The Impact of Precision of Algorithmic Advice on Human Sequential Decision-Making: Model and Experiments

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As artificial intelligence (AI) becomes increasingly integrated into decision-making processes, questions remain about its long-term impact on human skill development and adaptability. This work investigates how the precision of algorithmic advice influences immediate and enduring decision-making behaviors in complex, sequential tasks. Through controlled behavioral experiments, participants navigated an electric vehicle (EV) charging scenario under uncertainty, receiving either precise numeric advice or broad strategic suggestion. Our results reveal that while precise advice improves short-term compliance and performance, it fails to foster transferable skills, as participants struggle to adapt once the advice is removed. In contrast, broad advice promotes exploratory behavior, leading to better long-term strategy retention and adaptability in new environments. These findings have significant implications for the design of AI decision-support systems, emphasizing the importance of balancing short-term optimization with sustainable human engagement and learning.

Contents

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1 Introduction

Artificial Intelligence (AI)-based systems have become critical tools supporting decision-making across industries such as supply chain management, healthcare, and transportation, offering real-time recommendations that enhance operational efficiency and reduce cognitive demands [Bertsimas and Kallus, 2020, Sun et al., 2022]. However, their broad use in decision-making processes offers challenges. On the one extreme, AI systems may not be used effectively due to a lack of trust, often termed algorithm aversion [Dietvorst et al., 2015]. In such situations, human discretion can lead to suboptimal outcomes for organizations [Sun et al., 2022]. On the other extreme, if AI assumes a dominant role in performing tasks, human decision-makers may lack sufficient practice or even experience a degradation in skills. [Macnamara et al., 2024]. For instance, in aviation, the extensive use of autopilot systems has been linked to a decline in pilots' manual flying skills, raising safety concerns when unexpected events require human intervention [Casner et al., 2014]. This is problematic, especially in high-stakes environments, where stakeholders broadly agree that final decisions should rest with humans [e.g., in healthcare, see British Medical Association, 2024].

Organizations thus face the dual challenge of leveraging AI to improve decision-making outcomes while ensuring that human decision-makers build and retain critical skills, to be able to effectively fulfill supervisory functions and jump in whenever automated solutions are unsuitable. To build and retain the skills necessary to make effective decisions independently, humans need practice and repetition. Consequently, if decision-makers are disengaged from the decision-making processes supported by AI systems, they cannot be expected to have the skills to effectively supervise the process or make decisions by themselves. At the same time, if decision-makers distrust AI systems, it is unlikely that the superior decision-making capabilities of the systems will be employed. Hence, we aim to explore whether algorithmic advice can be designed to support decision-making processes while also fostering engagement and, ultimately, learning.

Our focus is on sequential decision-making tasks. These present unique challenges, requiring individuals to navigate trade-offs between immediate gains and future consequences. For example, electric vehicle (EV) drivers must decide when and where to recharge to minimize total travel time while accounting for uncertainties such as traffic delays and non-linear charging rates. In such scenarios, AI-generated advice has the potential to simplify decisions, yet its design may fundamentally shape users' behavior. Precise, directive advice, offering clear numeric recommendations, has been shown to improve short-term performance by reducing cognitive load [Mosier et al., 1998]. However, it often discourages active engagement and exploration, potentially limiting users' ability to adapt strategies to unfamiliar contexts [Bastani et al., 2024, Macnamara et al., 2024]. By contrast, broad, strategic advice encourages exploratory behavior, fostering deeper engagement with task dynamics and the development of transferable skills [Argote and Miron-Spektor, 2011, Gick and Holyoak, 1980]. Yet, such advice may introduce ambiguity, making it harder for users to extract actionable insights and comply effectively in the short term [Kelly and Simmons, 2016].

In this paper, we investigate how the precision of algorithmic advice—precise versus broad—affects short-term performance, long-term strategy retention, and adaptability in sequential decision-making tasks. To explore these dynamics, we conducted two controlled behavioral experiments using a simulated EV charging task. In Study 1, we examine the immediate impact of precise versus broad advice on task performance, focusing on how these advice structures influence compliance and behavioral strategies. The results show that precise advice significantly improves task efficiency during the advice phase by guiding participants toward optimal actions, whereas broad advice fosters more exploratory behavior, leading to diverse but less consistent strategies.

Building on these findings, Study 2 explores whether the type of advice provided influences participants' ability to retain and transfer learned strategies when navigating more dynamic and uncertain environments. By incorporating a post-advice phase without advice, we directly evaluate the extent to which participants develop generalizable decision-making skills through engagement with the algorithmic advice. The results reveal that participants exposed to broad advice, who effectively employ it, demonstrate superior learning and adaptability. They frequently retain near-optimal strategies in new contexts, while participants reliant on precise advice often revert back to suboptimal behaviors after losing access to advice.

This paper contributes to ongoing research in behavioral operations management and human-AI collaboration by addressing a critical gap: how the design of algorithmic advice shapes both immediate performance and long-term human learning. Our findings underscore the need for a nuanced approach to AI system design: one that balances short-term optimization with sustainable human learning, particularly in complex and uncertain environments.

1.1 Related Works and Contributions

Artificial intelligence (AI) is increasingly integrated into decision-making processes, offering real-time recommendations that enhance operational efficiency across industries such as supply chain management, finance, and healthcare [Bertsimas and Kallus, 2020, Ibanez et al., 2018]. By automating routine decisions and optimizing complex workflows, AI tools have demonstrated the ability to improve short-term performance and streamline operations. However, these benefits come with challenges, particularly in sequential decision-making tasks where users must balance immediate efficiency with long-term adaptability [Bastani et al., 2024, Macnamara et al., 2024, Sun et al., 2022]. In such contexts, the ability of AI systems to shape human decision-making behavior over time—whether by fostering learning or reinforcing dependence—remains an open question in behavioral operations and human-AI collaboration.

