Who's in Charge of Charging? Investigating Human-Machine-Cooperation in Smart Charging of Electric Vehicles

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Abstract. We investigated the effect of varying the level of cooperation in a smart charging agent (SCA) on user perception and behavior. Our study involved manipulating the SCA's cooperativeness by varying its degree of automation and the amount of information sharing with the user and measuring effects on changes in user behavior, perceived goal alignment, the user's awareness of the SCA's information processing, and perceived cooperativeness. Our hypothesis that a lower degree of automation of the SCA would increase human-agent cooperation was not supported by our results. Instead, participants in the high-automation condition chose a later charging endpoint more often, implying greater cooperation. Our hypothesis that a higher amount of information shared by the SCA would increase human-agent cooperation was only partially confirmed. Cooperation led to a more positive user experience, but the correlation was only moderate to strong. The study shows the limitations of using the degree of automation as a sole measure of human-machine cooperation and highlights the need to explore other operationalizations of human-machine cooperation. Further research is needed to explore other scenarios and variations in the information provided to the user to better understand human-machine cooperation in the context of smart charging.

Keywords: Human-Machine-Cooperation · Human-Machine-Interaction · Smart Charging · Battery Electric Vehicles · Demand Side Management

1 Introduction

The transition to utilizing renewable energy sources, such as wind and solar power, is crucial for achieving a sustainable energy system. However, the integration of these sources into the power grid poses significant challenges due to

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their inherently variable nature. To address these challenges and ensure a stable power grid, it is necessary to implement measures such as decentral energy generation and storage, as well as flexibly adjusting energy demand, also known as demand-side management. These measures will not only stabilize the power grid but also enable greater penetration of renewable energy into the energy mix. The idea of demand-side management specifically is to alleviate strain on the power grid by incentivizing large energy consumers to shift consumption to periods of increased renewable energy availability and decreased energy demand [1,6]. Furthermore, the immediate use of renewable energies at their time of availability cannot only lead to more efficient use of energy resources at the energy system level but also at the consumer level [20].

An energy consumer unit that is of particular interest for demand side management is the battery electric vehicle (BEV) since it has a large storage unit as well as a high energy demand that can easily be flexibilized through approaches like smart charging. With smart charging, consumers can adjust the charging of their BEV in real time to electricity prices and availability. This process is typically controlled by an automated system (agent), which relies on user preferences and other information, such as energy availability, to optimize the process (e.g., [18]). Therefore, smart charging cannot only lead to a stabilization of the power grid and a reduction in CO_2 emissions but also in lower costs for the consumer [11].

So how do we design a smart charging agent (SCA) that encourages people to regulate their charging behavior to ensure an efficient allocation of energy resources? We suggest that a cooperative approach to system design might help support the effective joint regulation of energy and other resources such as time, information, or comfort. Prior work shows that human-machine-cooperation not only copes with the shortcomings of many current automation approaches but also enables greater flexibility in the shared action and, all in all, enhances the joint performance of the human and the system [2,16,25].

2 Background

Comparative-cognition research has demonstrated a unique motivation for humans to collaborate. Tomasello and Vaish [26] state that "human social interaction and organization are fundamentally cooperative in ways that the social interaction and organization of other great apes simply are not" (p. 239). In recent years, several authors tried to utilize this inherent motivation of humans to cooperate to facilitate human-machine interaction (HMI). The construct of human-machine-cooperation has been discussed for many different use cases, such as driver assistance [17,19,27] or human-robot interaction [9]. However, there is no full consensus on how to define cooperation, and different authors propose different operationalizations of cooperation for different contexts [2,15,28,30]. Moreover, while the effects of cooperative automation design have been investigated in many human-technology contexts, as of writing, we are not aware of any study that has investigated a cooperative approach in the domain of smart charging.

2.1 Formalizing Cooperation

There is a multitude of theories and models on cooperation from different disciplines such as social psychology [13], philosophy [3], and human factors [4,5,7,10,14]. In the following, we conceptualize cooperation based on the similarities between these theories.

How to Design a Cooperative SCA? Klein et al. [14] propose four requirements for successful cooperation between a human and an automated system: An agreement to work together, a common ground, mutual directability, and mutual predictability. For this study, we manipulate the latter two aspects, *directability and predictability*, as we assume the other two prerequisites are already fulfilled by the design of the SCA.

Previous work in the context of automated driving has often operationalized directability by the degree of automation of the system. Several studies find that participants report a higher feeling of safety, pleasure, and trust when interacting with a cooperative system with which they share the task of driving compared to a higher automated system [17,27]. On the other hand, research in artificial intelligence shows that the perceived predictability of the system can be promoted through additional information on the inner workings of the system, which also promotes trust [12,21].

