.

Further Analyses

Significant contrast tests showed that experienced EnDynA improvement (H1b) and average consumption improvement (H3b) were highest in the trace display group and lowest in the control group. Therefore, we further examined the relationship between these two dependent variables. To this end, we performed a Pearson correlation between the mean of both variables across all trials. The correlation test showed a significant weak correlation (r = -.27, p = .019, Figure 6 left), indicating lower energy consumption for participants expressing a higher experienced EnDynA. In contrast, correlations between actual EnDynA and energy consumption (r=.05, p=.670) and between actual and experienced EnDynA (r=.10, p=.389) were not significant.

Both display groups showed higher experienced EnDynA levels than the control group, suggesting a supportive effect of the displays. Nevertheless, we investigated whether participants attributed their improved experienced EnDynA to the display rather than other energy-related information like sounds or other experimental design elements. The EnDynA enabling scale assessed the EnDynA associated with the display, not the participants' experienced EnDynA. We performed a Pearson correlation between the EnDynA enabling scale mean score and the mean EnDynA scale score for trips 3 to 8 (when the display was in use). The results showed a strong correlation (r=.77, p<.001), indicating that participants' perception of the displays as EnDynA-enabling strongly aligns with their mean experienced EnDynA across trips 3 to 8.

4 Discussion

Summary of the Results

The objective of the present study was to examine drivers' improvement in EV operational ecodriving using ICDs with different extents and qualities of task-relevant energy information provision and the role of EnDynA in this process. Specifically, we investigated how EnDynA contributes to improving energy-efficient driving and how display information provision levels influence this improvement. We hypothesized (in summary):

(H1) Experienced EnDynA improves over the course of trials (H1a) with the strongest improvement in the trace display group (H1b)

(H2) The accuracy of energy consumption estimates improves over the course of trials (H2a) with the strongest improvement in the trace display group (H2b).

(H3) Participants improve energy-efficient driving over the course of trials (H3a) with the strongest improvement in the trace display group (H3b).

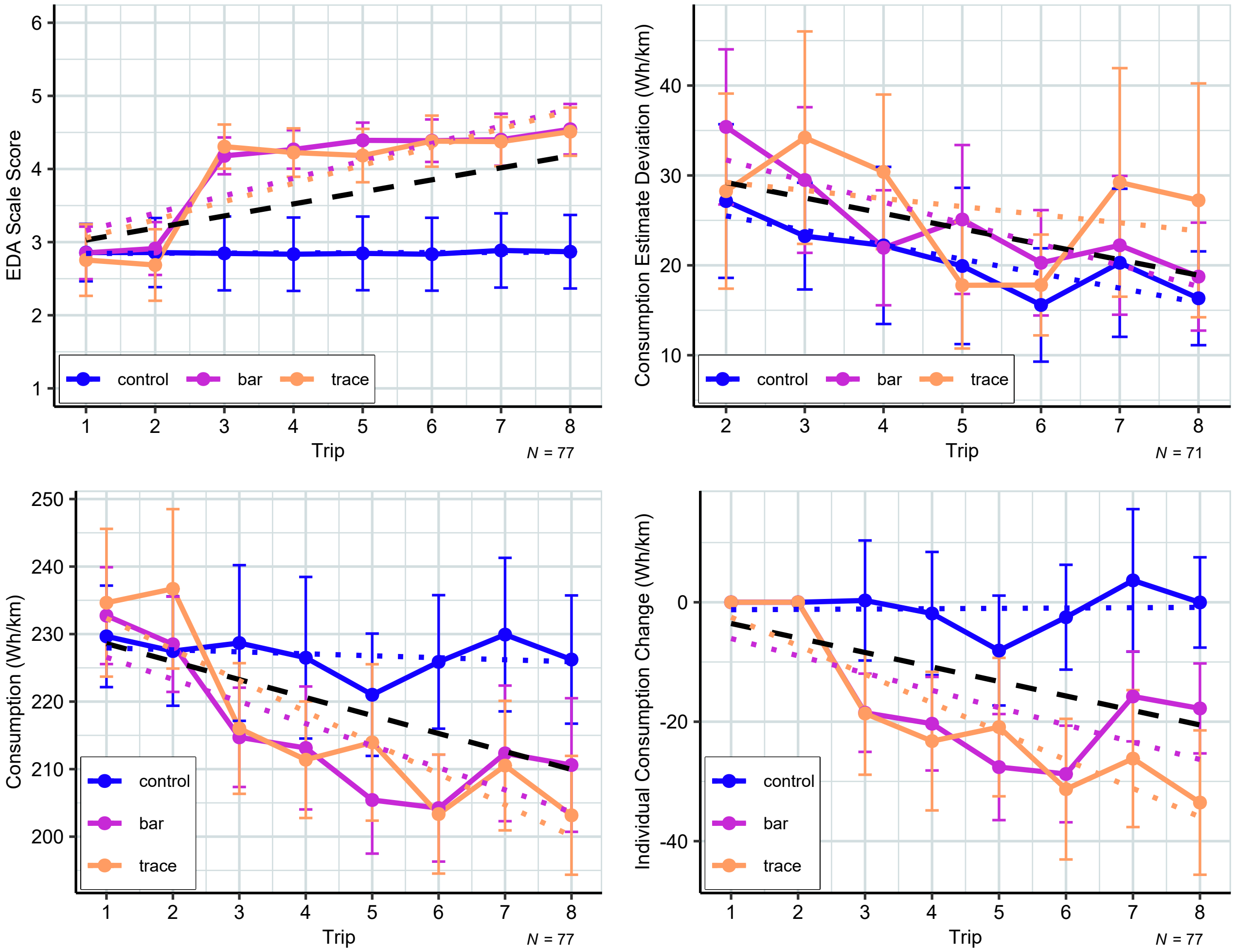
(H4) Participants with lower experienced EnDynA express a stronger intention to use energy information for improvement.

The results partially supported our hypotheses. H1a, H2a, and H3a were confirmed: experienced EnDynA, actual EnDynA, and energy-efficient driving improved over the course of trials. The strongest improvements in experienced EnDynA and energy-efficient driving occurred in the high information provision condition (trace display), while the control group showed the weakest improvements, supporting

ministered from the second trial onwards.

Figure 5

Dependent Variables Mean Values per Trip and Group



Note. Improvement in the EnDynA score (top left, H1), consumption estimate deviation (top right, H2), energy consumption (bottom left, H3), and mean individual difference to baseline trials 1 and 2 (bottom right) over the course of trials per group. At trip 3, the displays are introduced in the display groups. Error bars represent the 95% confidence interval, dotted lines the linear trend.

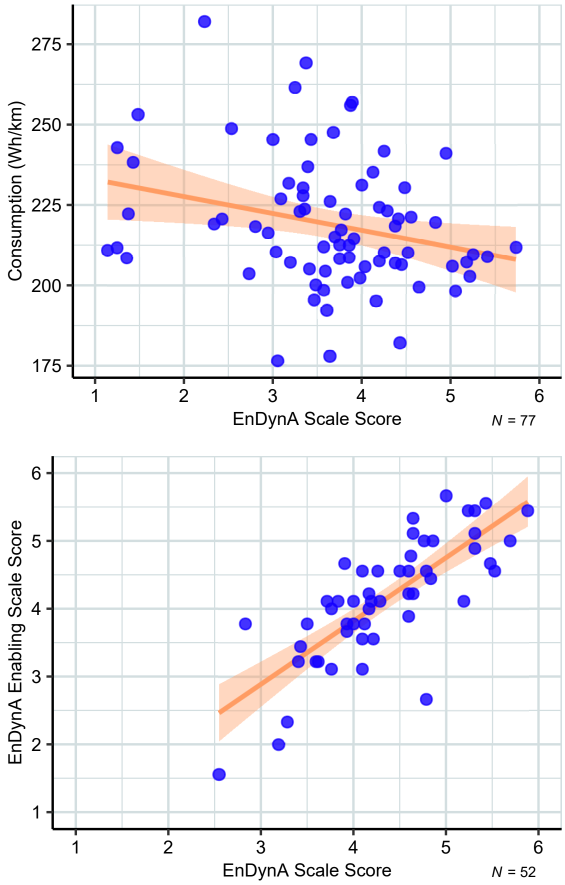
H1b and H3b. H2b was not supported due to no significant differences in consumption estimate accuracy improvements between the groups (only an overall improvement over the course of trials, H2a). This lack of group differences may stem from primarily assessing only level 2 situation awareness (SA), which is less predictive of overall performance compared to level 3 SA (Wickens, 2015). H4 was unexpectedly not supported, as higher experienced EnDynA correlated with a greater intention to improve EnDynA, contrary to our hypothesis. This finding suggests that drivers confident in their EnDynA are more motivated to seek improvements, likely due to enhanced self-efficacy. Exploratory analyses revealed a negative correlation between experienced EnDynA and energy consumption, underscoring its role in operational ecodriving. Also, experienced EnDynA positively correlated with participants' ratings of the displays' EnDynA-enabling, suggesting that the displays contributed to the improvement of EnDynA.

Implications

Our findings offer insights into the impact of ICDs on ecodriving and enhance the understanding of human-vehicle interaction in EV energy efficiency. Our evidence demonstrates that ICDs can significantly reduce energy consumption when used over repeated trials with proper introduction. Although ICDs are a standard feature in EVs, no prior study has empirically demonstrated their impact on energy consumption in an experimental setting, making these findings critical and contributing to more comprehensive models of display de-

Figure 6

Correlations of EnDynA Scale Mean Score With Average Consumption (top) and With EnDynA Enabling Scale Score (bottom).



Note. The orange line represents the linear trend, and the area around the line represents the 95% confidence interval. The sample size of the correlation with the EnDynA enabling scale is smaller because only display groups administered the EnDynA enabling scale.

sign elements and behavior (e.g., Sanguinetti et al., 2018). These models can then also support the development of more sophisticated ecodriving interfaces (e.g., including predictive elements).

Drawing from situation awareness, we identified EnDynA as a concept explaining how ecodriving displays might influence energy-related human action regulation. The correlation between experienced EnDynA and energy consumption underlines this. EnDynA provides a theoretical basis for designing, implementing, and evaluating ecodriving displays. The newly developed EnDynA and EnDynA enabling scales provide tools for assessing energy-specific situation awareness and energy feedback displays, which may benefit empirical studies on energy-efficient action regulation. In a broader sense, EnDynA contributes to understanding and explaining human experience and behavior in energy-relevant human-machine interaction situations (in line with, e.g., Nienhüser et al., 2012; Rasmussen et al., 2018).

Our findings contribute to the discussion about the conceptual divergence of subjective and objective situation awareness (Edgar et al., 2018; Endsley, 2020). The lack of a relationship between actual and experienced EnDynA supports the notion that these aspects conceptually differ. However, in our study, it was *experienced* EnDynA that predicted driving performance, not *actual* EnDynA. This may be explained by participants' greater willingness to act, driven by higher EnDynA (as described by Endsley, 2020).

Limitations and Future Research

Our sample consisted mainly of participants with limited EV driving experience, providing insight into novice drivers and their learning processes. However, it does not reflect the broader EV driver population. Future studies should include a more diverse sample with varying experience and familiarity with EVs.

The present study used only two driving scenes, limiting the representation of real-world driving conditions and energy-relevant maneuvers. The limited diversity of these scenes might constrain the generalizability of our findings (c.f., Gödker, Schmees, et al., 2024). Future research should include a broader range of driving scenes designed for energy-related studies to improve the results' ecological validity and diagnosticity. Moreover, conducting real-world field studies on closed and secured test tracks would provide insights into the effectiveness of the displays in real-world conditions. A possible explanation for the lack of group differences in the consumption estimates accuracy improvement (H2b) could be that the total driving time of about 8×4 minutes was insufficient to enhance the EnDynA. This could be further tested with longer driving durations.

Our static driving simulator lacks longitudinal g-force information, which is crucial information in ecodriving. While this limitation affects all participants similarly, the visual instantaneous consumption data may be a suitable substitute. Further investigation is needed on how this visual information interacts with longitudinal forces in real vehicles.

In our study, videos were used to introduce the displays to the display groups, while the control group did not watch a video. This may have disadvantaged the control group in terms of ecodriving improvement. The videos described the display elements to ensure participants understood the displayed information. There were no additional tips or information on how to drive energy efficiently (see supplementary material). The strong correlation between the EnDynA enabling scale and the EnDynA scale indicates that participants credited their improvement primarily to the displays.

Overall, we believe the video's impact on energy consumption was minimal.

The energy model used in the simulated EV only approximates real-world physics and energy dynamics. This limitation is inherent to current EV simulation frameworks (Gödker, Schmees, et al., 2024). Future studies should focus on further developing and refining the energy models used in EV driving simulations. Improving energy models would ensure simulated energy consumption better reflects real-world conditions, enhancing the reliability and applicability of findings.

The present study's independent variable (information provision) was operationalized as condition groups, including an extreme control group (no display). These groups were chosen to represent configurations comparable to real-world vehicles. However, this choice may have limited the theoretical implication of the results. Future studies could benefit from using a more detailed, continuous scale to operationalize the independent variable. This approach would enable a deeper analysis of how different display design elements affect EnDynA and ecodriving performance.

Lastly, future stages of display development should investigate the impact of ICDs on safety-related behavior metrics. For more comprehensive risk-benefit analyses, the positive effects of ICDs should be compared with less safety-intrusive displays, such as average consumption displays with delayed feedback.

Conclusion

The present empirical driving simulator study demonstrated the potential of ICDs to support operational ecodriving in EVs. It contributes to understanding drivers' energy-related action regulation and offers insights for designing future in-vehicle feedback systems. Enhancing drivers' EnDynA through displays with a greater energy information provision is a promising tool for promoting sustainable driving behaviors, which can be evaluated using the experienced EnDynA self-rating scale.