A fundamental challenge in AI-assisted decision-making is optimizing the design of algorithmic advice to enhance both immediate task performance and sustainable human learning. Research in behavioral operations has highlighted how different types of advice affect user behavior. Precise numerical advice, which offers explicit and directive recommendations, can simplify decision-making, leading to high compliance and immediate performance gains [Mosier et al., 1998]. However, such advice often discourages active engagement, exploration, and strategic thinking, which are critical for users to transfer learned strategies to new or uncertain environments [Macnamara et al., 2024]. By contrast, broad strategic advice, which provides general guidelines rather than specific directives, has been shown to encourage exploratory learning and adaptation [Argote and Miron-Spektor, 2011, Gick and Holyoak, 1980]. Broader advice fosters deeper engagement with task dynamics and promotes the development of transferable skills, aligning with theories of organizational learning and transfer learning. However, its ambiguity can make compliance more challenging, potentially hindering short-term performance [Kelly and Simmons, 2016]. These trade-offs are particularly relevant in sequential decision-making settings, where decision-makers must balance reactive optimization with proactive strategy development [Bastani et al., 2024, Bavafa and Jónasson, 2021].

Existing research on AI adoption has also explored user interactions with algorithmic recommendations, particularly focusing on trust, compliance, and decision-making outcomes. Users often reject AI recommendations after observing even minor errors, a phenomenon known as algorithm aversion [Dietvorst et al., 2015, Green and Chen, 2019]. Conversely, when AI tools consistently outperform humans, users may become over-reliant, deferring to AI systems without critically evaluating recommendations [Mosier et al., 1998, Rastogi et al., 2022]. While these studies emphasize trust dynamics in AI-assisted decision-making, they often overlook how different types of advice influence users' ability to retain and adapt decision strategies over time, particularly in dynamic and uncertain environments [Vereschak et al., 2021].

Within the domain of human-computer interaction (HCI), a complementary body of literature examines how to design recommendation systems that effectively support users' decision-making. Early HCI research focused on interface usability, information presentation, and minimizing cognitive overload. More recent studies have shifted toward understanding trust, transparency, user control, and the broader user experience with AI systems [Vereschak et al., 2021, Zangerle and Bauer, 2022]. For instance, HCI scholars studying in-car navigation and EV charging systems have explored how to communicate real-time traffic and battery information, mitigate cognitive overload through well-timed alerts, and ensure inclusivity for users with diverse sensory or physical capabilities [Froehlich et al., 2019, Nakhimovsky et al., 2010, Wang et al., 2014]. These studies underscore the importance of designing systems that not only optimize immediate outcomes but also empower users to make adaptive and informed decisions over time.

Our key contributions are threefold. First, we provide empirical evidence that while precise advice enhances short-term performance, it does not necessarily foster deeper learning. In contrast, broad advice leads to greater adaptability and skill retention, aligning with theories of transfer learning and behavioral adaptation—assuming that participants are capable of effectively employing the advice. Second, our study extends prior work on AI-assisted decision-making by examining how advice structures impact learning in dynamic environments where decisions are interdependent and uncertainty is present. Finally, our research provides a theoretically grounded and empirically validated framework for understanding how AI-generated recommendations shape human decision-making over time. As a result, it offers insights for the design of decision-support tools in domains such as supply chain management, healthcare, and transportation, where balancing short-term AI assistance with long-term human skill development is critical.

2 Model of Sequential Decision-Making

We study sequential decision problems, wherein a human makes decisions—possibly supported by AI tools—at multiple time steps, in order to achieve an over-arching goal. Our experimental setting will consider the driver of an electric vehicle that has to make charging decisions at one of multiple potential stops—each potential stop then corresponds to a "time" step. Alternatively, one might consider, for example, a supply chain manager that has to make ordering decisions for each week. Here, a week corresponds to a time step. Decisions are linked because the action in one period constraints (or enhances) the choices in a later period.

In general, we assume that the decision-maker interacts with a system over a finite horizon N, which at any time $i \in \{1, \dots, N\}$ is in one of finitely many states $s_i \in S$. For example, in the case of the supply chain manager, a state s_i could represent the current inventory position. In the case of driving an electric vehicle, a state s_i might represent the remaining charge. Given the state, the decision-maker chooses an action $a_i \in A$, such as how many units to order or how much to charge the vehicle. We will assume that A is also finite. In response to the chosen action, the system probabilistically transitions to a new state s_{i+1}, with distribution $p(s_{i+1}|s_i, a_i) = P(s_i, a_i, s_{i+1})$. For example, the inventory position in the next review period depends on how much new demand there was, while the electric vehicle driver's charge at the next stop depends on the traffic. We define as a policy a function $\pi : S \to Prob(A)$ that maps a state to a probability distribution over actions, that is, $\pi(s_i, a_i) = p(a_i|s_i)$.

Naturally, estimating a policy $\pi(s_i, a_i)$ directly from an observed set of trajectories $\tau = \langle(s_1, a_1), (s_2, a_2), \dots, (s_N, a_N)\rangle$ is challenging. First, the number of trajectories for a single decision-maker is frequently limited, but different decision-makers may employ different policies. Second, because the state space S may be large, it would require generalizing π to rarely observed or completely unobserved states. Instead, using the details of our experimental setup, we classify individual state-action pairs in a decision-maker's trajectory. We then use the resulting sequences of classified decisions across individuals to generate clusters of decision-makers with similar behavior (see, for example, Section 4.2). As Figure 6 shows, this allows us to qualitatively derive “typical” policies. By observing how these policies change with the addition (or removal) of advice, we are able to analyze the impact of algorithmic advice on decision-making—see, e.g., Figures 7 and 8.

Note that, an alternative approach could involve inverse reinforcement learning, which estimates π from the observed trajectories without the need to observe all states, by assuming the decision-maker optimizes an unknown reward function and learning that reward function instead [Hanawal et al., 2018]. We leave this approach to future research.

