Enhancing Trust in Smart Charging Agents—The Role of Traceability for Human-Agent-Cooperation

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Enhancing trust in smart charging agents—The role of traceability for human-agent-cooperation

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Abstract. Achieving climate neutrality will require a major transformation of the transportation sector, likely leading to a surge in demand for electric vehicles (EVs). Charging EVs with renewable electricity poses a challenge to grid stability due to supply fluctuations. At the same time, EVs offer the potential to improve grid stability through managed charging. The complexity of this charging process can limit user flexibility and require more cognitive effort. Smart charging agents powered by artificial intelligence (AI) can address these challenges by optimizing charging profiles based on grid load predictions, but users must trust such systems to attain collective goals in a collaborative manner. In this study, we focus on traceability as a prerequisite for understanding and predicting system behavior and trust calibration. Subjective information processing awareness (SIPA) differentiates traceability into transparency, understandability, and predictability. The study aims to investigate the relationship between traceability, trust, and prediction performance in the context of smart charging agents through an online experiment. $N = 57$ participants repeatedly observed cost calculations made by a schematic algorithm, while the amount of disclosed information that formed the basis of the cost calculations was varied. Results showed that higher amount of disclosed information was related to higher reported trust. Moreover, traceability was partially higher in the high information group than the medium and low-information groups. Conversely, participants' performance in estimating the booking costs did not vary with amount of disclosed information. This pattern of results might reflect an explainability pitfall: Users of smart charging agents might trust these systems more as traceability increases, regardless of how well they understand the system.

Keywords: smart charging, human-machine cooperation, explainability, trust, human-technology interaction, battery electric vehicles

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1 Introduction

The EU aims for climate neutrality by 2050, which necessitates a comprehensive transformation of the transport sector, including a 90% reduction in emissions [11]. Consequently, the demand for electric vehicles (EVs) will rise strongly within the next years. It has been argued that this demand will pose a challenge for the stability of the power grid [19] – particularly if EVs are charged with renewable electricity, which is subject to large fluctuations in supply and might not be flexible enough to meet the also fluctuating energy demands by users at all times [5]. Conversely, EVs offer a great potential for increasing grid stability through managed and bidirectional charging, that is, EVs can store or provide excess energy to the grid as needed [23]. As a consequence, the complexity of the charging process increases, limiting user flexibility or requiring more planning and technical understanding. Thus, the collective benefit of grid stability may come at a cost for the individual user, who might face a restriction of personal resources (e.g., time, comfort, cognitive resources [19]).

Smart charging agents relying on techniques from the field of artificial intelligence (AI) offer one solution to combine protection of users' personal resources with optimal utilization of renewable energy, for instance, by calculating and implementing optimal charging profiles based on grid load predictions [1]. From the user's perspective, this means that their cognitive effort required to organize a complex charging process is minimized. What remains is that users of smart charging systems need to balance between different goals, either stemming from individual needs (e.g., flexibility) or collective ones (e.g., sustainable energy consumption). Individual users may well pursue selfish goals in this regard (i.e., maximize their personal gain, e.g., by booking EVs from a car share fleet without delay), but overall, the finite and fluctuating nature of renewable energy resources requires that users also pursue collective goals (i.e., maximize the collective gain, e.g., by shifting their EV booking window) – in other words, users need to make a tradeoff between egoistic and altruistic behavior. Smart charging agents offer the potential to assist users in achieving not only individual, but also collective goals. The usage of such a smart charging agent can thus be understood as a cooperative, joint activity [15, 18], because both partners (the user and the smart charging agent) are working towards (shared) goals that neither can achieve on their own. To realize the potential of smart charging agents for sustainable electromobility, it is crucial to maximize users' perception of advantages from cooperating with the system.