5 Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the authors used ChatGPT and Grammarly in order to improve the readability of the manuscript and enhance the English language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Allison, C. K., Fleming, J. M., Yan, X., Lot, R., & Stanton, N. A. (2021). *Assisted Eco-Driving: A Practical Guide to the Design and Testing of an Eco-Driving Assistance System (EDAS)* (1st ed.). CRC Press. Retrieved August 2, 2022, from https://www.taylorfrancis.com/books/9781003081173

Arend, M. G., Franke, T., & Stanton, N. A. (2019). Know-how or know-why? The role of hybrid electric vehicle drivers' acquisition of eco-driving knowledge for eco-driving success. *Applied Ergonomics*, *75*, 221–229. https://doi.org/10.1016/j.apergo.2018.10.009

Axsen, J., Plötz, P., & Wolinetz, M. (2020). Crafting strong, integrated policy mixes for deep CO2 mitigation in road transport. *Nature Climate Change*, *10*, 809–818. https://doi.org/10.1038/s41558-020-0877-y

Barkenbus, J. N. (2010). Eco-driving: An overlooked climate change initiative. *Energy Policy*, *38*(2), 762–769. https://doi.org/10.1016/j.enpol.2009.10.021

BeamNG GmbH. (2022). BeamNG.tech. https://www.beamng.tech/

Beloufa, S., Cauchard, F., Vedrenne, J., Vailleau, B., Kemeny, A., Mérienne, F., & Boucheix, J.-M. (2019). Learning eco-driving behaviour in a driving simulator: Contribution of instructional videos and interactive guidance system. *Transportation Research Part F: Traffic Psychology and Behaviour*, *61*, 201–216. https://doi.org/10.1016/j.trf.2017.11.010

Bingham, C., Walsh, C., & Carroll, S. (2012). Impact of driving characteristics on electric vehicle energy consumption and range. *IET Intelligent Transport Systems*, *6*(1), 29. https://doi.org/10.1049/iet-its.2010.0137

Birrell, S. A., McGordon, A., & Jennings, P. A. (2014). Defining the accuracy of real-world range estimations of an electric vehicle. *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2590–2595. https://doi.org/10.1109/ITSC.2014.6958105

Buckless, F. A., & Ravenscroft, S. P. (1990). Contrast coding: A refinement of ANOVA in behavioral analysis. *Accounting Review*, 933–945.

Chada, S. K., Görges, D., Ebert, A., Teutsch, R., & Subramanya, S. P. (2023). Evaluation of the driving performance and user acceptance of a predictive eco-driving assistance system for electric vehicles. *Transportation Research Part C: Emerging Technologies*, *153*, 104193. https://doi.org/10.1016/j.trc.2023.104193

Dijksterhuis, C., Lewis-Evans, B., Jelijs, B., de Waard, D., Brookhuis, K., & Tucha, O. (2015). The impact of immediate or delayed feedback on driving behaviour in a simulated Pay-As-You-Drive system. *Accident Analysis & Prevention*, *75*, 93–104. https://doi.org/10.1016/j.aap.2014.11.017

Donkers, A., Yang, D., & Viktorović, M. (2020). Influence of driving style, infrastructure, weather and traffic on electric vehicle performance. *Transportation Research Part D: Transport and Environment*, *88*, 102569. https://doi.org/10.1016/j.trd.2020.102569

Edgar, G. K., Catherwood, D., Baker, S., Sallis, G., Bertels, M., Edgar, H. E., Nikolla, D., Buckle, S., Goodwin, C., & Whelan, A. (2018). Quantitative Analysis of Situation Awareness (QASA): Modelling and measuring situation awareness using signal detection theory. *Ergonomics*, *61*(6), 762–777. https://doi.org/10.1080/00140139.2017.1420238

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors*, *37*(1), 32–64. https://doi.org/10.1518/001872095779049543

Endsley, M. R. (2015). Situation awareness misconceptions and misunderstandings. *Journal of Cognitive Engineering and Decision Making*, *9*(1), 4–32. https://doi.org/10.1177/1555343415572631

Endsley, M. R. (2020). The Divergence of Objective and Subjective Situation Awareness: A Meta-Analysis. *Journal of Cognitive Engineering and Decision Making*, *14*(1), 34–53. https://doi.org/10.1177/1555343419874248

Endsley, M. R., Bolté, B., & Jones, D. G. (2003). *Designing for situation awareness: An approach to user-centered design*. Taylor & Francis.

Endsley, M. R., & Connors, E. S. (2008). Situation awareness: State of the art. *2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century*, 1–4. https://doi.org/10.1109/PES.2008.4596937

Franke, T., Attig, C., & Wessel, D. (2019). A personal resource for technology interaction: Development and validation of the affinity for technology interaction (ATI) scale. *International Journal of Human–Computer Interaction*, *35*(6), 456–467. https://doi.org/10.1080/10447318.2018.1456150

Franke, T., Görges, D., & Arend, M. G. (2019). The Energy Interface Challenge. Towards Designing Effective Energy Efficiency Interfaces for Electric Vehicles. *Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 35–48. https://doi.org/10.1145/3342197.3344526

Franke, T., Rauh, N., Günther, M., Trantow, M., & Krems, J. F. (2016). Which Factors Can Protect Against Range Stress in Everyday Usage of Battery Electric Vehicles? Toward Enhancing Sustainability of Electric Mobility Systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *58*(1), 13–26. https://doi.org/10.1177/0018720815614702

Fuller, R. (2011). Driver Control Theory. In *Handbook of Traffic Psychology* (pp. 13–26). Elsevier. https://doi.org/10.1016/B978-0-12-381984-0.10002-5

Gödker, M., & Franke, T. (2024). Assessing Energy-Related Situation Awareness Using Self-Controlled Occlusion During Electric Vehicle Driving Scenes. In G. Praetorius, C. Sellberg, & R. Patriarca (Eds.), *Advances in Human Factors of Transportation. AHFE (2024) International Conference. AHFE Open Access* (pp. 286–296, Vol. 148). AHFE International. https://doi.org/10.54941/ahfe1005219

Gödker, M., Moll, V. E., & Franke, T. (2024). Energy Consumption Displays in Electric Vehicles: Differential Effects on Estimating Consumption and Experienced Energy Dynamics Awareness. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 00187208231222154. https://doi.org/10.1177/00187208231222154

Gödker, M., Schmees, S., Bernhardt, L., Heidinger, J., Görges, D., & Franke, T. (2024). Driving Simulation for Energy Efficiency Studies: Analyzing Electric Vehicle Eco-Driving With EcoSimLab and the EcoDrivingTestPark. *Proceedings of the 16th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 32–42. https://doi.org/10.1145/3640792.3675706

Günther, M., Kacperski, C., & Krems, J. F. (2020). Can electric vehicle drivers be persuaded to eco-drive? A field study of feedback, gamification and financial rewards in Germany. *Energy Research & Social Science*, *63*, 101407. https://doi.org/10.1016/j.erss.2019.101407

Heidinger, J., Bernhardt, L., & Franke, T. (2023). Ecosimlab - A Low-Cost Driving Simulator Environment for Examining Human Factors in Vehicle Energy Efficiency. *Adjunct Proceedings of the 15th International Conference on Automotive User Inter-*

faces and Interactive Vehicular Applications, 66–70. https://doi.org/10.1145/3581961.3609881

Huang, Y., Ng, E. C., Zhou, J. L., Surawski, N. C., Chan, E. F., & Hong, G. (2018). Eco-driving technology for sustainable road transport: A review. *Renewable and Sustainable Energy Reviews*, *93*, 596–609. https://doi.org/10.1016/j.rser.2018.05.030

Kang, M., Ragan, B. G., & Park, J.-H. (2008). Issues in Outcomes Research: An Overview of Randomization Techniques for Clinical Trials. *Journal of Athletic Training*, *43*(2), 215. https://doi.org/10.4085/1062-6050-43.2.215

Macadam, C. C. (2003). Understanding and Modeling the Human Driver. *Vehicle System Dynamics*, *40*(1-3), 101–134. https://doi.org/10.1076/vesd.40.1.101.15875

Marmaras, C., Xydas, E., & Cipcigan, L. (2017). Simulation of electric vehicle driver behaviour in road transport and electric power networks. *Transportation Research Part C: Emerging Technologies*, *80*, 239–256. https://doi.org/10.1016/j.trc.2017.05.004

Michon, J. A. (1985). A Critical View of Driver Behavior Models: What Do We Know, What Should We Do? In L. Evans & R. C. Schwing (Eds.), *Human Behavior and Traffic Safety* (pp. 485–524). Springer US. https://doi.org/10.1007/978-1-4613-2173-6_19

Moll, V. E., & Franke, T. (2021). Biased energy efficiency perception based on instantaneous consumption displays – Indication for heuristic energy information processing. *Applied Ergonomics*, *94*, 103399. https://doi.org/10.1016/j.apergo.2021.103399

Nash, C. J., Cole, D. J., & Bigler, R. S. (2016). A review of human sensory dynamics for application to models of driver steering and speed control. *Biological Cybernetics*, *110*(2-3), 91–116. https://doi.org/10.1007/s00422-016-0682-x

Nienhüser, D., Bär, T., Kohlhaas, R., Schamm, T., Zimmermann, J., Gumpp, T., Strand, M., Bringmann, O., & Zöllner, J. M. (2012). Energy efficient driving and operation strategies based on situation awareness and reasoning. *it - Information Technology*, *54*(1), 5–16.

Pampel, S. M., Jamson, S. L., Hibberd, D., & Barnard, Y. (2017). The activation of eco-driving mental models: Can text messages prime drivers to use their existing knowledge and skills? *Cognition, Technology & Work*, *19*(4), 743–758. https://doi.org/10.1007/s10111-017-0441-3

Pampel, S. M., Jamson, S. L., Hibberd, D. L., & Barnard, Y. (2015). How I reduce fuel consumption: An experimental study on mental models of eco-driving. *Transportation Research Part C: Emerging Technologies*, *58*, 669–680. https://doi.org/10.1016/j.trc.2015.02.005

R Core Team. (2023). *R: A language and environment for statistical computing* (manual). R Foundation for Statistical Computing. Vienna, Austria. https://www.R-project.org/

Rasmussen, H. B., Lützen, M., & Jensen, S. (2018). Energy efficiency at sea: Knowledge, communication, and situational awareness at offshore oil supply and wind turbine vessels. *Energy Research & Social Science*, *44*, 50–60. https://doi.org/https://doi.org/10.1016/j.erss.2018.04.039

Rosenthal, R., Rosnow, R. L., & Rubin, D. B. (2000). *Contrasts and effect sizes in behavioral research: A correlational approach* (1st ed.). Cambridge Univ. Press.

Sanguinetti, A., Dombrovski, K., & Sikand, S. (2018). Information, timing, and display: A design-behavior framework for improving the effectiveness of eco-feedback. *Energy Research & Social Science*, *39*, 55–68. https://doi.org/10.1016/j.erss.2017.10.001

Sanguinetti, A., Queen, E., Yee, C., & Akanesuvan, K. (2020). Average impact and important features of onboard eco-driving feedback: A meta-analysis. *Transportation Research Part F: Traffic Psychology and Behaviour*, *70*, 1–14. https://doi.org/10.1016/j.trf.2020.02.010

Sivak, M., & Schoettle, B. (2012). Eco-driving: Strategic, tactical, and operational decisions of the driver that influence vehicle fuel economy. *Transport Policy*, *22*, 96–99. https://doi.org/10.1016/j.tranpol.2012.05.010

Sureth, A., Moll, V., Nachtwei, J., & Franke, T. (2019). The golden rules of ecodriving? The effect of providing hybrid electric vehicle (HEV) drivers with a newly developed set of ecodriving-tips. *Transportation Research Part F: Traffic Psychology and Behaviour*, *64*, 565–581. https://doi.org/10.1016/j.trf.2019.07.003

Thatcher, A. (2013). Green ergonomics: Definition and scope. *Ergonomics*, *56*(3), 389–398. https://doi.org/10.1080/00140139.2012.718371

Titz, J., & Burkhardt, M. (2021). Cofad: An R package and shiny app for contrast analysis. *Journal of Open Source Software*, *6*(67), 3822. https://doi.org/10.21105/joss.03822

Titz, J., & Burkhardt, M. (2024). *Cofad: Contrast analyses for factorial designs* (tech. rep.). https://github.com/johannes-titz/cofad

Wang, G., Makino, K., Harmandayan, A., & Wu, X. (2020). Eco-driving behaviors of electric vehicle users: A survey study. *Transportation Research Part D:*

Transport and Environment, *78*, 102188. https://doi.org/10.1016/j.trd.2019.11.017

Wickens, C. D. (2015). Situation Awareness: Its Applications Value and Its Fuzzy Dichotomies. *Journal of Cognitive Engineering and Decision Making*, *9*(1), 90–94. https://doi.org/10.1177/1555343414564571

Wickens, C. D., & Carswell, C. M. (2021). Information Processing. In G. Salvendy & W. Karwowski (Eds.), *Handbook of Human Factors and Ergonomics* (1st ed., pp. 114–158). Wiley. https://doi.org/10.1002/9781119636113.ch5

Wiens, S., & Nilsson, M. E. (2017). Performing Contrast Analysis in Factorial Designs: From NHST to Confidence Intervals and Beyond. *Educational and Psychological Measurement*, *77*(4), 690–715. https://doi.org/10.1177/0013164416668950

Appendix A
Consumption Improvement Estimate Prompt

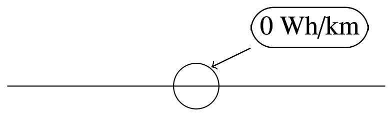
Table A1

Consumption Improvement Estimate Prompt

How many Wh/km did you consume more or less in this trip than in the last accident-free experimental trip (not test drive)? (average consumption)

A positive value on the slider means that you estimate that you have used more energy in this journey than in the last accident-free trip, and a negative value means that you have used less energy than in the last accident-free trip.

Please enter your estimate using this slider:



-200 Wh/km 200 Wh/km

On this route, a consumption of 100 Wh/km to 300 Wh/km (∅ 200 Wh/km) is usual, depending on the driving style. If you have not yet completed an accident-free journey with which you can compare this journey, please set the slider to 0.

Note. By moving a slider handle, participants were supposed to indicate their consumption improvement estimate on a vertical slider ranging from -200 to 200 Wh/km. For original German items, see Table B2.