3 Experimental Design: Sequential Decision-Making Game

To empirically examine how humans learn and adapt their sequential decision-making, we develop an experimental framework in which participants receive incentives to perform well on repeated tasks, alongside machine-generated advice presented in various formats. Our experiment proceeds in three distinct phases:

Pre-Advice Phase. Participants begin by completing two to three rounds of the same sequential decision-making task without any AI assistance. This baseline allows us to observe how individuals initially approach a novel task and refine their strategies purely through trial and error.

With-Advice Phase. Next, participants encounter the same or similar tasks while receiving machine-generated recommendations designed to enhance performance. In this phase, we implement our main treatment conditions—varying both the precision of the advice (e.g., “precise" vs. “broad") and the level of uncertainty (e.g., “average" vs. “extreme"). These conditions enable us to investigate how participants respond to different forms of AI guidance and adapt their decisions over time based on observed outcomes

Post-Advice Phase. Finally, participants no longer receive AI advice, and the environment can remain similar or change substantially. This setup allows us to measure the extent to which participants retain and transfer any newly acquired skills to novel scenarios, independent of ongoing AI input.

Our between-subject factorial design randomly assigns participants to treatment combinations spanning advice precision and uncertainty level. To contextualize the task, we use an electric vehicle (EV) charging scenario. Participants operate an EV through multiple highway segments that vary in distance and traffic uncertainty, deciding when and how much to recharge in order to minimize total travel time. AI recommendations are provided in real time, offering different levels of precision on optimal charging behavior.

The EV-charging context is particularly apt because it distills key features of real-world sequential decision processes that benefit from algorithmic guidance while leaving ultimate control—and the option to deviate—firmly in human hands. This design thus illuminates both the immediate effects of AI advice and its enduring influence on learning and performance.

Sequentiality. A decision-making process is only truly sequential if the decisions made at some time enable or constrain the decisions made at a later time. EV charging inherently involves a series of connected decisions, with drivers needing to plan when and where to charge their vehicles along their journey. Clearly, a decision to exit and fully charge after a road segment makes it less likely to need charging after the next one.

Complexity. While not all sequential decision-making processes must be complex, complexity is key to make decision-support tools relevant. In our case, the charging process itself introduces such complexity. When charging electric batteries, power delivery is non-uniform, implying a variable but non-linear cost for charging [Montoya et al., 2017]. At the same time, it is reasonable to expect that the time to exit a road, set up the charger, and pay is relatively independent of the amount charged. This complex cost structure, with variable and fixed costs, compound the decision-making challenge, requiring individuals to balance immediate charging needs with long-term considerations of efficiency.

Granular decisions. Many sequential decision-making processes are complex because of the large and potentially infinite number of potential choices at each step. For example, a supply chain manager may order any number of goods. However, much of the literature considers decisions with a relatively small number of potential choices, often as few as two. In EV charging, the actual amount of charge is continuous, with users facing a spectrum of charging options ranging from 0% to 100% battery capacity. Recognizing that charging to full capacity or completely depleting the battery ("all or nothing" choices) may not always be optimal, individuals must navigate this continuum to find the most advantageous charging strategy tailored to their specific needs and preferences. For simplicity, we discretize the charging interval at the level of percentage points.

Uncertainty. Uncertainty adds an additional layer of complexity. It is also a key driver for human biases and, thus, critical to scenarios in which human decision-makers deviate from algorithmic recommendations. When making decisions about how to charge, drivers need to anticipate traffic congestions and road conditions that can impact the feasibility and timing of a sequence of charging decisions. Generally, a driver does not have the full information about the upcoming traffic, so they risk running out of charge by accident. The cost of running out of charge could be fairly high, not just to the driver but also to the society (e.g., other road users). In 2023, a Tesla ran out of power in the middle of the highway in the United Kingdom and blocked the traffic for 11 hours [Pyman, 2023]. In fact, insurance that supports drivers when running out of charge is increasingly becoming available.[1] How individuals perceive and take actions in response to uncertain traffic also depends on their own risk preferences.

3.1 Details of the Experimental Design

We begin by describing the experimental driving task, then explain how individual tasks are integrated into the overall game structure. Finally, we detail our approach to collecting behavioral trace data and discuss any pertinent assumptions.

3.1.1 Task: Driving an EV to the Destination. The main experimental task requires participants to operate a virtual electric vehicle (EV) from an origin to a destination along a highway, aiming to minimize total travel time (measured in "in-game minutes"). Multiple exits ("stops") segment the highway, each connected by road segments of certain lengths. Both time and distance are expressed in in-game minutes, and the EV's charge is measured in percentage points, where 1 percentage point of charge is equivalent to 1 in-game minute of travel. The length of each road segment is displayed to participants.

Traffic introduces uncertainty by adding a random delay to each segment. Participants are shown a range of possible delays, and the actual delay is drawn from a uniform distribution over that range. For instance, if a segment indicates "[+5, +10]," the segment length is increased by a uniformly distributed delay of between 5 and 10 in-game minutes. Consequently, the EV must have enough charge to cover both the segment's base length and any additional traffic-induced delay.

[1] See, e.g., https://www.admiral.com/car-insurance/electric, https://www.aviva.co.uk/insurance/motor/electric-car-insurance/

At each stop, participants can recharge the EV up to a maximum of 100% of total charge. Figure 1 illustrates the task layout. While the length of every segment is visible by default, only the next segment's traffic range is displayed automatically; ranges for subsequent segments are only revealed if the participant chooses to click on them. This design feature allows us to assess whether participants invest effort in gathering information before making their decisions.

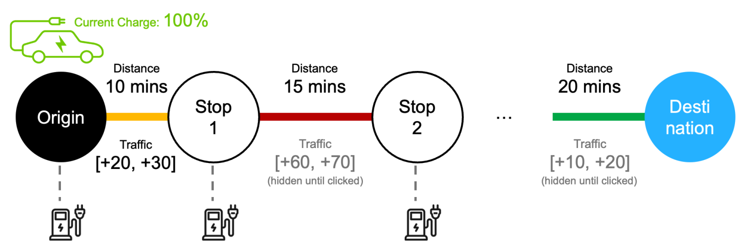


Fig. 1. Illustration of the experimental task. Each circle represents a highway exit ("stop") and a line between two circles represents a highway segment. Each segment is labeled with its length (in units of travel time) and the traffic range. The car symbol indicates the current location (the origin in this example) and the current level of charge is displayed next to it.