One core variable for enhancing cooperation between users and an AI system such as a smart charging agent is trust [3]. Trust plays a role within human-agent interaction in the field of smart charging, because this interaction is characterized by degrees of uncertainty on part of the users (see [20]) – in contrast to the agent, users do not have access to all relevant technical information that determines the charging management (e.g., probability of peak load, distance to previous bookings in an EV carsharing context). Hence, users have to rely on the agent's functionality, i.e., trust the agent. Past research has suggested that trust in AI systems can be increased by AI explainability, i.e., providing comprehensible and transparent explanations of the algorithm's decisions [6, 26]. In this sense, explainability refers to enabling a deepened knowledge about the system's general functionality [16]. A related concept that has been applied to trust in AI systems is traceability, which can be related to situation awareness theory [10]. Traceability stresses that knowledge representations about how the system works (i.e., the mental model) does not capture the awareness of the system's status (i.e., the situation model). However, awareness of the system's status is necessary to understand momentary system behavior and to predict future states. For instance, a user cooperating with a smart charging agent in a car sharing fleet might know that the agent incorporates weather data (general knowledge). However, if the user is not made aware in a given situation that the weather data used by the system differs from the user's expectations, the calculated energy consumption of the EV may not be understandable to the user, which is likely to lead to incorrect predictions of the EV's energy consumption in the future. Hence, for the present study, we focused on traceability because it captures more complex decision-making processes than explainability, which are relevant in the domain of cooperating with smart charging agents.

The subjective information processing awareness (SIPA) has been proposed as a construct which differentiates traceability into three subfacets: transparency, understandability, and predictability [24]. Conceptually related situation awareness, SIPA refers to “the experience of being enabled by a system to perceive, understand and predict its information processing” [25]. A first study focusing on traceability of automated insulin delivery (AID) systems highlighted the importance of differentiating the three subscales and the close connection between SIPA and trust [24]. Based on results regarding the relationship between explainability, traceability, and trust, we test the following hypotheses: (H1) SIPA increases with an increase in relevant explaining information disclosed by the smart agent; (H2) trust increases with an increase in relevant explaining information disclosed by the smart agent; and (H3) SIPA and trust are positively correlated.

In addition to subjective assessments of traceability and trust, capturing behavioral variables is central to understanding the impact of efforts for human-centered design of AI systems: A system that is better traceable should enhance the user's understanding and acceptance, and it should support the interaction success, which should become observable in the user's behavior. Accordingly, better experienced predictability should be related to better predictions about the system's behavior. Hence, we predict that (H4) prediction performance increases with an increase in relevant explaining information disclosed by the smart agent; and (H5) predictability and prediction performance are positively correlated.

To investigate our hypotheses on the role of traceability for trust as a prerequisite for human-agent cooperation in the smart charging domain, we designed an online experiment similar to the one reported in [24]. Specifically, a schematic EV car sharing booking simulation was developed to create stimuli that participants were presented repeatedly. These stimuli depicted the booking calculations based on 10 sources of information, of which a varying amount was disclosed to the participants (see Section 2.2).

2 Method

A car-sharing booking simulation experiment was conducted using the online platform Labvanced [12] The study was approved by the ethics committee of the University of Lübeck (tracking number 21-375).

2.1 Participants

Complete datasets were gathered from N = 64 participants. Outlier detection was based on response times (according to [20]) and response patterns (i.e., data sets without variance on the SIPA scale were excluded). N = 57 participants remained and were included in the analyses. Of those, n = 42 (74%) were women, n = 13 (23%) were men, and n = 2 (4%) were non-binary. Age varied between 18 and 63 (M = 24.11, SD = 9.50). Ninety percent of participants were students.

The majority of the participants did not have experience in driving electric vehicles: 46 participants (81%) indicated that they had driven a combustion vehicle in the past, whereas only 3 (5%) had driven a BEV, 4 (7%) had driven a hybrid vehicle, and 2 (4%) had driven a plug-in hybrid vehicle. Eleven participants (20%) indicated not to have any driving experience. Seven participants (12%) reported to have used car sharing in the past. The sample was characterized by a slightly below-average affinity for technology interaction (M = 3.16, SD = 1.18, significant difference from the scale mean 3.5, $t(56)$ = -2.20, p = .032, d = -0.29, weak effect; [13]).