Appendix B
Measurements in Original German Language

Table B1

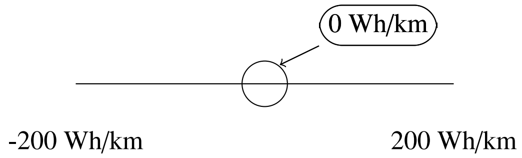
All Items of the Energy Dynamics Awareness (EnDynA) Scale (Original German Text)

Item	Text
1	Ich habe einen sehr guten Einblick in die Energieflüsse des Systems.
2	Ich kann den Einfluss verschiedener Faktoren auf den Energieverbrauch präzise einschätzen.
3	Ich verstehe, welche meiner Handlungen die Energiedynamik beeinflussen.
4	Ich kann den Energieverbrauch in zukünftigen Situationen präzise vorhersagen.
5	Ich weiß genau, wie ich den Energieverbrauch optimieren kann.
6	Ich bin nicht sicher, inwieweit mein Verhalten zur Optimierung des Energievebrauchs richtig war.
7	Ich bin mir sicher, Fehler in meinem energieeffizienten Verhalten bemerken zu können.
8	Ich habe das Gefühl, energieeffiziente Handlungen auswählen zu können.
9	Ich fühle mich bei der Optimierung des Energieverbrauchs sicher.

Note. The instruction of the scale indicated the rating scheme ("Bitte geben Sie den Grad Ihrer Zustimmung zu folgenden Aussagen an."). The agreement to the 9 items had to be indicated on a 6-point Likert scale reading: *stimmt gar nicht*, *stimmt weitgehend nicht*, *stimmt eher nicht*, *stimmt eher*, *stimmt weitgehend*, *stimmt völlig*, coded as 1–6 for data analysis. In the current analysis, item 6 was excluded due to its poor item statistics.

Table B2

Consumption Improvement Estimate Prompt (Original German Text)

Wie viel Wh/km haben Sie in dieser Fahrt mehr oder weniger verbraucht als in der letzten unfallfreien Experimentalfahrt (nicht Probefahrt)? (Durchschnittsverbrauch) *Ein positiver Wert auf dem Schieberegler bedeutet, dass Sie schätzen, in dieser Fahrt mehr als in der letzten unfallfreien Fahrt verbraucht zu haben, bei einem negativen Wert weniger als in der letzten unfallfreien Fahrt.*
Bitte geben Sie Ihre Schätzung über diesen Regler an:  Auf dieser Strecke ist ein Verbrauch von 100 Wh/km bis 300 Wh/km (∅ 200 Wh/km) je nach Fahrweise üblich. Sollten Sie noch gar keine unfallfreie Fahrt durchgeführt haben, mit der Sie diese Fahrt vergleichen können, stellen Sie den Regler bitte auf 0.

Note. By moving a slider handle, participants were supposed to indicate their consumption improvement estimate on a vertical slider ranging from -200 to 200 Wh/km.

Table B3

All Items of the EnDynA Improvement Intention Scale (Original German Text)

Item	Text
1	Ich habe fest vor, mithilfe der mir zur Verfügung stehenden Informationen, meinen Energieverbrauch beim nächsten Mal zu optimieren.
2	Ich habe fest vor, mit den mir zur Verfügung stehenden Informationen bestehende Fehler in meinem Verständnis der Energiedynamik zu korrigieren.
3	Ich habe fest vor, aus den mir zur Verfügung stehenden Informationen die relevanten Informationen zu identifizieren.

Note. The instruction of the scale indicated the rating scheme ("Bitte geben Sie den Grad Ihrer Zustimmung zu folgenden Aussagen an."). The agreement to the 3 items had to be indicated on a 6-point Likert scale reading: *stimmt gar nicht*, *stimmt weitgehend nicht*, *stimmt eher nicht*, *stimmt eher*, *stimmt weitgehend*, *stimmt völlig*, coded as 1–6 for data analysis.

Table B4

All Items of the EnDynA Enabling Scale (Original German Text)

Item	Text
1.	Durch diese Anzeige bekomme ich einen sehr guten Einblick in die Energieflüsse des Systems.
2.	Mithilfe dieser Anzeige kann ich den Einfluss verschiedener Faktoren auf den Energieverbrauch präzise einschätzen.
3.	Es ist für mich durch diese Anzeige verständlich, welche meiner Handlungen die Energiedynamik beeinflussen.
4.	Diese Anzeige erlaubt mir, den Energieverbrauch in zukünftigen Situationen präzise vorherzusagen.
5.	Durch diese Anzeige weiß ich genau, wie ich den Energieverbrauch optimieren kann.
6.	Die Anzeige hilft mir nicht einzuschätzen, inwieweit mein Verhalten zur Optimierung des Energieverbrauchs richtig war.
7.	Durch die Anzeige bin ich mir sicher, die Fehler in meinem energieeffizienten Verhalten bemerken zu können.
8.	Durch die Anzeige fühle ich mich sicher, energieeffiziente Handlungen auswählen zu können.
9.	Durch die Anzeige fühle ich mich bei der Optimierung des Energieverbrauchs sicher.

Note. The instruction of the scale indicated the supporting object ("Wie bewerten Sie die Energieanzeige, die Ihnen während der letzten Fahrten zur Verfügung stand?"), followed by an explanation of the rating scheme ("Bitte geben Sie den Grad Ihrer Zustimmung zu folgenden Aussagen an."). The agreement to the 9 items had to be indicated on a 6-point Likert scale reading: *stimmt gar nicht*, *stimmt weitgehend nicht*, *stimmt eher nicht*, *stimmt eher*, *stimmt weitgehend*, *stimmt völlig*, coded as 1–6 for data analysis.

Appendix C
Descriptive Driving Statistics

Table C1

Descriptive Driving Data Statistics for all Trips per Group

Trip (Route) Group	1 (A) *M* (*SD*)	2 (B) *M* (*SD*)	3 (A) *M* (*SD*)	4 (A) *M* (*SD*)	5 (A) *M* (*SD*)	6 (A) *M* (*SD*)	7 (B) *M* (*SD*)	8 (B) *M* (*SD*)
Duration (s)								
control	253.2 (29.1)	245.1 (20.6)	238.6 (13.4)	239.5 (13.1)	240.4 (17.4)	236.6 (11.6)	235.1 (14.0)	235.3 (13.0)
bar	250.4 (20.3)	243.3 (11.8)	245.7 (11.3)	248.2 (11.8)	249.7 (16.1)	250.0 (15.5)	246.2 (16.6)	243.4 (15.0)
trace	249.8 (16.2)	240.2 (14.9)	246.6 (13.3)	247.5 (12.4)	251.9 (27.9)	251.8 (12.1)	244.1 (11.3)	246.1 (10.2)
Average Energy Consumption (Wh/km)								
control	228.4 (18.2)	226.3 (20.7)	228.7 (29.4)	226.5 (30.5)	221.5 (22.3)	225.9 (25.2)	229.9 (29.0)	226.2 (24.2)
bar	225.2 (46.2)	228.5 (19.7)	214.7 (20.9)	213.1 (25.9)	205.4 (22.5)	204.2 (22.5)	212.3 (28.1)	210.6 (27.6)
trace	234.6 (25.6)	236.7 (27.6)	216.0 (22.6)	211.4 (20.2)	209.1 (34.1)	203.3 (20.6)	210.5 (22.4)	203.2 (20.6)
Standard Deviation of Acceleration								
control	1.02 (0.18)	1.00 (0.13)	0.98 (0.17)	0.97 (0.18)	0.96 (0.16)	0.98 (0.20)	1.03 (0.18)	1.00 (0.15)
bar	1.05 (0.17)	1.04 (0.13)	0.91 (0.14)	0.91 (0.16)	0.86 (0.14)	0.84 (0.15)	0.92 (0.18)	0.91 (0.16)
trace	1.06 (0.16)	1.09 (0.19)	0.92 (0.19)	0.87 (0.14)	0.92 (0.26)	0.83 (0.15)	0.90 (0.17)	0.88 (0.17)
Standard Deviation of Speed								
control	15.8 (1.8)	16.2 (1.1)	14.3 (0.9)	14.1 (1.0)	14.0 (1.6)	14.0 (1.0)	16.0 (2.1)	15.8 (2.2)
bar	15.6 (1.9)	16.3 (1.5)	14.0 (1.3)	13.8 (1.3)	13.8 (1.2)	13.8 (1.4)	15.9 (2.3)	15.6 (1.9)
trace	15.3 (2.0)	16.2 (1.6)	14.2 (1.4)	14.5 (2.5)	14.5 (2.0)	13.8 (1.9)	15.9 (3.2)	15.0 (2.8)

Note. $N = 77$. The standard deviations of acceleration and speed mean the standard deviation per person and trip as an inverse indicator of the *smoothness* of the driving style.

Article 4: Two Types of Eco-Driving Support - The Effects of an Instantaneous Consumption and an Optimal Speed Display on Energy-Efficient Driving and Energy Dynamics Awareness

Two Types of Eco-Driving Support - The Effects of an Instantaneous Consumption and an Optimal Speed Display on Energy-Efficient Driving and Energy Dynamics Awareness

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Supporting energy-efficient driving is essential for sustainable mobility, particularly in electric vehicles (EVs), where operational eco-driving (or ecodriving) can significantly reduce energy consumption. This study investigates the effects of two types of ecodriving displays—an Instantaneous Consumption Display (ICD) and an Optimal Speed Display (OSD)—on energy consumption and energy-related situation awareness (Energy Dynamics Awareness, EnDynA). Using the EcoSimLab EV driving simulator, N = 94 participants were assigned to three display conditions- ICD, OSD, and control group- and completed multiple driving trials under different situation complexities. Results showed that both display types improved EnDynA and ecodriving performance compared to the control group. The OSD, which provided predictive speed recommendations, was particularly effective in more complex driving scenarios. In contrast, the ICD, offering real-time consumption feedback, facilitated learning in simpler scenarios. These findings highlight the importance of adaptive ecodriving support systems that balance real-time feedback with predictive guidance.

1 Introduction

Supporting drivers in reducing energy consumption is essential for sustainable mobility. In electric vehicles (EVs), an energy-efficient driving style (*eco-driving* or *ecodriving*) benefits both individuals (e.g., cost savings, sustainability motives, enhanced competence in low-battery situations; Barkenbus, 2010; Bingham et al., 2012; Franke et al., 2016) and society (e.g., reduced greenhouse gas emissions, lower grid infrastructure demand; Axsen et al., 2020; Franke, Görges, & Arend, 2019; Marmaras et al., 2017). Interventions or assistance to improve ecodriving has proven effective in internal combustion engine vehicles (ICEVs; e.g., Allison et al., 2021; Beloufa et al., 2019; Sanguinetti et al., 2020) with even greater effects in EVs (Yan et al., 2021). This indicates the significant potential of a human-centered driver-vehicle interaction design to promote the sustainable use of electric vehicles. However, it also raises the question of what the psychological mechanisms of effective ecodriving displays are.

Besides external factors (e.g., type of road or wind speed; Birrell et al., 2014; Donkers et al., 2020), driver behavior plays a crucial role in reducing energy consumption (Braun & Rid, 2018). Among strategic and tactical decisions (e.g., vehicle maintenance, route choice, vehicle load; Evans, 1979; Mole et al., 2019; Sivak & Schoettle, 2012), operational driving maneuvers — such as velocity selection and acceleration or deceleration execution — are key determinants of energy efficiency (see also Huang et al., 2018; Wang et al., 2020). Operational ecodriving can be described as an action regulation control loop, akin to control-theoretic models of driver behavior (Macadam, 2003; Mole et al., 2019; Nash et al., 2016), grounded in human information processing (Wickens & Carswell, 2021). Beyond automatic, unconscious vehicle control processes, drivers continuously observe their environment, interpret relevant information, and act based on their knowledge and driving goals (e.g., safety, time efficiency, energy conservation). Decisions involve selecting optimal speed profiles (e.g., acceleration, deceleration) to align with one's driving goals (safety, time, energy efficiency), which are then implemented via vehicle controls such as pedals or cruise control. Observational studies have already documented the difference between various operational maneuver profiles in their energy efficiency (e.g., Galvin, 2017) and simulation studies provide information about how the maneuvers should optimally be executed (e.g., Chada et al., 2023). However, the invisibility and volatility of energy dynamics make it difficult for drivers to accurately perceive and comprehend efficiency-related information (Gödker, Moll, & Franke, 2024; Moll & Franke, 2021). This hinders the evaluation of energy efficiency and disrupts operational ecodriving control loops. To support effective ecodriving, energy-related information must be both perceivable and actionable (Franke, Görges, & Arend, 2019). Literature on ICEVs (Sanguinetti et al., 2020) and EVs (Gödker, Schrills, & Franke, 2024) indicates that consumption feedback displays (energy feedback) help to improve ecodriving by providing information relevant for learning. Empirical studies on ecodriving tips and assistive driving functions (optimal behavior guidance) in EVs also demonstrate their potential to enhance efficiency (Chada et al., 2023; Sureth et al., 2019). Building on previous work regarding mental and situation models in ecodriving (Arend et al., 2019; Pampel et al., 2015, 2017; Sureth et al., 2019), we assume that an informed cognitive state enables drivers to adapt their driving style to dynamic conditions. Situation awareness (Endsley, 1995, 2015) is considered a requirement for adequate decisions and actions in safety-related dynamic situations. It is comprised of three levels: (1) perception, (2) comprehension, and (3) prediction of relevant elements in the system and the environment. Drawing on the theory of situation awareness – with a focus on energy dynamics (Nienhüser et al., 2012; Thill & Riveiro, 2015) – we have previously introduced the concept of *Energy Dynamics Awareness (EnDynA)* to describe how drivers' perceive and utilize energy-related information for ecodriving (Gödker & Franke, 2024; Gödker, Moll, & Franke, 2024). Consequently, system design must support drivers' EnDynA to enable effective ecodriving. Situation awareness theory suggests that displays should be goal-relevant and reduce cognitive workload (Endsley et al., 2003), thereby aiding the understanding of energy consumption factors and integrating seamlessly into mental models (see also Endsley & Connors, 2008).