At each stop, the driver decides whether to proceed directly to the next highway segment or exit to recharge, given the current charge level of the EV. Exiting incurs a fixed *exit time* of 30 in-game minutes, representing the detour to the charging station plus set-up and payment overhead. If the driver chooses to exit, they then select how many percentage points of charge to add to the battery (an integer from 0 to 100). The *charging time* is modeled to reflect real-world nonlinearity in EV charging, such that adding charge from a low battery level requires less time per percentage point than doing so from a higher level—see (1). As a result, it can be more efficient to add smaller amounts of charge frequently; however, each exit also triggers the fixed overhead cost. The total time required for exiting and charging refkects both aspects—see (2). Denote the current charge level as s and the additional charge as ℓ. We then have:

$$f(x) = \lfloor 0.2 \cdot x^{1.55} \rceil \tag{1}$$

$$Y(\ell, s) = \left\{ \begin{array}{ll} f(100) - f(s) + 30, & \text{if } s + \ell \geq 100 \\ f(\ell + s) - f(s) + 30, & \text{if } 0 < \ell < 100 - s \\ 0, & \text{otherwise} \end{array} \right\}. \tag{2}$$

Drivers can choose their desired charge through a slider, which allows them to explore the nonlinearity of the charging time function.

Once a driver proceeds from the current stop, either after charging or without charging, the actual traffic is realized and added to the travel time. We let the traffic range and realization be independent of the driver's choice to exit and charge. If the driver has enough charge to cover the next highway segment (base travel time plus traffic time), they arrive at the next exit with some charge remaining, possibly zero. However, if the car does not have enough charge to reach the next exit, the driver incurs the *emergency charge penalty* of 300 in-game minutes and arrives at the next stop with a 0% level of charge (i.e., the emergency charge is just enough for the driver to reach the next stop).

The task is considered successfully completed once the driver reaches the destination regardless of the amount of remaining charge. The total travel, exit, and charging times, as well as any emergency charge penalties will be added up as the total completion time, which is the performance outcome of interest.

3.1.2 Maps. We refer to a tuple of origin (indicated with index 0), destination, intermediate stops, and connecting segments as a *map*. Each round of the experiment contains a single map. The key differentiating factors across maps (or rounds) are: (i) the number of stops N, (ii) the length of each segment i, d_i, (iii) the traffic range of each segment i, $[+\underline{t}_i, +\bar{t}_i]$, and (iv) the initial charge of the EV, s_0. We design each map such that the driver will never be able to complete the trip with her initial charge. In other words, the driver must exit to charge at least once in each map to reach their destination without running empty and incurring an emergency charge penalty. The realized traffic at each segment will be different across segments and across rounds, even for the same map. However, participants experience the same sequence of traffic ranges and realizations across the rounds.

3.1.3 Optimal charging decisions. Optimal charging decisions are identified through numerical optimization of the dynamic program faced by drivers. Let $\tau_i(s_i, a_i, t_i)$ denote the total time required to travel from stop i to stop $i+1$, including charging time and (random) traffic time t_i. Let $V(N, s_N) = 0$ and recursively define $V(i, s_i) = \max_{a_i} \mathbb{E}_{t_{N-1}} [\tau_i(s_i, a_i, t_i) + V(i+1, s_{i+1}]$ for any segment $i \in \{0, \ldots, N-1\}$ (where s_{i+1} is based on the starting charge s_i, the charging decision a_i, and the charge required for traveling across segment i accounting for traffic).

Then, the optimal decision $a_i^*(s_i)$ at exit i and with charge s_i is given by $a_i^*(s_i) \in \arg\max_{a_i} V(i, s_i)$. Hence, for each segment i and each possible charging level s_i, we find the optimal charging decisions through recursion and store it in a look-up table.

Importantly, each map is designed such that for certain segments, the optimal strategy is to exit and charge exactly what is required to drive through the current segment, assuming traffic is at its worst ($\bar{t}_i$). We refer to this strategy as *splitting*. For other segments, the optimal strategy is to exit and charge exactly what is required to drive through the multiple segments, assuming again that traffic is at its worst ($\bar{t}_i$ and $\bar{t}_{i+1}$). We refer to the latter strategy as *batching*. Across maps, we choose parameters such that, when batching is optimal, the optimal charge should enable to cover exactly two segments at worst-case traffic, but never more. Figure 2 provides an example illustration.

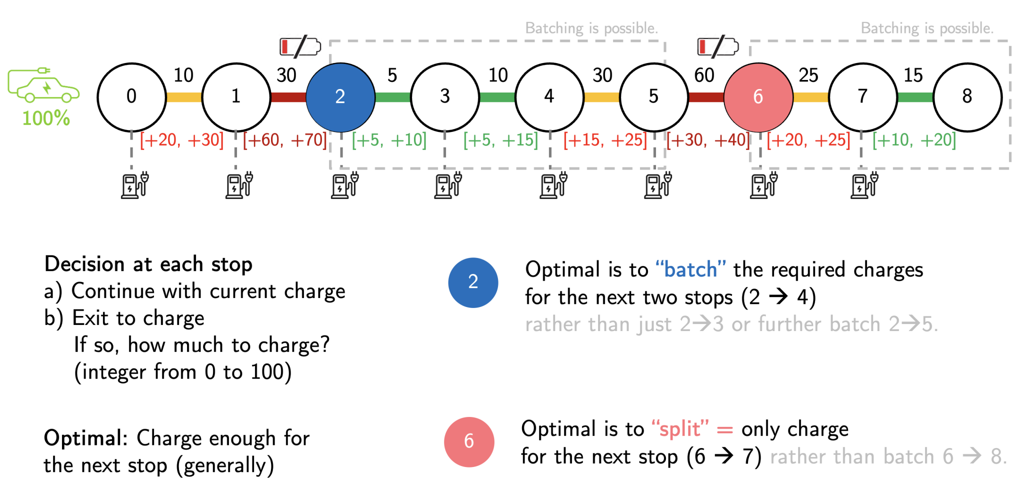


Fig. 2. Illustration of batching and splitting.