Students from the University of Lübeck were rewarded with course credits. In addition, the three participants with the best performance in the performance block could win €20 each. This additional prize was used to provide an extra incentive for motivation in the performance task.

2.2 Experimental Environment and Procedure

For assessing participants' perception of the traceability of a smart charging agent within an online experiment, a schematic algorithm was designed. This algorithm calculated the resource efficiency of booking an EV from a car-sharing fleet based on simulated data, displayed as abstract booking costs (i.e., tokens). The cost calculation was based on 10 features (e.g., time of booking start and end, expected network power demand, likelihood of a peak load). Fewer tokens indicated higher resource efficiency. For the present experiment, the algorithm was used to calculate 50 booking costs, which were presented to participants as the result of a supposed artificial intelligence system (i.e., this was a wizard-of-oz experiment, see Figure 1).

In five subsequent observation blocks, the participants were asked to observe 10 cost calculations made by the algorithm. After each observation block, participants rated their subjective experience with the algorithm (T1-T5). To evaluate participants' ability to predict the algorithm's results, a performance block followed, in which participants were asked to estimate booking costs based on the disclosed information (20 estimations in total). Participant's performance was measured by comparing their estimates with the actual booking costs (T6); however, this information was not provided to them to rule out learning effects.

The traceability of the algorithm was experimentally manipulated by varying how much of information used for cost calculation was disclosed to the participant (low, medium, high information; between-factors design). Participants in the low-information condition (*n* = 18) received information about the beginning and end of the booking, the expected kilometers, and the customer ID (the latter having no effect on the token calculation). Participants in the medium-information condition (*n* = 20) received additional information about the distance to the previous booking in hours, the distance to the next booking in hours, the state of charge after the previous booking, and the minimum state of charge for the next booking. Participants in the high-information condition (*n* = 19) received additional information about expected grid power demand, probability of peak load, expected charge consumption, and expected green power share (the latter having no effect on the token calculation).

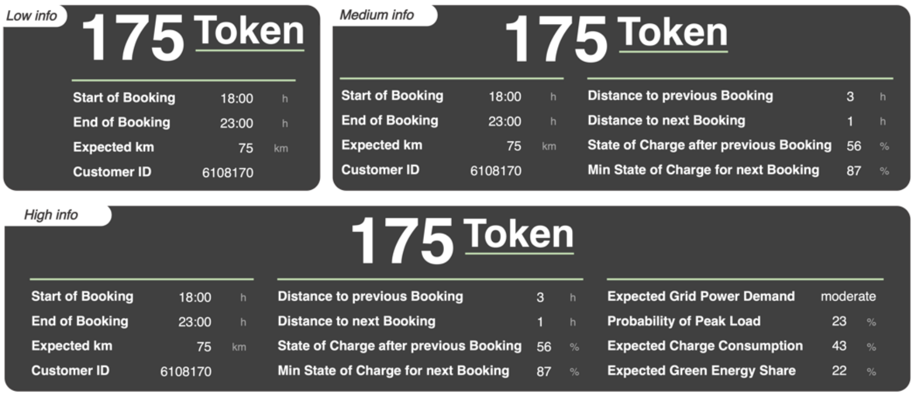

Fig. 1. Stimuli from the study as they were shown to participants for the three conditions.

2.3 Measures

To assess the reliability of the used scales, we calculated McDonald's omega (ω) in addition to Cronbach's alpha (α), since the latter is not well-suited for short scales [7]. For traceability facets, which consist of only two items each, the Spearman-Brown coefficient was used to assess their reliability [9].