How to Measure Successful Cooperation Between Humans and the SCA? We propose measuring the effects of our SCA manipulation as follows. First, we assess the perceived quality (*perception*) of the human-SCA interaction with respect to the following aspects: (1) goal alignment, (2) system understanding, and (3) perceived cooperativeness. Second, we observe induced behavioral changes in the human charging patterns (*behavioral change*). In addition, we measure user experience as a function of the user's perceived cooperativeness of the interaction.

Goal alignment. It has been proposed that the need for cooperation between two or more agents arises from an interdependence that results from shared goals or overlapping intentions [3–5,10,13,14,26]. Hence, to measure cooperation on a motivational (intentional) level, we assess users' perceived goal alignment with the SCA.

Understanding of the system. Multiple theories emphasize the importance of shared representation, knowledge, and beliefs between the interaction partners as well as some degree of mutual predictability and reliability in cooperation [3,5,7,10,13,14]. To measure cooperation on a cognitive level, we assess the users' level of awareness and understanding of the system and its information processing.

Perceived cooperativeness. We measure if the interaction with the SCA was perceived as cooperative by the user. To that end, we developed a five-item-scale to measure perceived cooperativeness specifically.

Behavioral change towards a shared goal. Last, according to Klein et al. [14], joint action entails "one or more participants relaxing some shorter-term local goals in order to permit more global and long-term goals to be addressed" (p. 6). For the context of smart charging, this can be understood as users giving up some flexibility and shifting their charging window to times of high energy availability to permit demand side management. Here, we measure cooperation on a behavioral level by assessing whether users shift their charging window upon request.

2.2 Hypotheses

In this study, we set out to examine the following three hypotheses:

- **H1:** A lower degree of automation should increase human-agent-cooperation (behavioral change and perception).
- **H2:** Increasing the amount of shared information should increase human-agent-cooperation (behavioral change and perception).
- **H3:** An increase in perceived human-agent-cooperation should lead to a better general user experience.

3 Method

3.1 Sample

Participants were recruited through mailing lists and social media. The experiment was conducted via the online survey platform LimeSurvey. All participants were required to speak German fluently. After excluding those participants who did not complete the questionnaire, those who took an unusually long time to complete the questionnaire, and those who showed no variance in their responses on any of the pages of the questionnaire, the final sample consisted of 91 participants (29% female) with an average age of $M = 42.3$ ($SD = 12.5$). In the sample, 76% had driven a BEV before, and 53% had prior experience with driving a BEV on a regular basis.

3.2 Experimental Design and Scenario

We conducted an experiment with a 2×2 between-subject design. Participants were presented with scenarios that included interactions with an SCA that varied in the degree of automation (low vs. high) and the amount of information sharing (low vs. high). In the beginning, participants were instructed to imagine themselves in the situation described in Fig. 1.

Next, participants were presented with a message from the SCA that asked them to prolong their charging window to increase the share of self-produced power. The message differed based on which experimental group participants were in.

Imagine the following scenario: You live in the greater Lübeck area in a single-family house. You own a PV system, a private wallbox and a battery electric vehicle. To charge your car at home, you use a smart charging agent. The charging agent supports you in ensuring that your car is charged with as much electricity as possible from your own PV system during each charging session. This is the most cost effective and climate friendly way to charge your car.

To do this, each time you plug in your car, you specify in an app when you need the car again and how much range you need for the next trip. Your charging agent uses this information, along with predicted production data from your PV system, to find an optimal charging window.

You plug in your car for charging on Friday evening after work with a remaining range of 15 km. The next day, you plan to leave in the afternoon at 2 p.m. because you have arranged to meet friends at Timmendorfer Strand. You plan a range of 120 km including a buffer for the trip.

Fig. 1. Introduction to the scenario presented to every participant.

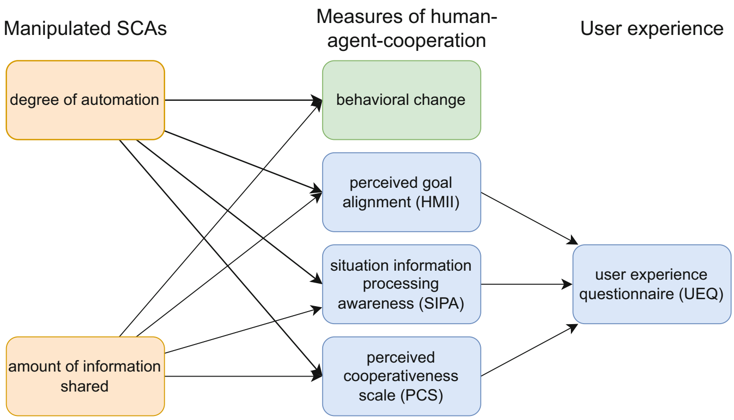

Fig. 2. Research design. Manipulated variables are shown in orange, measures variables are shown in green (behavioral variable) and blue (subjective variables). (Color figure online)

3.3 Experimental Manipulation

For an overview of manipulated and measured variables see Fig. 2.