3.1.4 Advice. We refer to a recommendation we provide to the participant to support their decision-making at each stop as an *advice*.

Universal advice optimization. Across our studies, every participant within the same experimental treatment condition receives the same advice generated by our algorithm ahead of time (e.g., no advice personalization). The algorithm takes a neutral view given the exact same public information provided (e.g., observing the range of estimated traffic but not the realized traffic). It solves for the optimal charge-up-to level for each exit given each of the possible current charge levels (e.g., 0 to 100%) backward from the destination.

Precision of the advice. Participants are presented with recommendations in real time on ideal charging behaviors with different levels of precision. On one end, *precise* advice indicates whether the driver should exit at the current stop and if so the optimal charge-up-to level. For example, "You should exit at this stop and charge up to 60%." On the other end, *broad* advice offers an overview of the strategy the driver should adopt; for example, "Charge enough to cover the next two segments."

3.1.5 Procedure and Study Flow. Across our different experimental studies, the common procedure is as follows. Participants first go through a series of instructions and practice rounds that help them comprehend the interface and the experimental tasks. They have to pass our comprehension check to be able to proceed to the main part of the study. The specific setup for each study is provided in its corresponding section. After the main part is completed, participants are asked questions regarding their in-game strategy, past experiences with EV charging and similar tasks, and demographic information. We recruit participants on Amazon Mechanical Turk and Prolific. Participants are paid a flat participation bonus and can earn additional bonuses based on their performance. Base and bonus payments are determined specifically for each study.

4 Study 1: Impact of Precision of Advice on Behavior

While algorithmic advice has the potential to improve decision-making outcomes, its effectiveness depends critically on how the advice is presented. Prior research highlights that the precision of recommendations can shape human responses, with precise advice often promoting compliance and immediate performance, and broader advice fostering more flexible, exploratory behavior. Study 1 investigates this trade-off in the context of a complex sequential decision-making task. Specifically, we examine how the precision of advice influences participants' ability to adopt optimal strategies during the advice phase, setting the stage for understanding its role in shaping decision-making behaviors in dynamic and uncertain environments.

4.1 Study Design and Detail

Study 1 follows the experimental design introduced in Section 3.1 but only consists of two distinct phases: a *pre-advice* phase without algorithmic advice and a subsequent *with-advice* phase where participants received algorithmic guidance. In the pre-advice phase, participants complete two rounds of the task without any advice, allowing us to observe natural decision-making patterns and initial learning. In the with-advice phase, participants complete two additional rounds while receiving one of two types of advice: *precise* or *broad*. Uncertainty levels are not varied in this study.

The experiment was pre-registered at https://aspredicted.org/sh2q-prjr.pdf and involved 60 participants recruited via Prolific in March 2023, resulting in a total of 3,360 decision points. The average payoff was $5.43, and the median completion time was 33.78 minutes (mean 38.68 minutes). Among participants, 36.07% were female, 40.98% were aged 25–44, 88.52% held a valid driver's license, 83.61% owned a car, and 11.48% owned at least one fully electric vehicle.

4.2 Results: *Precise Advice Immediately Improves Performance*

The results reveal that advice precision significantly influences both immediate performance and the nature of participants' decision-making strategies (see Figure 3). Participants who receive precise advice demonstrate a substantial reduction in total travel time compared to those who receive broad advice. On average, precise advice reduces travel time by 13.4% relative to the pre-advice performance. This improvement potentially stems from participants' close adherence to the specific numeric recommendations, which effectively reduces decision complexity and guides them toward specific optimal or near-optimal solutions.

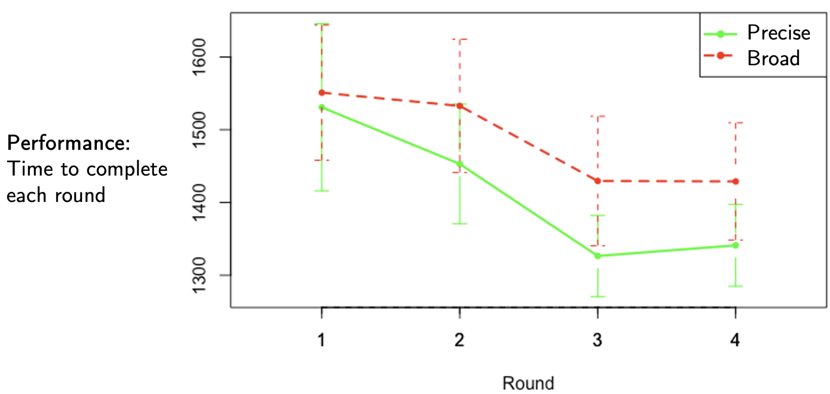
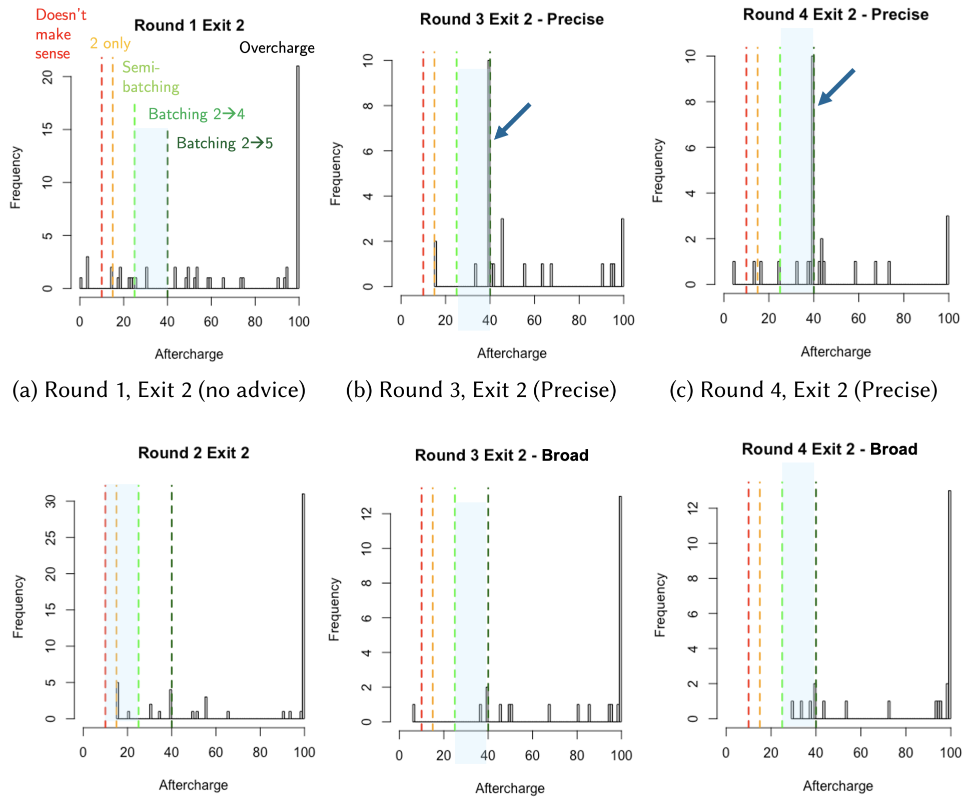