For assessing traceability, the 6-item Subjective Information Processing Awareness (SIPA) scale [24] was used. The scale measures traceability on the three subscales transparency, understandability, and predictability with 2 items each. Responses were provided on a 6-point Likert scale from 1 (*completely disagree*) to 6 (*completely agree*). Regarding the overall scale, Cronbach's alpha varied between $\alpha = .89$ and $\alpha = .93$ and McDonald's omega varied between $\omega = .88$ and $\omega = .92$, which indicates good to excellent reliability. Regarding the transparency subscale, consistency varied between $R = .62$ and $R = .94$. The consistency of the understandability subscale varied between $R = .93$ and $R = .94$. The consistency of the predictability subscale varied between $R =$

.92 and R = .97. Hence, the consistency of the three subscales can be interpreted as moderate to high.

Trust was assessed with the 5-item Facets of Systems Trustworthiness (FOST) scale [14]. Responses were provided on a 6-point Likert scale from 1 (*completely disagree)* to 6 (*completely agree*). Cronbach's alpha varied between α = .91 and α = .96 and also McDonald's omega varied between ω = .91 and ω = .96, which indicates excellent reliability.

For assessing participant's prediction performance, 20 of the 50 stimuli created with the booking simulation environment were changed in such a way that no prediction of the algorithm was displayed, but the different levels of information disclosure (depending on the condition). Participants were prompted to estimate the output of the algorithm (i.e., the estimated number of tokens). The deviation of each estimate from the simulated number of tokens was determined per person and a sum value was calculated, which was used as an indicator of performance.

3 Results

3.1 Descriptive Analyses

Table 1 depicts means and standard deviations for the dependent variables that were assessed after the five observation blocks (SIPA, SIPA subscales, FOST) for the whole participant group as well as for the three experimental conditions.

Table 1. Descriptive statistics for the dependent variables assessed after the observation blocks.

Variable	*N*	T1		T2		T3		T4		T5	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
SIPA	57	3.34	1.07	3.29	1.01	3.32	0.97	3.51	1.20	3.32	1.06
Low info	18	3.39	1.17	3.16	0.97	3.18	0.83	3.10	1.06	3.10	0.86
Medium info	20	3.57	1.15	3.24	0.95	3.22	0.84	3.24	1.15	2.89	0.78
High info	19	3.04	0.84	3.46	1.12	3.56	1.19	3.68	1.15	3.68	1.24
SIPA transparency	57	4.13	1.20	4.12	1.19	4.14	1.10	4.01	1.31	3.96	1.22
Low info	18	4.28	1.39	4.22	1.17	4.08	1.03	3.92	1.32	4.06	1.12
Medium info	20	4.30	1.16	4.13	1.17	4.30	0.95	4.05	1.38	3.80	1.26
High info	19	3.82	1.03	4.03	1.30	4.03	1.32	4.05	1.29	4.05	1.30
SIPA understandability	57	3.10	1.27	3.06	1.21	3.07	1.16	3.18	1.28	2.93	1.22
Low info	18	3.08	1.22	2.81	1.23	2.94	0.92	2.83	1.18	2.72	1.10
Medium info	20	3.33	1.47	3.08	1.23	2.78	1.16	2.98	1.37	2.45	0.93
High info	19	2.87	1.10	3.29	1.21	3.50	1.28	3.71	1.17	3.63	1.32

SIPA predictability	57	2.78	1.25	2.68	1.13	2.75	1.19	2.85	1.24	2.77	1.17
Low info	18	2.81	1.38	2.44	1.20	2.50	1.26	2.56	1.38	2.53	1.14
Medium info	20	3.08	1.43	2.53	0.99	2.58	1.13	2.70	1.06	2.43	0.89
High info	19	2.45	0.81	3.08	1.14	3.16	1.26	3.29	1.21	3.37	1.27
FOST	57	3.65	1.00	3.39	1.01	3.35	1.09	3.51	1.20	3.32	1.06
Low info	18	3.50	1.15	2.79	0.77	3.03	0.23	3.12	1.17	3.01	0.80
Medium info	20	3.90	0.84	3.65	0.98	3.41	1.10	3.55	1.22	3.04	0.93
High info	19	3.53	1.00	3.68	1.02	3.58	1.14	3.83	1.16	3.90	1.21

Table 2 depicts means and standard deviations for participants' performance in estimating the booking costs calculated by the algorithm. As a performance indicator, the sum of deviations of participants' estimates from the simulated booking costs was calculated.