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For our study, we define the primary ecodriving task as (1) selecting optimal speed profiles and (2) executing them. This involves configuring driving maneuvers, which requires both a deep understanding of optimal strategies and precise EnDynA aligned with current driving goals.

We look at two types of display support that we expect to support this ecodriving task: an *Instantaneous Consumption Display* (ICD), a standard built-in feature in many vehicles, and an *Optimal Speed Display* (OSD), a novel and innovative approach to assist ecodriving by recommending the optimal speed profile. ICDs visualize disaggregated and instantaneous energy information. This allows drivers to perceive and comprehend the consumption during specific route sections or driving maneuvers and understand the influence of situational factors (e.g., terrain) or actions (e.g., strong acceleration). By enhancing the data and temporal granularity, ICDs might better help understand energy dynamics and, ultimately, learn ecodriving (Gödker, Schrills, & Franke, 2024; Sanguinetti et al., 2018). On the other hand, OSDs do not visualize the energy currently being consumed but an optimal speed profile, which is calculated based on a vehicle model, the route/environment, and driving goals (c.f., Section 2). OSDs require a state of technology that is not yet installed in passenger vehicles but is, for the present study, already generated in driving simulations. The distinctive feature of this system is that it offers not only insights into the (short-term) past and present, as is the case with ICDs, but also forecasts regarding the short-term future. This capability enhances level 3 situation awareness/EnDynA (prediction of relevant elements), which may constitute an advantage over traditional ICDs. For both displays, the energy-related information must be integrated with an overall EnDynA and weighted against one's driving goals to ultimately decide on optimal maneuvers and perform them.

Present Study and Hypotheses

The present study's objective was to examine improvements in EV operational ecodriving and EnDynA using displays with different support strategies. We hypothesize that ICDs and OCDs affect both EnDynA and ecodriving to various degrees. We assessed the energy-specific situation awareness, EnDynA, as an indicator of the informed cognitive state of the driver during this action regulation that is required for correct decisions and actions. We assessed two ecodriving metrics as dependent variables linked to ecodriving maneuver selection and performance: 1. energy consumption and 2. deviation from the optimal speed profile, which more directly reflects drivers' driving behavior.

The present study investigated whether an ecodriving display that provides support in deciding on optimal speed profiles (by visualizing the optimal speed profile) helped to improve ecodriving better than a standard display visualizing disaggregated instantaneous consumption that supports perceiving the consequences of driving maneuvers on energy consumption and a control group without display. We hypothesize that improvement in ecodriving is possible through repeated trials but that the type of display moderates this process. Specifically, we formulate the following hypotheses:

H1: Participants indicate that their experienced EnDynA improves over the course of trials (H1a). The improvement is strongest for the OSD and weakest for the control group (H1b).

H2: Participants improve ecodriving over the course of trials (H2a). The improvement in ecodriving is strongest for the OSD and weakest for the control group (H2b).

2 Method

Participants

In total, 105 participants were recruited via the mailing list and the learning management system forums of the University of Lübeck and social media. Participants had to be at least 18 years old, possess a driving license, and be fluent in German to be included in the experiment. Participants volunteered to participate in the study, and informed consent was required. All participants were compensated €18,62 (based on the German minimum wage) for their time in the study or course credit for psychology and media informatics students. Ethics approval for this study was granted by the Ethics Committee of the University of Lübeck before the start of the experiment (tracking numbers 2023-680 and 2023-680_1).

Of all participants, four aborted the experiment due to simulation sickness, and seven had significant irregular procedures (e.g., major display failures), resulting in a sample of $N = 94$ participants. Of this sample, five participants had corrupted driving data sets due to temporary technical problems in the data logging. Therefore, we excluded these datasets from all analyses that used driving simulator data (energy consumption and speed), resulting in a reduced sample $N' = 89$.

All participants' ages ranged from 18 to 38 years ($M = 23.0$, $SD = 3.7$). 59 participants stated to be female (62.8%) and 35 male (37.2%; none stated their gender to be diverse). The mean total driving experience with every kind of vehicle was $M = 38602$ km ($SD = 115578$ km, $N = 88$; due to a technical error in the survey, we did not collect this information from every participant). 20 participants (21.3% of the sample) had already driven an EV at least 50 km with a total driving experience of $M = 1228$ km ($SD = 2245$ km). We assessed the Affinity for Technology Interaction (ATI) scale (Franke, Attig, & Wessel, 2019) to characterize the sample regarding user diversity in human-technology interaction as it has shown relevancy in previous studies (Gödker, Moll, & Franke, 2024). The sample had a mean ATI score of $M = 3.97$ ($SD = 1.14$, possible range: 1 – 6), being higher than a German population quota sample (3.61 as described in Franke, Attig, & Wessel, 2019).

Electric Vehicle Driving Simulator

The study was conducted in the *EcoSimLab* electric vehicle driving simulator of the Institute of Multimedia and Interactive Systems of the University of Lübeck with a simulated Renault Zoe EV and the *EcoDrivingTestPark* as driving environment (Gödker, Schmees, et al., 2024). The hardware setup consisted of three 55″ 120 Hz monitors arranged to form a 180° field of view and a single car seat with a Fanatec gaming simulation wheelbase and pedals. An original Renault Zoe steering column and wheel, driver seat, and shifting lever were mounted for a Renault Zoe appearance and input validity. The steering wheel and pedals had calibrated force feedback. The simulation software used was BeamNG.tech 0.28[1], a variant of the BeamNG.drive driving simulation game (BeamNG GmbH, 2022). The energy consumption was calculated using an energy model created by Heidinger et al. (2023) and further advanced in Gödker, Schmees, et al. (2024) in the simulation software to accurately represent the energy dynamics and specific consumption of the real-world reference vehicle.

The EcoDrivingTestPark is a driving environment with seven driving scenarios. The scenarios are designed to induce various energy-relevant maneuvers. This implies that energy consumption should vary depending on whether drivers successfully perform operational ecodriving throughout these maneuvers. The scenarios are implemented in map sectors on a BeamNG.tech map (see Figure 1). Each sector begins and ends with an identical tunnel that contains a teleport portal. The exterior is not visible because of a slight curve at the end of the tunnels. Hence, the driver's view remains consistent throughout the teleport process, making the teleport barely noticeable. This concept allows for the free combination and randomization of sector order. The present analyses revealed that, due to fast speed limit changes, sector five was too difficult, leading to numerous speed limit violations and, hence, incomparable driving data sets. Therefore, we decided to exclude sector five entirely from the analysis. For a deeper understanding of the human-vehicle-environment interaction, we created sector blocks of different situation complexities (Fastenmeier & Gstalter, 2007). To this end, we asked traffic psychology researchers to rate videos of driving scenes for each sector on a self-created

[1] https://beamng.tech/blog/beamng-tech-028

questionnaire based on the SAFE analysis by Fastenmeier (1995) in a previous research (Banach & Gödker, 2024). We then clustered the sectors and assigned them to either the high-complexity or low-complexity block. All sectors included in the present analyses are briefly described in Table 1. In the experiment, participants started on a parking lot with a teleportation tunnel to enter the first sector (i.e., the first to drive, not always sector one). The teleport tunnel of the last sector always led to the parking lot to stop the vehicle and end the trip.

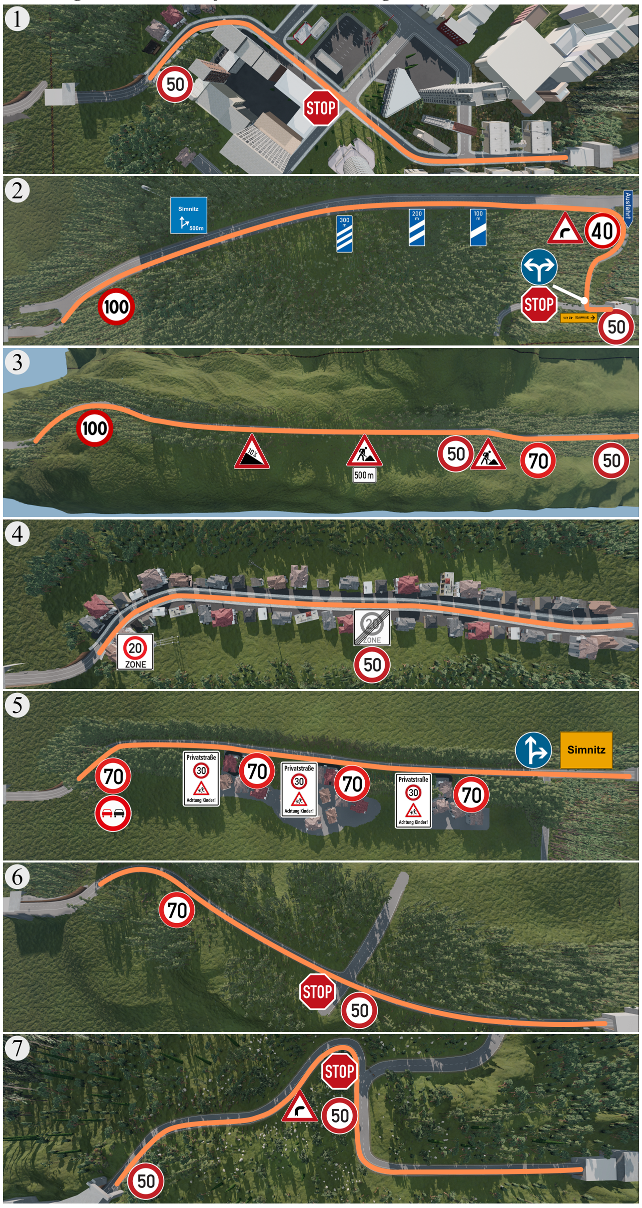
Energy Displays

We used two different ecodriving displays (see Figure 2) on a 10.5″ Samsung Galaxy S4 tablet. The tablet was mounted below the simulation monitors to the right of the steering wheel. The OSD presented an energy-efficient velocity profile derived from a pre-computed dynamic programming (DP) optimization that factors in route characteristics (e.g., road curvature, speed limits, stop signs, road gradient), a realistic vehicle model of a Renault ZOE Q90 (also refer to Gödker, Schmees, et al., 2024; Heidinger et al., 2023), and the time constraints that were also instructed to the participants (Section 2).

While there are multiple ways to solve the underlying optimal control problem (e.g., Pontryagin's Minimum Principle), dynamic programming yields the global optimum and has proven effective in balancing trade-offs among energy consumption, travel time, and comfort in automotive contexts (Sciarretta et al., 2015). Building on the DP-based framework detailed in Lin et al. (2014), the approach discretized the route into equidistant segments and systematically evaluated feasible motor torque and velocity combinations. Rather than optimizing each segment independently, the DP algorithm considered the entire route to ensure every local decision supported the global objective of minimizing energy consumption while meeting practical driving constraints, thus producing a precomputed velocity profile. The OSD compared this optimal speed with the driver's actual speed over the previous and upcoming 150 meters, providing clear feedback on how close the driver was to the most efficient speed. Additionally, an *action cue* (as green arrows in the center of the display) indicated the recommended speed 50 meters ahead, further guiding energy-efficient driving. A vehicle symbol in the center of the display was used to augment the action cue. Meanwhile, the ICD showed energy consumption in kilowatt-hours per 100 kilometers (kWh/100 km) over the same 150 meter interval in the past, illustrating instantaneous consumption and the consumed energy for recent maneuvers. A line in the positive range and an orange area under the curve indicated that energy was consumed, while a line in the negative range and a blue area under the curve showed that energy was regained. A vehicle symbol and orange or blue arrows in the center of the display augmented the current instantaneous consumption. The amplitude of the curve and the height of the arrows indicate the amount of energy. Both displays updated at 10 Hz, providing periodic prompts encouraging adherence to the optimal driving strategy.

Figure 1

Driving Scenarios of the EcoDrivingTestPark



Note. Bird's eye view of the seven sectors of the EcoDrivingTestPark. The driving direction of all sectors is from left to right. The route is marked as an orange line, and the traffic sign symbols show where the traffic signs are located. Sector five has been excluded from the analysis.

Table 1

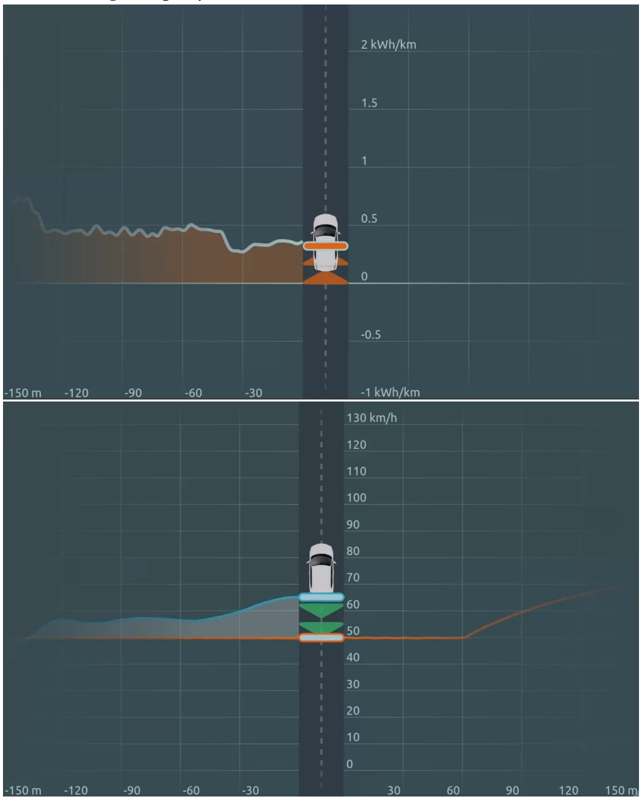
Description of the Sectors.

Sector	Situation Complexity	Duration (s) *M* (*SD*)	Distance (m) *M* (*SD*)	Consumption (kWh/100km) *M* (*SD*)
1	low	67.5 (4.6)	707.4 (0.9)	11.0 (1.5)
2	high	87.6 (6.3)	1341.2 (2.1)	17.2 (3.2)
3	high	80.6 (4.1)	1411.3 (1.0)	-1.0 (3.9)
4	low	93.1 (6.2)	701.9 (0.9)	9.3 (1.1)
6	low	74.1 (4.0)	825.1 (1.1)	25.9 (1.5)
7	high	68.6 (4.4)	717.2 (2.1)	12.9 (2.0)

Note. *N'* = 89; descriptive statistics and characteristics of all sectors included in the analyses. Sector five (originally in the high-complexity block) has been excluded from the analyses.