Fig. 3. Performance as measured by completion time across rounds and types of advice.

To further investigate the impact of advice precision on participant behavior, we focus on Exit 2 across four rounds, where the optimal strategy is to batch to cover the two segments connecting Exits 2 through 4. Figure 4 illustrates the distribution of strategies adopted by participants at this critical decision point, with the shaded region indicating the optimal range for batching. *Aftercharge* is defined as the new total charge level after re-charging. In Round 1, prior to receiving any advice, participant behavior is highly variable, with strategies ranging from suboptimally charging below the required minimum for the next segment to overcharging to the maximum capacity. By Round 2, a small fraction of participants has independently learned to batch the optimal amount, as reflected by an increased concentration within the shaded region.

Figures 4b–4c demonstrate the effectiveness of precise advice in guiding participants toward optimal behavior. A significant majority of participants who receive precise advice charge within the optimal range, as indicated by the clustering highlighted by the blue arrows. This outcome underscores the clarity and directness of precise recommendations in communicating the optimal strategy. In contrast, Figures 4e–4f reveal that participants receiving broad advice—although receiving conceptually similar guidance—exhibit greater variability in their charging decisions, with far fewer converging on the optimal range. These observations suggest two key insights. First, precise advice is demonstrably more effective in inducing optimal strategies, likely due to its explicit and actionable nature. Second, the lower compliance observed with broad advice may stem from its perceived lack of specificity, which could make the recommendations seem counterintuitive or ambiguous to participants.

Behavioral clustering analysis further reveals distinct patterns in participants' decision-making by allowing us to approximate participants' strategies π. For this purpose, we first classify participant's state-action-pairs (s_i, a_i), relative to the optimal decision, into simplified decision categories c_i.



(a) Round 1, Exit 2 (no advice) (b) Round 3, Exit 2 (Precise) (c) Round 4, Exit 2 (Precise)

(d) Round 2, Exit 2 (no advice) (e) Round 3, Exit 2 (Broad) (f) Round 4, Exit 2 (Broad)

Fig. 4. Distribution of strategy exhibited in Exit 2 where the optimal strategy is to batch charge for two segments ("Batching 2 to 4") across rounds and types of advice.

Recall that the time-minimizing decision is either to charge for one upcoming segment or two, taking into account worst-case traffic. If a participants makes a charging decision that would certainly lead to running out of charge on the upcoming segment, we classify the decision as "out." If a participant's charging decision allows to drive either one or two segments (for some realization of the uncertain traffic within the given intervals), and the optimal decision is to charge for the same number of segments, we classify the decision as "in" or "optimal." If the participant's charging decision allows driving a single segment, but it would be optimal to charge for two segments, we classify the decision as "below." Finally, if the participant's charging would allow to drive more than the optimal number of segments, the decision is classified as "above" (unless the participant reaches this level without adding any charge, in which case the decision is considered to be "in"). This classification is also described visually in Figure 5.

Next, we generate clusters of participants, using sequence clustering, where each participant's decisions (as classified above) across all exits and rounds within one phase of the game (pre-advice, with-advice) is considered a single sequence. For example, with two rounds pre-advice, and seven exits at which to make decisions, a participant's sequence of classified decisions would be $\langle c_1^1, \dots, c_7^1, c_1^2, \dots, c_7^2 \rangle$. To cluster these sequences, we used the TraMineR package [McVicar

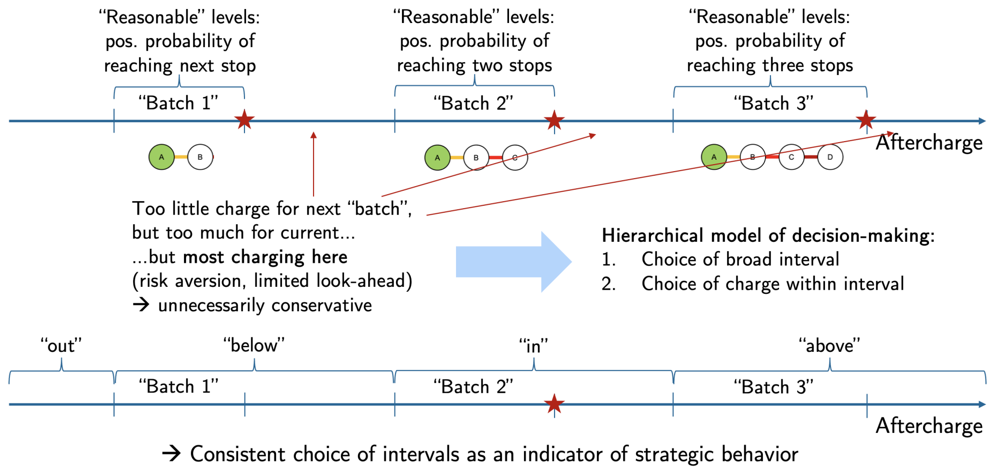


Fig. 5. Classification of charging decisions.