First, we manipulated the level of cooperation of the SCA through the system's degree of automation (*directability*). The degree of automation was altered according to the levels of automation of decision and action selection by Parasuraman [22]. Participants in the low-level condition got a pop-up message from a level three agent that suggested two alternative charging endpoints while participants in the high automation condition interacted with a level six agent that automatically prolonged the charging window of the user and gave them a restricted time to veto (see Fig. 3).

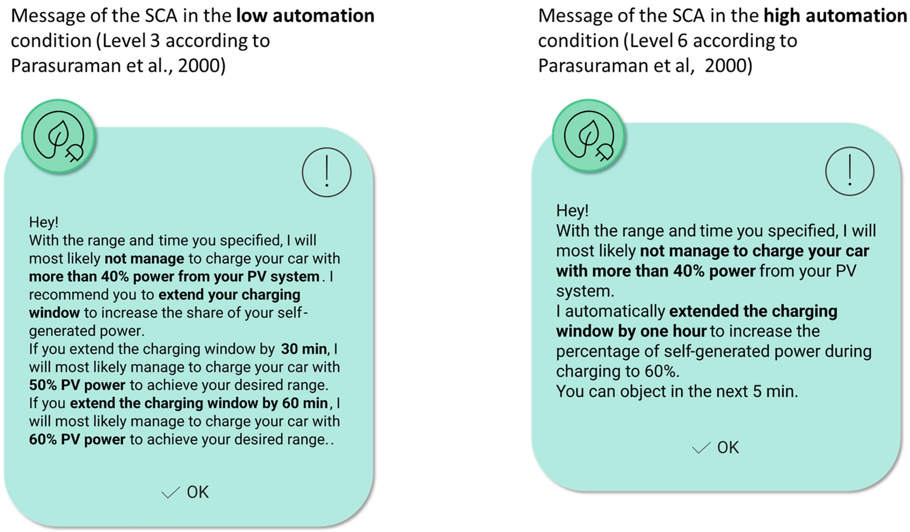

Fig. 3. Messages from two smart charging agents (SCA) showing different levels of automation.

Second, we manipulated the level of cooperation of the SCA through the amount of information shared with the user (*predictability*). Participants in the low-information group only got information about the expected share of photovoltaic power for their next charging window, whereas participants in the high-information group got additional information on the weather forecast and the projected amount of photovoltaic power (see Fig. 4).

3.4 Measures

To measure the effects of our independent variables on human-agent-cooperation, we assessed the following metrics based on our formalization of cooperation described in Sect. 2.1.

To assess participants' perceived goal alignment, we administered the conflict subscale of the Human-Machine-Interaction-Interdependence Questionnaire (HMII, [29]). A low score on this scale would indicate a high perceived goal alignment. Further, we measured participants' understanding of the system through the Subjective Information Processing Awareness Scale (SIPA, [24]). SIPA describes the experience of being enabled by a system to perceive, understand and predict its information processing. A low score on this scale would indicate a low awareness and understanding of the system and its information processing. Last, to quantify behavioral changes, we measured whether participants prolonged their charging window.