Table 2. Descriptive statistics for participants' performance within the performance block.

Variable	*N*	T6	
		M	*SD*
Mean sum of deviations from estimated fit	57	1509	706
Low info	18	1613	1047
Medium info	20	1486	424
High info	19	1436	556

3.2 Hypotheses Testing

For analyzing differences between the three experimental conditions (H1, H2, H4), planned contrast analyses were conducted for each of the dependent variables and points of measurement [22]. The different amounts of information disclosed to each group and the corresponding relationship between attributes were used to determine the weights (i.e., lambda values). It was assumed that each attribute (i.e., a total of low info: 4, medium info: 8, or high info: 12) could be related to each other attribute seen in one condition. The number of relations between attributes is given by the binomial coefficient (i.e., the number of attributes over two). Thus, the number of relations between attributes was for low info = 6, for medium info = 28, and for high info = 66. Following [2] to calculate the weights, the following lambda values for the contrast analysis were defined: $\lambda_{low} = -2.5$, $\lambda_{med} = -0.5$, $\lambda_{high} = 3$; for a similar approach see [24]. Results are depicted in Table 3. Effect sizes were interpreted according to [4].

Table 3. Planned contrast analyses results.

Variable	*T*	*p*	95% CI	$r_{\text{(effect size)}}$
SIPA overall score				
T1	-1.16	.252	[-3.07, 0.82]	.15
T2	0.95	.347	[-0.98, 2.74]	.13
T3	1.28	.205	[-0.64, 2.91]	.17
T4	1.64	.108	[-0.38, 3.73]	.22
T5	2.07	**.043**	[0.06, 3.65]	.27
SIPA transparency				
T1	-1.28	.207	[-3.59, 0.79]	.17
T2	-0.49	.628	[-2.76, 1.68]	.07
T3	-0.28	.784	[-2.31, 1.75]	.04
T4	0.28	.780	[-2.09, 2.78]	.04
T5	0.11	.916	[-2.14, 2.38]	.01
SIPA understandability				
T1	-0.66	.514	[-3.10, 1.57]	.09
T2	1.18	.242	[-0.92, 3.55]	.16
T3	1.69	.097	[-0.33, 3.83]	.22
T4	2.25	**.029**	[0.28, 4.84]	.29
T5	2.79	**.007**	[0.80, 4.93]	.35
SIPA predictability				
T1	-1.21	.237	[-3.48, 1.06]	.16
T2	1.84	.072	[-0.17, 3.90]	.24
T3	1.80	.077	[-0.22, 4.09]	.24
T4	1.91	.060	[-0.10, 4.35]	.25
T5	2.54	**.014**	[0.55, 4.60]	.32
FOST				
T1	-0.13	.895	[-1.95, 1.71]	.02
T2	2.64	**.011**	[0.54, 3.97]	.33
T3	1.47	.148	[-0.53, 3.43]	.19
T4	1.77	.083	[-0.26, 4.09]	.23
T5	2.90	**.005**	[0.81, 4.46]	.37
Performance (Mean sum of deviations from estimated fit)				
T6	-0.72	.478	[-1776, 842]	.10

Note. Significant differences are bold-faced for better readability.