and Anyadike-Danes, 2002]. Figure 6 depicts the clustering results for the pre-advice phase. We validate the strategies associated with each cluster by analyzing the textual feedback provided by participants and the performance (in terms of in-game minutes) for participants across a cluster.

The majority of participants in the baseline phase (54%) fall into the "overcharge" cluster, characterized by excessive charging driven by risk aversion. These participants often charge to levels far beyond what is optimal, resulting in higher total travel times. A smaller proportion (20%) exhibit "smart" strategies aligned with optimal batching, while the remaining participants display either random or undercharging behaviors.

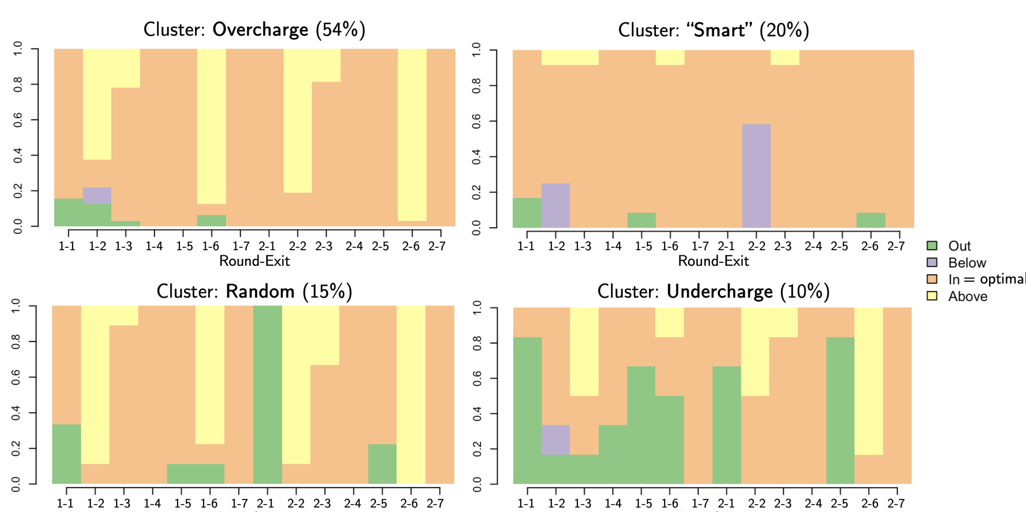


Fig. 6. Clustering sequences of behavior without advice. Each bar indicates the percentage of participants in the cluster that have followed a certain type of action at the indicated round and exit, as indicated by the color-coding.

Participants' learning trajectories differ based on the type of advice received. Figure 7 illustrates how participants update their strategies after receiving either the precise or broad advice in the last two rounds of the game, by illustrating the movement of participants from the pre-advice clusters to the with-advice clusters. Precise advice is effective for supporting a change in participant's behavior across clusters, except the "overcharge" clusters. Approximately half of the participants overcharging without advice continue to do so even when precise numerical advice was available, further hinting at the prevalence of risk aversion. In contrast, broad advice is only partially effective in changing participants' behaviors across clusters—except those that previously exhibited a "smart" strategy. Such a behavior in the first two rounds is a good indicator of their ability to take the advice and achieve near-optimal charging behavior.

By the second round of the with-advice phase (round 4), nearly all participants, regardless of advice type, begin to adopt either strategies consistent with the advice (and, thus, the optimal strategy), or conservatively charge more than indicated by the optimal strategy—even when the latter includes batching. This behavior marks a significant departure from the incremental charging observed in the initial pre-advice phase. However, participants receiving precise advice display faster convergence to a near-optimal strategy, as the numeric recommendations directly supported this behavior. Broad advice facilitates exploratory behavior but results in greater variability in performance, as participants tested a wider range of strategies.

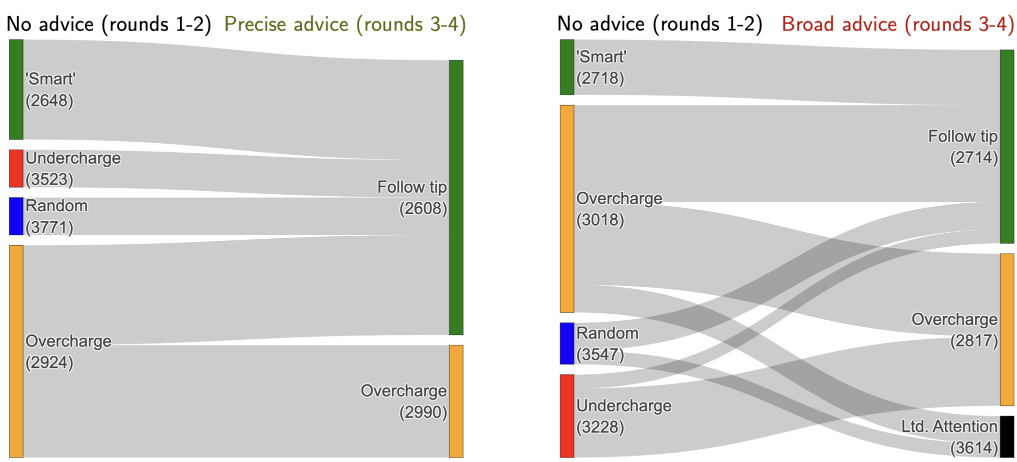


Fig. 7. Trajectory of decision-behaviors by type of advice. Numbers in parentheses indicate the average in-game time for participants in a cluster across rounds within the relevant phase.