Figure 2

Ecodriving Displays



Note. Both ecodriving displays used in the present study; top: Instantaneous Consumption Trace Display (ICD); bottom: Optimal Speed Display (OSD).

Measures

Experienced Energy Dynamics Awareness

As a subjective indicator of EnDynA, we assessed experienced EnDynA with the EnDynA scale (Gödker, Moll, & Franke, 2024; Gödker, Schrills, & Franke, 2024). Based on previous research (Gödker, Schrills, & Franke, 2024), we omitted one item (previously item 6), resulting in a self-constructed 8-item scale with a 6-point Likert agreement rating scheme (1 = *completely disagree* to 6 = *completely agree*; Table 2). The scale assessed an individually experienced situation awareness related to energy transformation and dynamics and the drivers' action confidence. Internal consistency of the scale was high on all administered occasions (Cronbach's α ranged between .91 and .96).

Table 2

Energy Dynamics Awareness (EnDynA) Scale

Item	Text
1	I have a very good overview of the energy dynamics of the system.
2	I can precisely estimate the influence of different factors on energy consumption.
3	I understand which of my actions influence the energy dynamics.
4	I am able to correctly predict energy consumption in future situations.
5	I know exactly how to optimize energy consumption.
6	I am sure I can notice errors in my energy-efficient behavior.
7	I feel confident in choosing energy-efficient actions.
8	I feel confident in optimizing energy consumption.

Note. The instructions explained the rating scheme ("Please indicate your level of agreement with the following statements."). The agreement to the eight items had to be indicated on a 6-point Likert scale reading: *completely disagree*, *largely disagree*, *slightly disagree*, *slightly agree*, *largely agree*, *completely agree*, coded as 1-6 for data analysis. For original German items, see Table A1.

Additionally, we developed a single-item EnDynA indicator to be used as an online prompt while driving. The indicator was introduced and explained before the experimental trials, and a printed copy was made visible next to the steering wheel. First, the rating scheme was explained (“Please indicate your level of agreement."), followed by the statement: "I have a precise understanding of the current and future energy consumption of the electric vehicle." The agreement had to be indicated on a 6-point Likert scale (from 1 to 6) reading: *completely disagree* = 1 to *completely agree* = 6. The study operator verbally prompted the single-item indicator by repeating a shortened version ("Understanding of the current and future energy consumption from 1 to 6?"), requesting an answer from the participant. We additionally administered the single-item indicator every time the 8-item scale was administered. The correlation between the single-item indicator and the mean EnDynA scale score ranged between $r = .69$ ($p < .001$) and $r = .85$ ($p < .001$).

Energy-Efficient Driving

To assess operational ecodriving performance as energy-efficient driving, we measured the standard metric kWh/100 km to describe average energy consumption for each trial. To calculate this metric, we determined the charging state of the simulated car at the beginning and end of the trip to calculate the absolute consumed energy in kWh. We then divided the consumed energy by the distance traveled scaled to 100 km. As a second indicator of optimal energy-efficient driving behavior, we calculated the absolute difference between the current speed and the current optimal speed (which was collected 10 times per second) and averaged all absolute differences per drive. The optimal speed was the value that was also displayed in the OSD but was unknown for the no-display group and the ICD group. With this metric, we can more directly estimate whether the different groups generally adopt the optimal behavior.

Situation Complexity and Workload

As indicators to assess the situation complexity of the sectors, we measured experienced situation complexity (situation complexity short scale, SCSS) and driving-specific subjective workload (Driver Activity Load Index, DALI; Pauzié, 2008). The SCSS was a self-created 6-item scale based on Fastenmeier and Gstalter (2007) and on the short questionnaire used in Banach and Gödker (2024) with a 6-point Likert agreement rating scheme (1 = *completely disagree* to 6 = *completely agree*; Table 3). Internal consistency was good or excellent on all administered occasions (Cronbach’s α ranged between .85 and .90). For an indicator of the subjectively experienced workload, we used a German DALI version (Parduzi, 2021) and edited the items to match our context (see final items in Table A3). The internal consistency of DALI was mainly acceptable and good (Cronbach’s α ranged between .69 and .85).

Table 3

Situation Complexity Short Scale

Item	Text
1	The time pressure when driving through the situations is high.
2	The accuracy required to fulfill the driving task is high.
3	There are many requirements to fulfill the driving task.
4	The scenes are highly complex.
5	The demands on information processing (e.g., perception processes, decision-making, and memory processes) are high.
6	The requirements for vehicle operation (e.g., keeping in the lane and maintaining the target speed) are high.

Note. The instructions explained the rating scheme (“Please indicate your level of agreement with the following statements.”) and what is understood as the *driving task* ("The term ’driving task’ refers to the entire range of actions that are performed during the driving scenes. This includes all tasks and requirements associated with driving and vehicle operation."). The agreement to the six items had to be indicated on a 6-point Likert scale reading: *completely disagree*, *largely disagree*, *slightly disagree*, *slightly agree*, *largely agree*, *completely agree*, coded as 1-6 for data analysis. For original German items, see Table A2.

Experimental Procedure

In this repeated-measures driving simulator experiment, participants were randomly assigned to one of three display conditions: 1. OSD, 2. ICD, and 3. no display/control (NOD). The core of the experiment was four trips in the EcoDrivingTestPark, first both complexity blocks without any display (baseline phase) and then both with the display according to their group (experimental phase).

At the start of the experiment, participants were informed about the experimental procedure, their consent for participation was obtained, and the first questionnaire was presented. First, they received more detailed information about the experimental method and procedure via an instructional video. Then, participants got used to the driving simulator by driving on our tutorial track (about 4 minutes) with several speed limits, curves, and hills. After the tutorial, we presented a second instructional video explaining to the participants their tasks and the rules of the EcoDrivingTestPark. Participants were asked the following:

1. Drive as efficiently as possible!

2. Follow the traffic signs to the fictional city of "Simnitz"! (This is to prevent participants from taking a wrong turn.)

3. Reach the destination of each sector within the time limit! The time limit for each sector was defined by the time a driver, who always tries to drive 90% of the speed limit, would need for the sector. (Like this, participants can always estimate whether they are more likely to reach the destination within the time limit without knowing the exact time limit or the sector.)

4. Follow the traffic rules! (German traffic rules apply here.)

5. Answer the online prompts every time you're in a teleportation tunnel!

Then, participants drove a test trip on two sectors to get used to the EcoDrivingTestPark and their tasks. The test sectors are not part of the core EcoDrivingTestPark sectors depicted in Figure 1. After the test trip, the first two measured trial trips (baseline phase), comprising all sectors clustered in both complexity blocks, were performed. Both the order of the complexity blocks and the order of the sectors in each block were randomized. After the baseline phase, participants watched a third video introducing their ecodriving display. The control group did not watch any video. Then, participants drove the test trip to get used to the display and the trial trips (experimental phase) again. After each trip during the whole experiment, participants returned to the laptop and answered an interim questionnaire containing the EDA scale (plus single-item indicator), situation complexity scale, and the DALI. After the baseline and the experimental phase, participants answered a questionnaire containing more general questions about the experiences in the preceding phase. After all trips, participants answered a questionnaire with personal characteristics. Then, participants were thanked and dismissed. The complete experimental procedure took about 90 minutes for one participant.

Data Transformation and Analyses

All analyses were performed using R-Studio (R Core Team, 2023). For all analyses related to consumption and speed data, we transformed all individual values to a sector-specific z-standardized value (regardless of phase or group) to be able to compare energy-efficient driving across sectors and compute meaningful values. Of all sector-specific trips of N' ($89 \times 12 = 1068$), the driving data of six trips was missing due to a technical data recording error (= 1062 trips). As preregistered, we excluded all trips that exceeded the time limit by an additional 20% (31), resulting in $N' = 89$ with 1031 sector trips. Before each analysis, to identify and exclude extreme values in the dataset, we applied the median absolute deviation (MAD) method within each sector. Observations were flagged as outliers if their value deviated by more than three times the MAD from the sector-specific median. Outliers were then removed from the dataset before further analysis.

Both hypotheses related to the *improvement* of the dependent variables from the baseline phase to the experimental phase with diverging effects based on the participants' assigned display condition. We computed an improvement score (the difference between the experimental value and the baseline value) for each participant for each sector. In the case of the consumption and the difference to the optimum speed, a smaller value indicates better driving performance; hence, a negative improvement score indicates a stronger improvement. If either the baseline or the experimental value in a sector was excluded or missing, the improvement score was handled as a missing value. We then averaged these six (or fewer) sector-specific improvement values to an overall improvement score for each participant. For hypotheses H1a and H2a, we calculated one-sample t-tests comparing the mean improvement with the value 0 (= no improvement). For H1b and H2b, we applied contrast analysis, which allows for more precise testing of hypotheses than omnibus F-test such as ANOVA (Buckless & Ravenscroft, 1990; Wiens & Nilsson, 2017) and assigned contrast weights based on display condition (NOD = -2, ICD = 0.5, OSD = 1.5)[2]. We followed the suggested contrast analysis steps by (Rosenthal et al., 2000) and computed the results using the *cofad* package (Titz & Burkhardt, 2021, 2024).

3 Results

All participants were assigned to one of three display groups via block randomization (Matts & Lachin, 1988, we used four blocks with a size of 30 with ten lots for each of the three groups that were randomly drawn from a pot): 1. OSD (34 participants, 36.1%), 2. ICD (29 participants, 30.9%), and 3. NOD (31 participants, 33.0%). Descriptive statistics are detailed in Appendix B.

[2]This analysis procedure differs in parts from the method described in the preregistration. There, we mistakenly planned to assign within-contrast weights to the phases. With this procedure, however, missing values (due to overtime or outlier trips) or their phase-related counterpart can excessively influence the overall score, although an improvement score could not be calculated at all. The current procedure ensures that only actual improvement values per sector are included. Moreover, the current method is easier to follow and interpret and is, therefore, favorable. Nevertheless, we additionally calculated the preregistered analysis and reported them in the appendix.

Manipulation Check

To check whether the two complexity blocks successfully manipulated the situation complexity as experienced by the drivers, we performed two two-way repeated measures multilevel models following Finch et al. (2014) and Snijders and Bosker (2012) using the *lmerTest*-package (Kuznetsova et al., 2017) to check for mean differences in the *situation complexity short scale* mean score and the *DALI* mean score between the four blocks (phase [baseline vs. experimental] × complexity [high vs. low]). In both models, we found a significant *complexity* main effect, $F_{comp}(1, 93) = 30.5$ for the SCSS, $p < .001$, $F_{comp}(1, 93) = 74.9$, $p < .001$ for the DALI, but no *phase* main effect, $F_{phase}(1, 93) = 0.5$, $p = .462$ for the SCSS, $F_{phase}(1, 93) = 0.3$, $p = .592$ for the DALI. We can, therefore, assume that there are two blocks of sectors with different effects on the subjectively experienced situation complexity and driver-related workload, i.e., situation complexity.

Hypotheses Analyses

To test H1a, we conducted a one-sample *t*-test, comparing the mean EnDynA ($M = 1.00$) scale score improvement against 0 (= no improvement). The results indicated a statistically significant difference, $t(93) = 8.3$, $p < .001$, $d = 0.86$, indicating a significant and strong improvement. To test H1b, we ran a contrast analysis with the following between contrasts: NOD = -2, ICD = 0.5, and OSD = 1.5. This resulted in statistics of $F(1,91) = 62.9$; $p < .001$ and an effect magnitude of $r = 0.62$, indicating a significant difference between the groups in relation to the tested contrast weights.

We tested H2 using both metrics of the DV *energy-efficient driving*: 1. average consumption and 2. speed difference to the optimal speed profile. Of all 1031 trips of N', outlier detection with the MAD method for average consumption led to the exclusion of 26 trips (= 1005 trips). Consequently, no improvement score could be calculated for one participant, leading to $N' = 88$ for these analyses. Outlier detection for speed difference to the optimal speed led to excluding 14 trips (= 1017 trips). We tested H2a with a one-sample *t*-test testing the improvement score of each metric against 0 (= no improvement). To test H2b, we also ran contrast analyses for the following between contrasts: NOD = -2, ICD = 0.5, and OSD = 1.5, using the improvement scores.

The one-sample *t*-test for the average consumption improvement (M = -0.26) indicated a significant difference, $t(87) = -4.8$, $p < .001$, $d = -0.51$, with a medium effect. For the speed difference to the optimal speed profile, the overall improvement ($M = -.64$) was also significantly different from 0, $t(88) = -9.7$, $p < .001$, $d = -1.03$, indicating a large effect.

To test H2b, the contrast analysis using the average consumption improvement resulted in statistics of $F(1, 85) = 5.01$; $p = .028$ and an effect magnitude of $r = 0.24$, indicating a significant difference between the groups in relation to the contrast weights. For the speed difference to the optimal speed profile, contrast analysis resulted in statistics of $F(1, 86) = 22.27$; $p < .001$ and an effect magnitude of $r = 0.44$, indicating a significant moderate effect (see Figure 3 for all improvement values per group).

Further Analyses

The significant results of the hypothesis tests prompted us to conduct further analyses to better understand the displays' supportive effect. To test whether situation complexity influences the impact of the displays, we calculated a 2 (complexity: low vs. high) × 3 (group: NOD, ICD, OSD) mixed-design ANOVA with the average consumption improvement score as the dependent variable (see Table 4). Here, the exclusion of trips (due to the time limit or outliers) led to the exclusion of 4 participants ($N' = 85$). A significant interaction was found between group and complexity, $F(2, 82) = 4.94$, $p = .009$, suggesting that the effect of complexity on average consumption improvement varies across groups. A significant group-by-complexity interaction indicated that display effects vary across complexity blocks. Post-hoc tests (Table 5) revealed that, under low complexity, the ICD group outperformed the NOD group, whereas under high complexity, the OSD group exceeded the ICD group.