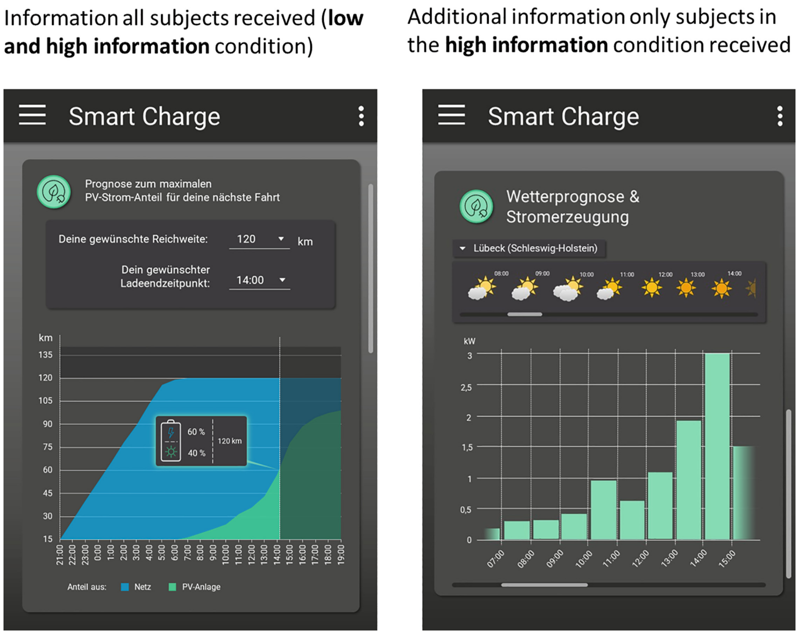

Fig. 4. Manipulated interface providing different levels of information from the smart charging agent (SCA).

As an additional measure for human-agent cooperation, we measured the perceived cooperativeness by a self-developed scale. The items were generated in a workshop with six students. As a basis, participants of this workshop got an introduction to various theories on cooperation and joint action research as well as examples of everyday interactions with automated systems. The scale uses a 6-point Likert response scale. A translation of the German items can be found in Fig. 5.

Additionally, we used the User Experience Questionnaire (UEQ, [23]) to measure participants' user experience through perceived attractiveness, pragmatic quality, and hedonic quality of the agent. We further surveyed the power and information certainty (human to system) sub-scales from the HMII [29] to check if our manipulation of the degree of automation and amount of shared information was successful.

1. *The agent supports me in achieving my goals.*
2. *The agent communicates its decisions and actions with me.*
3. *The agent helps me make better decisions.*
4. *The agent's actions are tailored to my personal circumstances.*
5. *The agent is cooperative.*

Fig. 5. The items of the perceived cooperativeness scale.

4 Results

4.1 Manipulation Check

Participants in the low-automation condition reported significantly higher perceived power in the situation ($U = 1452$, $p_{\text{one-tailed}} < .001$) with a medium effect size $r = .37$. We conclude that the manipulation of the degree of automation was successful. For the variation of the amount of information shared, there was no significant difference in the reported information certainty (human to system) between the low and high amount of given information condition ($U = 984$, $p_{\text{one-tailed}} = .369$). Therefore, results regarding the difference in the amount of given information should be regarded with caution.

4.2 Regression Analysis

To examine our first and second hypotheses, we conducted four different regression analyses for each of our dependent measures.

The first analysis was performed for the variable *behavioral change* measured by the chosen charging endpoint. Since the charging endpoint variable was not normally distributed, we transformed this measure into a dichotomous variable on whether participants choose to prolong the charging window (1) or not (0). We performed a binomial logistic regression (see Table 1) on the respective data. We found that a higher degree of automation led to a significantly higher probability of changing the behavior, i.e., adjusting the charging window.

For the other three measures, we calculated linear regression analysis as the data fulfilled all statistical requirements. We did not find an effect of the experimental manipulations on *perceived goal alignment*, as measured by the HMII's conflict subscale ($R^2 = .016$, $p = .483$, Table. 2, *Conflict regression*), nor on the *perceived cooperativeness* ($R^2 = .013$, $p = .564$, Table. 2. *Perceived cooperativeness regression*). The regression model for the variable system understanding (*SIPA*) showed an effect for the amount of shared information ($R^2 = .068$, $t = 2.48$, $p = .046$), Table. 2, *SIPA regression*, such that a higher amount of information led to a better system understanding.

Table 1. Results of the binomial logistic regression (OR: odds ratio).

Parameter	Estimate	Standard error	z-value	p-value (two-tailed)	Standardized OR	95 % CI for OR
Intercept	−3.09	1.12	−2.77	.006	1.68	[0.99, 2.98]
Degree of automation	2.80	0.55	5.09	<.001	4.08	[2.45, 7.31]
Amount of information	−0.39	0.53	−0.73	.465	0.82	[0.48, 1.39]

Table 2. Linear regression results for conflict, SIPA, and perceived cooperativeness.

Parameter	Standardized beta coefficient	Standard error	t-value	p-value (one-tailed)
Conflict regression				
Degree of automation	0.122	0.12	1.16	.125
Amount of information	0.045	0.12	0.43	.665
SIPA regression				
Degree of automation	−0.035	0.19	−0.35	.367
Amount of information	0.256	0.19	2.48	.008
Perceived cooperativeness regression				
Degree of automation	−0.084	0.19	−0.79	.215
Amount of information	0.072	0.19	0.68	.250

4.3 Correlations with Reported User Experience

In the UEQ, participants overall reported a slightly positive attractiveness ($M = 0.98$, $SD = 1.07$), hedonic ($M = 0.79$, $SD = 0.89$), and pragmatic quality for the SCA independent of the experimental condition ($M = 1.22$, $SD = 0.87$). To examine our third hypothesis, we calculated correlations between our four measures of cooperation and the three subscales of the UEQ.