Results showed that regarding the overall SIPA score, only at T5 a significant contrast was found with participants in the high-info group having a significantly higher

SIPA mean score than participants in the low-info and medium-info groups (moderate effect). Regarding the SIPA subscale transparency, the three groups did not differ in their ratings. Significant differences were found for understandability at T4 and T5, with participants in the high-info group having significantly higher scores than participants in the low-info and medium-info groups (moderate effect). Moreover, a significant difference was found for predictability at T5, with participants in the high-info group again having significantly higher scores than participants in the low-info and medium-info groups (moderate effect). Thus, H1 was partially supported.

In terms of trust, significant differences were found at T2 and T5, with participants in the high-info group having significantly higher scores than participants in the low-info and medium-info groups (moderate to large effect). Hence, H2 was partially supported. One-tailed correlation analyses were conducted for testing the relationship between SIPA (subscales) and trust. Since multiple variables studied were not normally distributed, Spearman's Rho was calculated. Results are depicted in Table 4. The size of correlation coefficients varied between $r_S = .46$ and $r_S = .89$, indicating a moderate to strong relationship. H3 was thus supported.

For the performance indicator, the planned contrast analyses did not show any significant differences. Thus, H4 was not supported. For testing the relationship between predictability and prediction performance, again one-tailed Spearman correlation analyses were conducted. The correlation was only significant between performance and prediction at T1 ($r_S = .27$, $p = .023$, medium effect). The support for H5 was therefore weak.

Table 4. Correlations between trust and SIPA for each point of measurement.

	Point of measurement	SIPA							
		Overall score		Transparency		Understandability		Predictability	
		r_S	p	r_S	p	r_S	p	r_S	p
Trust	T1	.66	<.001	.49	<.001	.60	<.001	.64	<.001
	T2	.79	<.001	.54	<.001	.76	<.001	.72	<.001
	T3	.81	<.001	.47	<.001	.83	<.001	.71	<.001
	T4	.89	<.001	.73	<.001	.83	<.001	.78	<.001
	T5	.84	<.001	.46	<.001	.86	<.001	.76	<.001

4 Discussion

4.1 Summary of Results

Using planned contrast analyses, it was shown that traceability partially varied with the amount of disclosed information (higher amount of information related to higher reported trust). Moreover, trust was partially higher in the high information group than the medium and low information groups. Analyses of the three subscales of traceability revealed that effects were existent for understandability and predictability, while no effect was found for transparency. As expected, strong relationships between traceability and trust were found. With respect to prediction performance, the results showed that participants' performance in estimating the booking costs did not vary with the amount of disclosed information and only marginally with experienced predictability.

4.2 Implications

While additional information enhanced subjective experiences of trust, understandability, and predictability of a smart charging agent for EV car sharing, they did not improve transparency ratings and estimation of the algorithm's output. Together with the lack of a robust link between experienced predictability and prediction performance, the findings suggest that participants may have experienced an explainability pitfall [8]: Users of smart charging agents might trust these systems more as traceability increases, regardless of how well they understand the system. Thus, such systems may elicit the false impression that users understand the system's functionality well enough to predict its outcomes, even though they are unable to do so, possibly causing unwarranted trust [17]. An alternative explanation for the findings could be that as information increases, the workload for attending to each piece of information and integrating it into a numerical estimate increases, which could worsen prediction performance. In this case, however, the medium-info group should have scored higher than the high-info group, which was not the case.

4.3 Limitations and Future Research

An important limitation of the study is the sample composition: The participants were mostly students with little or no experience with EVs and carsharing. Although the understanding of the situation was increased by a contextual introduction and tested by knowledge questions at the beginning of the study, a sample consisting of actual users of EV carsharing services should be recruited to increase external validity.

Furthermore, the way in which the participants' prediction performance was assessed should be questioned. In real-world scenarios, users of smart charging agents do not need to predict the results of the algorithm in such an explicit manner. Hence, it might be fruitful to develop a way to measure predictive performance that has higher ecological validity.

4.4 Conclusion

ToDo…

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