Table 4

Repeated Measures ANOVA Results

Factor	df	F	p	η_p^2
Group	(2, 82)	2.33	.103	0.05
Complexity	(1, 82)	1.82	.181	0.02
Group × Complexity	(2, 82)	4.94	.009	0.11

Table 5

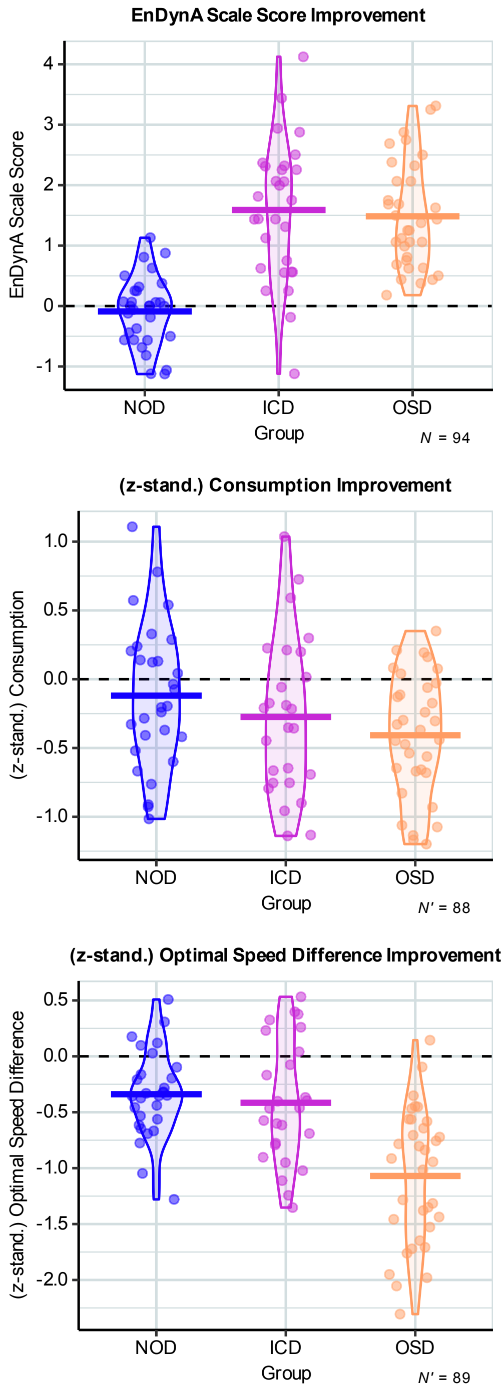
Pairwise Comparisons Between Groups at Each Complexity Level

Contrast	Estimate	SE	t-ratio	p	d
Low Complexity					
NOD - ICD	0.56	0.21	2.7	.024	-0.34
NOD - OSD	0.40	0.20	2.0	.109	0.30
ICD - OSD	-0.16	0.21	-0.8	.708	0.72
High Complexity					
NOD - ICD	-0.25	0.19	-1.3	.387	0.76
NOD - OSD	0.20	0.17	1.1	.497	0.54
ICD - OSD	0.45	0.18	2.4	.046	-0.21

Figure 5 illustrates the progress of the dependent variable metrics across the chronological sequence of the sectors.

Figure 3

Improvement Scores per Group for Each DV Metric



Note. Improvement in the EnDynA scale score (top, H1), average energy consumption (middle, H2), and speed difference to optimal speed (bottom, H2); colors represent groups; NOD = no display, ICD = Instantaneous Consumption Display, OSD = Optimal Speed Display. Improvement was calculated by subtracting the baseline value from the experimental value for each participant and sector and then averaging these values for each participant.

For experienced EnDynA, we used the single-item indicator. The visualization shows that the improvement in consumption was relatively constant throughout the sectors in the ICD and OSD groups. In contrast, the experienced EnDynA (in both display groups) and the speed difference to the optimal speed (only in the OSD group) showed a notable and abrupt improvement in the first sector following the introduction of the display.

4 Discussion

The present study's objective was to examine how two distinct types of ecodriving displays—an Instantaneous Consumption Display (ICD) and an Optimal Speed Display (OSD)—affect energy-efficient driving (ecodriving) and drivers' Energy Dynamics Awareness (EnDynA) in electric vehicles. Beyond mere improvements in consumption values, the findings underscore the significance of display-based feedback for refining drivers' mental models and situation awareness concerning energy dynamics.

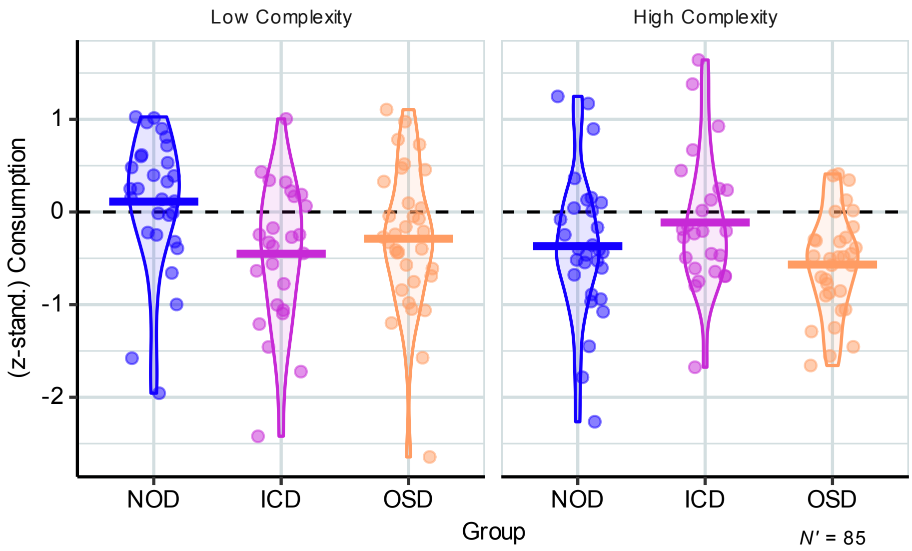
Summary and Interpretation of the Results

All participants demonstrated notable improvement in energy consumption across repeated trials, suggesting that even sole practice and familiarization with the technical system and the route can foster better ecodriving. However, the level of improvement in energy-efficient driving was linked to the type of display provided. This indicates that ecodriving displays can support drivers' learning processes.

When comparing the ICD to the OSD, we found significant differences. Both the ICD and OSD supported participants' understanding of how their driving maneuvers related to energy consumption (EnDynA). The contrast analysis testing ordered contrasts (NOD: -2, ICD: 0.5, OSD: 1.5) showed significant results supporting the ordinal character of our hypothesis, but as shown in Figure 3, the mean values for ICD and OSD are only slightly different. However, it is noteworthy that in the ICD group, there is a significant variance in improvement values. In contrast, none of the participants in the OSD group experienced a decline in their EnDynA. This suggests that additional psychological or situational factors may influence the improvement in experienced EnDynA among those using the ICD, leading to the broader distribution of results. Energy-efficient driving was improved more in the OSD group than in the ICD group, indicated by both DV metrics related to ecodriving. The NOD group improved the least. Further analyses showed that in more complex driving scenarios, participants using the OSD showed stronger performance improvements than the ICD group. By offering a straightforward target speed derived from an optimized algorithm, the system seems to simplify the decision-making process in action regulation. The ICD proved valuable for translating drivers' immediate actions into direct feedback

Figure 4

(z-stand.) Consumption Improvement per Complexity Block



on consumption. This fosters an experimental style of learning—drivers can test a maneuver and see how it influences the current consumption curve. In simpler driving scenarios—where participants have more mental capacity to interpret ongoing changes—this immediate consumption feedback helped them adapt their behavior. ICD drivers thus outperformed those without any display in these relatively undemanding situations, which replicates our previous research findings where a simple driving scenario was used (Gödker, Schrills, & Franke, 2024).

Theoretical Implications

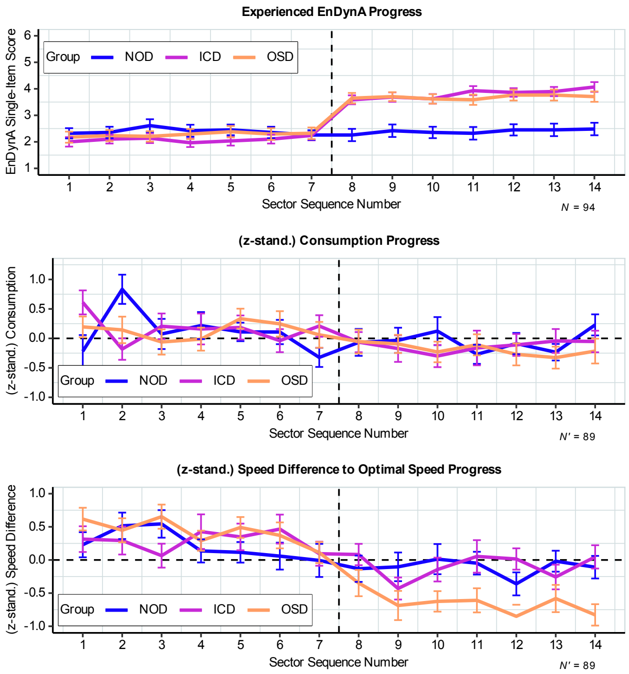
Existing work on ecodriving systems has already shown the effectiveness of feedback displays in supporting more efficient driving in both IVECs and EVs (e.g., Sanguinetti et al., 2020). The present paper adds to the cumulative scientific literature (e.g., Sanguinetti et al., 2018) by providing empirical results of contrasting (a) a "classic" real-time consumption display and (b) a forward-looking assistive system that recommends the upcoming optimal speed. Our findings suggest that each display type can address different challenges. In line with the assumption of Sanguinetti et al. (2018), immediate feedback (as in the ICD) helps drivers understand how their actions affect current consumption. Optimal action guidance, as in the OSD, mainly helps drivers manage complexity; they can "offload" parts of the planning load onto the display and make more confident decisions in dynamic traffic. Crucially, the study emphasizes the interaction between the effectiveness of the display type and scenario complexity. OSD's prediction-focused guidance was especially valuable under more demanding conditions, while the ICD excelled at supporting learning under simpler ones. This aligns with theoretical findings about decision support systems (Phillips-Wren & Adya, 2020), also in other context, e.g., flying (Sarter & Schroeder, 2001). Important to note, that this is only true for perfect reliability and accuracy of the guiding system, as in our present research, because failures might cause *out of the loop*-problems (Parasuraman et al., 2000). The continuous feedback- as in the ICD- can support robust, transferrable ecodriving habits by making the consequences of different maneuvers transparent. While the OSD might be more effective for short-term improvements in performance, future research should examine whether ICD-like displays lead to stronger retention of ecodriving knowledge when the display is eventually removed, which would be comparable to findings in the field of motor skill learning (e.g., Buchanan & Wang, 2012; Schmidt & Wulf, 1997).

Methodological Implications

From a methodological perspective, this study contributes several valuable insights to ecodriving research and beyond. First, the EnDynA scale further proved useful as an easily administerable questionnaire for assessing energy-related situation awareness in a dynamic driving context similar to previous research (Gödker & Franke, 2024; Gödker, Moll, & Franke, 2024). By capturing drivers' self-reported perceptions of their energy understanding, the scale allows researchers and practitioners to quantify changes in mental models over time or across interventions. Additionally, the new single-item indicator adds an online experienced En-

Figure 5

Progress of the DV Metrics Scores per Group Across the Sector Sequence



Note. Progress in the single-item EnDynA score (top), average energy consumption (middle), and speed difference to optimal speed (bottom); colors represent groups; NOD = no display, ICD = Instantaneous Consumption Display, OSD = Optimal Speed Display. Note that the sequence number does not relate to the sector number, as the order of the sectors was randomized. Sector five was also excluded, yet the original sector sequence number was used for this graph. Hence, 14 sectors are depicted. In the second half, the displays were used.

DynA assessment method. Second, building on previous research (Gödker, Schmees, et al., 2024), this research contributes to show, that the EcoSimLab and EcoDrivingTestPark are a flexible yet rigorous simulation environment that can be tailored to various route complexities and display conditions. The setup ensures controlled experimental conditions, repeatability, and detailed data tracking—key advantages that are often difficult to achieve in field studies. Finally, the newly constructed Situation Complexity Short Scale (SCSS) is a practical tool to measure drivers' perceived complexity of given road segments or traffic conditions (instead of their perceived mental load). It builds on a strong theoretical foundation of what needs to be considered in the complexity of situations (Fastenmeier & Gstalter, 2007).

Practical Implications

The results imply that predictive driver-assistance systems like an OSD—capable of computing short-term optimal speed profiles—might offer efficiency gains in real-world settings. Even if such technology is not yet installed in vehicles as standard, implementing it in electric vehicles will probably help reduce overall energy consumption. An integrated approach might combine ICD and OSD features, automatically switching modes depending on route complexity. A purely exploratory instantaneous consumption trace might suffice in simpler conditions, encouraging drivers to learn from minor adjustments. In more intricate or safety-critical contexts, the system could provide a recommended target speed, relieving the driver of excessive cognitive load.

Limitations

In the present driving simulator study, both displays were designed to provide theoretically distinguishable types of energy-efficient driving support to be used in an empirical experiment. Neither underwent more safety-focused investigations that would absolutely be necessary before usage under real-world conditions. A realistic risk-benefit analysis is needed after a safety-oriented design iteration and tests. Instead, our objective was to gain knowledge about ecodriving display elements and their consequences for driver experience and behavior to serve as a basis for further developments and design considerations. Although the driving simulator was carefully designed to capture realistic dynamics (including route complexity, steering wheel force feedback, and an EV-specific energy model), genuine traffic conditions and psychological factors—like real-world risk, interaction with other drivers, or stress—remain only partially replicated. Follow-up field studies (under safe conditions) are vital to confirm these results. The OSD's recommended speed was determined using a dynamic programming approach. However, real-world driving conditions—such as construction, traffic congestion, or sudden obstacles—require continuous adaptation. To ensure that OSD remains effective despite these variations, real-time recalculations are essential. Since our dynamic programming solution is computed offline and not designed for real-time execution, model predictive control (MPC) will be used to handle dynamic events. MPC will serve as a reference-tracking mechanism, enabling the system to follow the precomputed dynamic programming solution while adapting to real-time changes (Weißmann et al., 2018). Future research could focus on improving scalability for real-time applications, such as instantaneous displays.