For the variables charging endpoint (*behavioral change*) and the HMIII conflict subscale (*perceived goal alignment*), Kendall's Tau was calculated. For *SIPA* and *perceived cooperativeness*, Pearson correlation coefficients are reported. All p-values are one-tailed. Results are shown in Table 3.

5 Discussion

We investigated the effect of varying the level of cooperation in a smart charging agent (SCA) on user perception and behavior. We manipulated the SCA's cooperativeness by varying its degree of automation and the amount of information sharing with the user and measured effects on changes in user behavior, perceived goal alignment, the user's awareness of the SCA's information processing, and perceived cooperativeness, measured by a five-item scale developed for the present study.

Table 3. Correlations between measures of cooperation and reported user experience.

	Charging time	Conflict	SIPA	Perceived Cooperativeness
Attractiveness	.05	-.05	.38***	.69***
Pragmatic quality	.04	-.03	.57***	.61***
Hedonic quality	.04	-.15*	.28**	.64***

*$p < .05$, **$p < .01$, ***$p < .001$

5.1 H1: A Low Degree of Automation Increases Cooperation

We hypothesized that a lower degree of automation of the SCA would increase human-agent cooperation. However, in three out of four analyses, the degree of automation had no significant effect on our measures of cooperation. For our behavioral variable, participants in the high automation condition chose a later charging endpoint more often than participants in the low automation condition. In other words, participants behaved more often cooperatively in the high-automation condition, which is contrary to our hypothesis.

5.2 H2: A High Amount of Information Shared Increases Cooperation

We hypothesized that a higher amount of information shared by the SCA should increase human-agent cooperation. However, in three out of four analyses, the amount of shared information had no significant effect on our measures of cooperation. There was a small positive effect on the amount of information shared on reported SIPA. Our second hypothesis was, therefore, only partially confirmed.

5.3 H3: Cooperation Leads to a More Positive User Experience

Two of the four cooperation measures correlated moderately to strongly with the three subscales of the UEQ (SIPA and perceived cooperativeness, see Table 3), indicating that higher cooperation (perception measures) led to a more positive user experience. There was a small negative correlation between our measure of perceived goal alignment and the hedonic quality of the SCA. None of the UEQ subscales correlated with our variable of cooperative behavior, i.e., the chosen charging endpoint. Our third hypothesis was, therefore, only partially confirmed.

5.4 Theoretical and Practical Implications

Cooperation is often operationalized by the degree of automation of a system, which is usually attributed to positive effects (such as higher reported pleasure and trust [17,27]. However, we could not replicate equivalent effects in our study. Most literature on human-automation cooperation focuses on use cases in which systems become more automated (such as manual driving developing towards autonomous driving), and users are expected to give up control in the future. This cannot be applied as easily to the use case of human-agent cooperation in smart charging, as described here. In the present scenario, users arguably *keep* more responsibility because they remain involved in the decision process also in the highly automated condition.

Additionally, charging your car might satisfy less hedonic needs compared to driving your car [8]. Thus, users might not want to stay in the loop and share the task as much compared to other use cases.

5.5 Conclusion and Outlook

We present a first study on human-machine cooperation in the context of smart charging. We developed a theoretically driven concept for designing different levels of cooperation in an SCA and for investigating its effect on the user. Contrary to our hypothesis, we did not find a positive effect of lower automation on our measures of cooperation (perception and behavior change). Instead, a high degree of automation even led to a higher probability for the user to shift the charging window, which we interpreted as a higher willingness to cooperate. We discussed that one potential reason for this result might be that the degree of automation as defined by Parasuraman [22] may have different implications in the context of smart charging compared to autonomous driving. It may be conceivable that human-machine cooperation on eye level has requirements that are different from those found in automation, and new concepts and approaches are required. Thus, future work should explore other operationalizations of human-machine cooperation within this context, focusing, for example, on shared responsibility [16].

Furthermore, the degree of information shared by the agent did hardly affect cooperation measures. The manipulation might not have had the intended effect overall. Here, a stronger variation in the provided information to the user might yield a higher effect. Another potential limitation might arise from the between-subject design since participants had no comparison for their assessment of the SCA. In addition, the study displayed only one use case (meeting with friends). A scenario with a more urgent appointment could have led to different user reactions. Taken together, we provide new insights for future research on how to design an SCA for human-machine cooperation successfully.

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