While data clearly showed improvements over multiple drives, whether these gains endure over weeks or months is a key question. Habit formation, fatigue, or even over-reliance could influence long-term outcomes. Longitudinal designs and "natural driving" conditions will be necessary to measure lasting changes in driver attitudes and behaviors.The study mostly involved younger participants, many of whom were unfamiliar with electric vehicles. Future work should capture a broader driver profile (e.g., professional drivers, EV owners, older adults) and investigate how individual differences (e.g., familiarity with tech) moderate the use of ecodriving displays.

Conclusion

This study demonstrates that ecodriving displays can significantly shape and improve ecodriving performance and energy-related situation awareness in electric vehicles. The two approaches — ICD versus OSD — show distinct advantages, with the OSD particularly enhancing energy efficiency and EnDynA in more complex scenarios and the ICD promoting feedback-based learning. These findings contribute to the overall understanding of the effect of display elements on energy-efficient driving. Also, they pave the way for developing adaptive, context-sensitive driver-support systems that cater to the varying demands of real-world driving and driver learning. Ultimately, integrating such systems in EVs and other sustainable transport solutions could yield considerable benefits for both individual drivers (through cost savings and reduced range anxiety) and society (by minimizing energy usage and emissions).

5 Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the authors used ChatGPT and Grammarly in order to improve the readability of the manuscript and enhance the English language. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Allison, C. K., Fleming, J. M., Yan, X., Lot, R., & Stanton, N. A. (2021, October). *Assisted Eco-Driving: A Practical Guide to the Design and Testing of an Eco-Driving Assistance System (EDAS)* (1st ed.). CRC Press. https://www.taylorfrancis.com/books/9781003081173

Arend, M. G., Franke, T., & Stanton, N. A. (2019). Know-how or know-why? The role of hybrid electric vehicle drivers' acquisition of eco-driving knowledge for eco-driving success. *Applied Ergonomics*, *75*, 221–229. https://doi.org/10.1016/j.apergo.2018.10.009

Axsen, J., Plötz, P., & Wolinetz, M. (2020). Crafting strong, integrated policy mixes for deep CO2 mitigation in road transport. *Nature Climate Change*, *10*, 809–818. https://doi.org/10.1038/s41558-020-0877-y

Banach, E. S., & Gödker, M. (2024). Assessing Driving Situation Complexity: Development and Pilot Evaluation of a Short Questionnaire with Traffic Psychology Experts. In T. M. Buzug, H. Handels, C. Hübner, A. Mertins, S. Müller, P. Rostalski, & N. Bunzeck (Eds.), *Student Conference Proceedings 2024*. Infinite Science Publishing.

Barkenbus, J. N. (2010). Eco-driving: An overlooked climate change initiative. *Energy Policy*, *38*(2), 762–769. https://doi.org/10.1016/j.enpol.2009.10.021

BeamNG GmbH. (2022). BeamNG.tech. https://www.beamng.tech/

Beloufa, S., Cauchard, F., Vedrenne, J., Vailleau, B., Kemeny, A., Mérienne, F., & Boucheix, J.-M. (2019). Learning eco-driving behaviour in a driving simulator: Contribution of instructional videos and interactive guidance system. *Transportation Research Part F: Traffic Psychology and Behaviour*, *61*, 201–216. https://doi.org/10.1016/j.trf.2017.11.010

Bingham, C., Walsh, C., & Carroll, S. (2012). Impact of driving characteristics on electric vehicle energy consumption and range. *IET Intelligent Transport Systems*, *6*(1), 29. https://doi.org/10.1049/iet-its.2010.0137

Birrell, S. A., McGordon, A., & Jennings, P. A. (2014). Defining the accuracy of real-world range estimations of an electric vehicle. *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2590–2595. https://doi.org/10.1109/ITSC.2014.6958105

Braun, A., & Rid, W. (2018). Assessing driving pattern factors for the specific energy use of electric vehicles: A factor analysis approach from case study data of the Mitsubishi i–MiEV minicar. *Transportation Research Part D: Transport and Environment*, *58*, 225–238. https://doi.org/10.1016/j.trd.2017.11.011

Buchanan, J. J., & Wang, C. (2012). Overcoming the guidance effect in motor skill learning: Feedback all the time can be beneficial. *Experimental Brain Research*, *219*(2), 305–320. https://doi.org/10.1007/s00221-012-3092-x

Buckless, F. A., & Ravenscroft, S. P. (1990). Contrast coding: A refinement of ANOVA in behavioral analysis. *Accounting Review*, 933–945.

Chada, S. K., Görges, D., Ebert, A., Teutsch, R., & Subramanya, S. P. (2023). Evaluation of the driving performance and user acceptance of a predictive eco-driving assistance system for electric vehicles. *Transportation Research Part C: Emerging Technologies*, *153*, 104193. https://doi.org/10.1016/j.trc.2023.104193

Donkers, A., Yang, D., & Viktorović, M. (2020). Influence of driving style, infrastructure, weather and traffic on electric vehicle performance. *Transportation Research Part D: Transport and Environment*, *88*, 102569. https://doi.org/10.1016/j.trd.2020.102569

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors*, *37*(1), 32–64. https://doi.org/10.1518/001872095779049543

Endsley, M. R. (2015). Situation awareness misconceptions and misunderstandings. *Journal of Cognitive Engineering and Decision Making*, *9*(1), 4–32. https://doi.org/10.1177/1555343415572631

Endsley, M. R., Bolté, B., & Jones, D. G. (2003). *Designing for situation awareness: An approach to user-centered design*. Taylor & Francis.

Endsley, M. R., & Connors, E. S. (2008). Situation awareness: State of the art. *2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century*, 1–4. https://doi.org/10.1109/PES.2008.4596937

Evans, L. (1979). Driver Behavior Effects on Fuel Consumption in Urban Driving. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *21*(4), 389–398. https://doi.org/10.1177/001872087902100401

Fastenmeier, W. (Ed.). (1995). *Autofahrer und Verkehrssituation: Neue Wege zur Bewertung von Sicherheit und Zuverlässigkeit moderner Straßenverkehrssysteme*. Dt. Psychologen-Verl.

Fastenmeier, W., & Gstalter, H. (2007). Driving task analysis as a tool in traffic safety research and practice. *Safety Science*, *45*(9), 952–979. https://doi.org/10.1016/j.ssci.2006.08.023

Finch, W. H., Bolin, J. E., & Kelley, K. (2014). *Multilevel modeling using R*. CRC Press.

Franke, T., Attig, C., & Wessel, D. (2019). A personal resource for technology interaction: Development and validation of the affinity for technology interaction (ATI) scale. *International Journal of Human–Computer Interaction*, *35*(6), 456–467. https://doi.org/10.1080/10447318.2018.1456150

Franke, T., Görges, D., & Arend, M. G. (2019). The Energy Interface Challenge. Towards Designing Effective Energy Efficiency Interfaces for Electric Vehicles. *Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 35–48. https://doi.org/10.1145/3342197.3344526

Franke, T., Rauh, N., Günther, M., Trantow, M., & Krems, J. F. (2016). Which Factors Can Protect Against Range Stress in Everyday Usage of Battery Electric Vehicles? Toward Enhancing Sustainability of Electric Mobility Systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *58*(1), 13–26. https://doi.org/10.1177/0018720815614702

Galvin, R. (2017). Energy consumption effects of speed and acceleration in electric vehicles: Laboratory case studies and implications for drivers and policymakers. *Transportation Research Part D: Transport and Environment*, *53*, 234–248. https://doi.org/10.1016/j.trd.2017.04.020

Gödker, M., & Franke, T. (2024). Assessing Energy-Related Situation Awareness Using Self-Controlled Occlusion During Electric Vehicle Driving Scenes. In G. Praetorius, C. Sellberg, & R. Patriarca (Eds.), *Advances in Human Factors of Transportation. AHFE (2024) International Conference. AHFE Open Access* (Vol. 148). AHFE International. https://doi.org/10.54941/ahfe1005219

Gödker, M., Moll, V., & Franke, T. (2024). Feeling comfortable? Exploring the relation between personality, competence, and range interaction in electric vehicles. In G. Praetorius, C. Sellberg, & R. Patriarca (Eds.), *Advances in Human Factors of Transportation. AHFE (2024) International Conference. AHFE Open Access* (Vol. 148). AHFE International. https://doi.org/10.54941/ahfe1005220

Gödker, M., Moll, V. E., & Franke, T. (2024). Energy Consumption Displays in Electric Vehicles: Differential Effects on Estimating Consumption and Experienced Energy Dynamics Awareness. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *0*(0). https://doi.org/10.1177/00187208231222154

Gödker, M., Schmees, S., Bernhardt, L., Heidinger, J., Görges, D., & Franke, T. (2024). Driving Simulation for Energy Efficiency Studies: Analyzing Electric Vehicle Eco-Driving With EcoSimLab and the EcoDrivingTestPark. *Proceedings of the 16th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 32–42. https://doi.org/10.1145/3640792.3675706

Gödker, M., Schrills, T. P. P., & Franke, T. (2024, July). Improved Ecodriving Using Instantaneous Consumption Displays in an Electric Vehicle Driving Simulator: The Role of Energy Dynamics Awareness [Preprint]. https://doi.org/10.31234/osf.io/zusyx

Heidinger, J., Bernhardt, L., & Franke, T. (2023). Ecosimlab - A Low-Cost Driving Simulator Environment for Examining Human Factors in Vehicle Energy Efficiency. *Adjunct Proceedings of the 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 66–70. https://doi.org/10.1145/3581961.3609881

Huang, Y., Ng, E. C., Zhou, J. L., Surawski, N. C., Chan, E. F., & Hong, G. (2018). Eco-driving technology for sustainable road transport: A review. *Renewable and Sustainable Energy Reviews*, *93*, 596–609. https://doi.org/10.1016/j.rser.2018.05.030

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software*, *82*(13), 1–26. https://doi.org/10.18637/jss.v082.i13

Lin, X., Görges, D., & Liu, S. (2014). Eco-driving assistance system for electric vehicles based on speed profile optimization. *2014 IEEE Conference on Control Applications (CCA)*, 629–634. https://doi.org/10.1109/CCA.2014.6981410

Macadam, C. C. (2003). Understanding and Modeling the Human Driver. *Vehicle System Dynamics*, *40*(1-3), 101–134. https://doi.org/10.1076/vesd.40.1.101.15875

Marmaras, C., Xydas, E., & Cipcigan, L. (2017). Simulation of electric vehicle driver behaviour in road transport and electric power networks. *Transportation Research Part C: Emerging Technologies*, *80*, 239–256. https://doi.org/10.1016/j.trc.2017.05.004

Matts, J. P., & Lachin, J. M. (1988). Properties of permuted-block randomization in clinical trials. *Controlled Clinical Trials*, *9*(4), 327–344. https://doi.org/10.1016/0197-2456(88)90047-5

Mole, C. D., Lappi, O., Giles, O., Markkula, G., Mars, F., & Wilkie, R. M. (2019). Getting Back Into the Loop: The Perceptual-Motor Determinants of Successful Transitions out of Automated Driving. *Human Factors*, *61*(7), 1037–1065. https://doi.org/10.1177/0018720819829594

Moll, V. E., & Franke, T. (2021). Biased energy efficiency perception based on instantaneous consumption displays – Indication for heuristic energy information processing. *Applied Ergonomics*, *94*, 103399. https://doi.org/10.1016/j.apergo.2021.103399

Nash, C. J., Cole, D. J., & Bigler, R. S. (2016). A review of human sensory dynamics for application to models of driver steering and speed control. *Biological Cybernetics*, *110*(2-3), 91–116. https://doi.org/10.1007/s00422-016-0682-x

Nienhüser, D., Bär, T., Kohlhaas, R., Schamm, T., Zimmermann, J., Gumpp, T., Strand, M., Bringmann, O., & Zöllner, J. M. (2012). Energy efficient driving and operation strategies based on situation awareness and reasoning. *it - Information Technology*, *54*(1), 5–16.

Pampel, S. M., Jamson, S. L., Hibberd, D., & Barnard, Y. (2017). The activation of eco-driving mental models: Can text messages prime drivers to use their existing knowledge and skills? *Cognition, Technology & Work*, *19*(4), 743–758. https://doi.org/10.1007/s10111-017-0441-3

Pampel, S. M., Jamson, S. L., Hibberd, D. L., & Barnard, Y. (2015). How I reduce fuel consumption: An experimental study on mental models of eco-driving. *Transportation Research Part C: Emerging Technologies*, *58*, 669–680. https://doi.org/10.1016/j.trc.2015.02.005

Parasuraman, R., Sheridan, T., & Wickens, C. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *30*(3), 286–297. https://doi.org/10.1109/3468.844354

Parduzi, A. (2021). *Bewertung der Validität von Fahrsimulatoren anhand vibro-akustischer Fahrzeugschwingungen* [Doctoral dissertation] [Doctoral dissertation, Technische Universität Berlin]. https://doi.org/10.14279/depositonce-12374

Pauzié, A. (2008). A method to assess the driver mental workload: The driving activity load index (DALI). *IET Intelligent Transport Systems*, *2*(4), 315. https://doi.org/10.1049/iet-its:20080023

Phillips-Wren, G., & Adya, M. (2020). Decision making under stress: The role of information overload, time pressure, complexity, and uncertainty. *Journal of Decision Systems*, *29*(sup1), 213–225. https://doi.org/10.1080/12460125.2020.1768680

R Core Team. (2023). *R: A language and environment for statistical computing* (manual). R Foundation for Statistical Computing. Vienna, Austria. https://www.R-project.org/

Rosenthal, R., Rosnow, R. L., & Rubin, D. B. (2000). *Contrasts and effect sizes in behavioral research: A correlational approach* (1st ed.). Cambridge Univ. Press.

Sanguinetti, A., Dombrovski, K., & Sikand, S. (2018). Information, timing, and display: A design-behavior framework for improving the effectiveness of eco-feedback. *Energy Research & Social Science*, *39*, 55–68. https://doi.org/10.1016/j.erss.2017.10.001

Sanguinetti, A., Queen, E., Yee, C., & Akanesuvan, K. (2020). Average impact and important features of onboard eco-driving feedback: A meta-analysis. *Transportation Research Part F: Traffic Psychology and Behaviour*, *70*, 1–14. https://doi.org/10.1016/j.trf.2020.02.010

Sarter, N. B., & Schroeder, B. (2001). Supporting Decision Making and Action Selection under Time Pressure and Uncertainty: The Case of In-Flight Icing. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *43*(4), 573–583. https://doi.org/10.1518/001872001775870403

Schmidt, R. A., & Wulf, G. (1997). Continuous Concurrent Feedback Degrades Skill Learning: Implications for Training and Simulation. *Human Factors*, *39*(4), 509–525.

Sciarretta, A., De Nunzio, G., & Ojeda, L. L. (2015). Optimal Ecodriving Control: Energy-Efficient Driving of Road Vehicles as an Optimal Control Problem. *IEEE Control Systems*, *35*(5), 71–90. https://doi.org/10.1109/MCS.2015.2449688

Sivak, M., & Schoettle, B. (2012). Eco-driving: Strategic, tactical, and operational decisions of the driver that influence vehicle fuel economy. *Transport Policy*, *22*, 96–99. https://doi.org/10.1016/j.tranpol.2012.05.010

Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: An introduction to basic and advanced multilevel modeling* (2nd ed). Sage.

Sureth, A., Moll, V., Nachtwei, J., & Franke, T. (2019). The golden rules of ecodriving? The effect of providing hybrid electric vehicle (HEV) drivers with a newly developed set of ecodriving-tips. *Transportation Research Part F: Traffic Psychology and Behaviour*, *64*, 565–581. https://doi.org/10.1016/j.trf.2019.07.003

Thill, S., & Riveiro, M. (2015). Situation awareness in eco-driving. *2015 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision*, 125–131. https://doi.org/10.1109/COGSIMA.2015.7108186

Titz, J., & Burkhardt, M. (2021). Cofad: An R package and shiny app for contrast analysis. *Journal of Open Source Software*, *6*(67), 3822. https://doi.org/10.21105/joss.03822

Titz, J., & Burkhardt, M. (2024). *Cofad: Contrast analyses for factorial designs* (manual). https://github.com/johannes-titz/cofad

Wang, G., Makino, K., Harmandayan, A., & Wu, X. (2020). Eco-driving behaviors of electric vehicle users: A survey study. *Transportation Research Part D: Transport and Environment*, *78*, 102188. https://doi.org/10.1016/j.trd.2019.11.017

Weißmann, A., Görges, D., & Lin, X. (2018). Energy-optimal adaptive cruise control combining model predictive control and dynamic programming. *Control Engineering Practice*, *72*, 125–137. https://doi.org/10.1016/j.conengprac.2017.12.001

Wickens, C. D., & Carswell, C. M. (2021, September). Information Processing. In G. Salvendy & W. Karwowski (Eds.), *Handbook of Human Factors and Ergonomics* (1st ed., pp. 114–158). Wiley. https://doi.org/10.1002/9781119636113.ch5

Wiens, S., & Nilsson, M. E. (2017). Performing Contrast Analysis in Factorial Designs: From NHST to Confidence Intervals and Beyond. *Educational and Psychological Measurement*, *77*(4), 690–715. https://doi.org/10.1177/0013164416668950

Yan, X., Allison, C., Fleming, J., Stanton, N., & Lot, R. (2021). The Benefit of Assisted and Unassisted Eco-Driving for Electrified Powertrains. *IEEE Transactions on Human-Machine Systems*, *51*(4), 403–407. https://doi.org/10.1109/THMS.2021.3086057

Appendix A
Measurements in Original German Language

Table A1

Energy Dynamics Awareness (EnDynA) Scale (Original German Text)

Item	Text
1	Ich habe einen sehr guten Einblick in die Energieflüsse des Systems.
2	Ich kann den Einfluss verschiedener Faktoren auf den Energieverbrauch präzise einschätzen.
3	Ich verstehe, welche meiner Handlungen die Energiedynamik beeinflussen.
4	Ich kann den Energieverbrauch in zukünftigen Situationen präzise vorhersagen.
5	Ich weiß genau, wie ich den Energieverbrauch optimieren kann.
6	Ich bin mir sicher, Fehler in meinem energieeffizienten Verhalten bemerken zu können.
7	Ich habe das Gefühl, energieeffiziente Handlungen auswählen zu können.
8	Ich fühle mich bei der Optimierung des Energieverbrauchs sicher.

Note. The instruction of the scale indicated the rating scheme (“Bitte geben Sie den Grad Ihrer Zustimmung zu folgenden Aussagen an.”). The agreement to the 8 items had to be indicated on a 6-point Likert scale reading: *stimmt gar nicht*, *stimmt weitgehend nicht*, *stimmt eher nicht*, *stimmt eher*, *stimmt weitgehend*, *stimmt völlig*, coded as 1–6 for data analysis.

Appendix B
Descriptive Results

Appendix C
Outdated Preregistered Analysis of Hypotheses

In this section, we present the results of the hypotheses analysis procedure as described in the preregistration. In the preregistration, we mistakenly planned to assign within-contrast weights to the *phases*. With this procedure, however, missing values (due to overtime or outlier trips) or their phase-wise counterpart can excessively influence the overall score, al-

Table A2

Situation Complexity Short Scale (Original German Text)

Item	Text
1	Der Zeitdruck beim Durchfahren der Situationen ist hoch.
2	Die erforderliche Genauigkeit zur Erfüllung der Fahraufgabe ist hoch.
3	Es gibt viele Anforderungen, um die Fahraufgabe zu erfüllen.
4	Die Szenen haben eine hohe Komplexität.
5	Die Anforderungen an die Informationsverarbeitung (z.B. Wahrnehmungsprozesse, Entscheidungen treffen und Gedächtnisprozesse) sind hoch.
6	Die Anforderungen aus der Fahrzeugbedienung (z.B. Spur halten und Sollgeschwindigkeit halten) sind hoch.

Note. The instructions explained the rating scheme ("Bitte geben Sie den Grad Ihrer Zustimmung an.") and what is understood as the *driving task* ("Unter 'Fahraufgabe' versteht man den Gesamtbereich der Handlungen, die im Verlauf der Fahrszenen ausgeführt werden. Dies umfasst sämtliche Aufgaben und Anforderungen, die mit dem Fahren und der Fahrzeugbedienung verbunden sind."). The agreement to the six items had to be indicated on a 6-point Likert scale reading: *stimmt gar nicht*, *stimmt weitgehend nicht*, *stimmt eher nicht*, *stimmt eher*, *stimmt weitgehend*, *stimmt völlig*, coded as 1–6 for data analysis.

though an improvement score could not be calculated. In contrast, the revised procedure described in Section 2 ensures that only actual improvement values per sector were included. Nevertheless, we report the outdated analysis for transparency:

For all analyses related to the average consumption, we transformed all individual energy consumption values to a sector-specific z-standardized value (regardless of phase or group) to compare energy-efficient driving across sectors and compute mean values. Of all sector-specific trips of N' ($89 \times 12 = 1068$), the driving data of six trips was missing due to a technical data recording error (= 1062 sector trips). We excluded all trips that exceeded the time limit by an additional 20% (31), resulting in $N' = 89$ with 1031 sector trips. We also excluded all outliers detected with the MAD method described in Section 2. This led to the exclusion of 26 trips in the analysis of the average consumption (= 1005 trips) and to 14 exclusions in the analysis of the speed difference to the optimal speed (= 1017 trips). In contrast to the revised procedure described in Section 2, we computed a phase mean value for each dependent variable for each participant (resulting in two values for each participant). We then assigned contrast weights for each measurement based

Table A3

Driver Activity Load Index (DALI) in German (and English translation)

Item	Text
1	Wie hoch waren die benötigten Aufmerksamkeitsressourcen während der Fahrt? (How high were the attention resources required during the trip?)
2	Wie groß war die visuelle Anforderung während der Fahrt? (How great was the visual demand during the trip?)
3	Wie groß war die akustische Anforderung während der Fahrt? (How great was the auditorial demand during the trip?)
4	Wie groß war der zeitliche Druck während der Fahrt? (How much time pressure was there during the trip?)
5	Inwieweit wurde die Fahraufgabe durch andere Aufgaben beeinträchtigt? (To what extent was the driving task impaired by other tasks?)
6	Wie sehr fühlten Sie sich während der Fahrt genervt, verärgert oder gestresst? (How annoyed, angry, or stressed did you feel during the trip?)

Note. The instructions explained the rating scheme ("Bitte geben Sie auf alle Fragen die Antwort, die am ehesten zutrifft. Geben Sie hierbei jeweils einen Wert zwischen 0 (= gering) und 5 (= hoch) an."; "Please give the answer to all questions that is most likely to apply. Please enter a value between 0 (=low) and 5 (=high).") and an indication of what should be considered ("Die Fragen beziehen sich auf die Fahrsituationen der gesamten letzten Fahrt."; "The questions relate to the driving situations of the entire last trip."). The answers on the rating scheme were coded as 0-5 for data analysis.

on the phase (baseline: -1, experimental: 1; constituting the linear trend) and display condition (constituting the group comparison of the linear trend, all contrasts described in Table C1). We computed the results using the "cofad" package (Titz & Burkhardt, 2021, 2024).

Regarding H1a (experienced EnDynA as the dependent variable), the contrast analysis resulted in statistics of $t(93) = 8.3$; $p < .001$ and an effect magnitude of $g = 0.86$, indicating a significant improvement in experienced EDA across all groups. Checking whether the OSD group improved the most and the NOD group the least (H1b), our contrast analysis resulted in statistics of $F(1, 91) = 62.9$; $p < .001$ and an effect magnitude of $r = 0.62$. Testing H2a, the contrast analysis using the average consumption in (kWh/100 km) resulted in statistics of $t(88) = 4.5$; $p < .001$ and an effect magnitude of $g = 0.48$. For the speed difference to the optimal speed, the contrast analysis resulted in

Table B1

Descriptive Statistics

Phase:	Baseline		Experimental	
Complexity:	Low	High	Low	High
Group	*M*(*SD*)	*M*(*SD*)	*M*(*SD*)	*M*(*SD*)
Experienced EnDynA (1 - 6)				
NOD	2.9 (1.2)	2.9 (1.2)	2.8 (1.3)	2.8 (1.2)
ICD	2.5 (0.9)	2.4 (1.0)	4.0 (0.8)	4.1 (0.7)
OSD	2.6 (1.1)	2.6 (1.1)	4.1 (0.8)	4.0 (0.9)
Average Consumption (kWh/100km)				
NOD	15.2 (0.8)	10.2 (2.4)	15.5 (0.8)	9.4 (1.9)
ICD	15.5 (0.9)	10.1 (2.1)	15.1 (0.8)	9.7 (1.6)
OSD	15.6 (1.2)	10.3 (2.6)	15.5 (0.8)	8.7 (2.2)
Speed Difference to Optimal Speed (km/h)				
NOD	5.4 (1.6)	6.9 (2.5)	4.9 (1.6)	6.4 (2.4)
ICD	5.5 (1.1)	6.7 (1.4)	4.8 (0.8)	6.0 (0.8)
OSD	5.9 (0.9)	6.7 (1.5)	4.4 (1.1)	5.2 (1.4)
Situation Complexity (1 - 6)				
NOD	3.4 (1.1)	3.7 (1.1)	3.0 (1.1)	3.2 (1.2)
ICD	3.6 (1.3)	3.9 (1.1)	3.7 (1.1)	3.7 (1.0)
OSD	3.1 (0.9)	3.5 (0.9)	3.4 (0.8)	3.7 (0.8)
DALI (0 - 5)				
NOD	1.7 (0.9)	2.1 (0.9)	1.4 (0.9)	1.7 (0.9)
ICD	1.9 (0.9)	2.1 (0.9)	2.1 (0.9)	2.3 (0.8)
OSD	1.5 (0.7)	1.9 (0.7)	1.9 (0.6)	2.1 (0.6)

Note. *Experienced EnDynA* = EnDynA scale mean score; *Situation Complexity* = situation complexity short scale mean score; *DALI* = Driver Activity Load Index scale mean score. N = 94, *average consumption* only includes N' = 89. NOD = no display (N = 31), ICD = instantaneous consumption trace display (N = 29), OSD = optimal speed display (N = 34).

Table C1

Contrast weights for each measurement for both hypotheses and the sample used

	Phase (Within)		Group (Between)			
Hypothesis	Baseline	Experimental	NOD	ICD	OSD	Sample
H1a	-1	1				N
H1b	-1	1	-2	0.5	1.5	N
H2a	1	-1				N'
H2b	1	-1	-2	0.5	1.5	N'

Note. Note that for H2, we used the difference to the optimum and the average consumption as a metric. Therefore, the direction of the linear trend represents an improvement in energy-efficient driving. NOD = no display (control group), ICD = instantaneous consumption trace display, OSD = optimal speed display.

statistics of $t(88) = 9.7$; $p < .001$ and an effect magnitude of $g = 1.03$. To check whether the OSD group improved the most and the NOD group the least (H2b) in their energy-efficient driving, the contrast analysis regarding average consumption resulted in statistics of $F(1, 86) = 1.55$; $p = .217$ and an effect magnitude of $r = 0.133$. For the speed difference to the optimal speed, the contrast analysis resulted in statistics of $F(1, 86) = 22.5$; $p < .001$ and an effect magnitude of $r = 0.44$.

To sum up, the results following the outdated analysis procedure lead to the same significant results as the revised procedure except that the contrast analyses checking whether the OSD group improved most and the NOD group least in average consumption (H2b) was not significant. While we believe our revised analysis procedure better investigates real improvement, the corresponding statistically significant result in the present research should be interpreted more cautiously.