5 Study 2: Impact of Environment and Learning Across Environments

Building on the findings of Study 1, which demonstrates the immediate effects of advice precision on decision-making behavior, we now turn to a more fundamental question: can advice foster enduring improvements in decision strategies beyond the duration of its availability? While Study 1 reveals how precise advice improves short-term compliance and performance, broad advice could potentially encourage exploratory behavior. Study 2 is designed to investigate this hypothesis directly by examining how participants adapt to new environments after the removal of advice. By incorporating a post-advice phase and varying environmental complexity, we aim to assess whether the nature of the advice provided influences participants' ability to retain and transfer learned strategies, particularly in scenarios with greater uncertainty or complexity.

5.1 Study Design and Detail

We adopt a 2×2 factorial design varying advice precision (*precise* vs. *broad*) and traffic realization (*centered* vs. *skewed*). Advice precision follows the same definitions introduced earlier. Traffic realization is included to assess how environmental challenges shape users' responses to machine-generated advice. Prior research in behavioral operations suggests that more challenging environments can sometimes hinder performance [e.g., Bavafa and Jónasson, 2021], but may also improve learning outcomes under time pressure or other stressors [e.g., Snyder et al., 2022]. Accordingly, in the *centered* condition, traffic aligns closely with the mean of its estimated range, while in the *skewed* condition, traffic tends toward the range's upper or lower limits, thereby serving as a proxy for a more challenging environment.

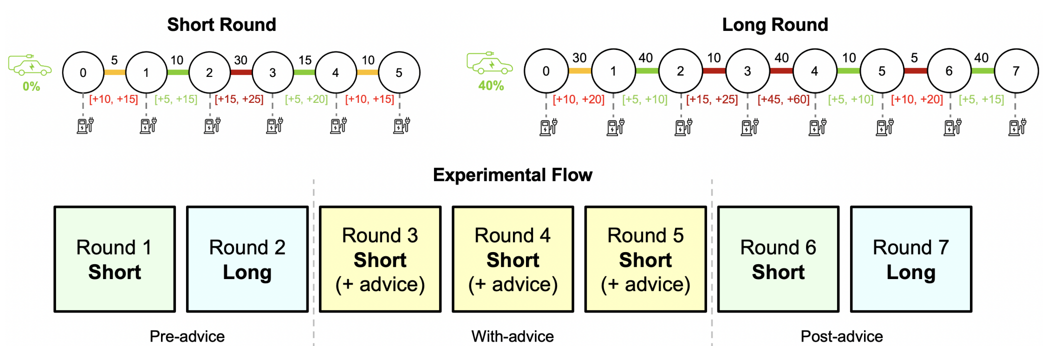


Fig. 8. Maps and Study Flow for Study 2.

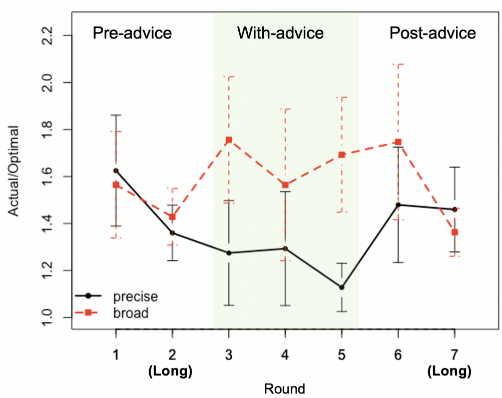
Another key feature of our design is to enable the analysis of (transfer) learning across two distinct highway maps: *short* and *long* (see Figure 8). The short map begins at 0% initial charge, compelling participants to exit and charge at the origin; although the player can charge at multiple stops, the origin is the only location where "batch-charging" is optimal. The long map begins at 40% initial charge and similarly offers multiple charging stops, with an optimal batch-charge at Exit 4. Our study proceeds in three phases: *Pre-Advice Phase:* Participants complete one round each of the short and long maps with no AI guidance. *With-Advice Phase:* Participants receive either *precise* or *broad* AI advice for three rounds on the short map. *Post-Advice Phase:* Advice is not available, and participants complete both a short and a long map round without any AI recommendations. By not providing advice for the long map at any point, we can assess whether exposure to advice on the short map carries over to the long map. Performance in the final round (Round 7) of the long map serves as our key measure of transfer learning.

This study was preregistered at https://aspredicted.org/r34m-g52q.pdf and administered via Amazon Mechanical Turk in October 2023, with 90 participants completing the task. The average payoff was \$5.14, and the median completion time was 39.5 minutes (mean 50.67 minutes). Among participants, 40% were female, 66.67% were aged 25–44, 95.56% held a valid driver's license, 91.11% owned a car, and 40% owned at least one fully electric vehicle.

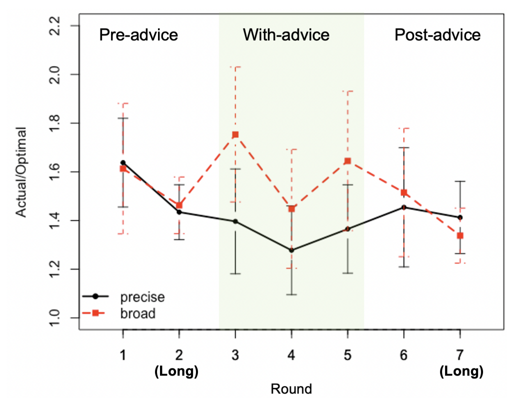
5.2 Results: *Broad Advice Helps Humans Adapt to New Environments*

Figure 9 illustrates our main findings using *normalized performance*, defined as each participant's completion time divided by the optimal completion time for that round (lower values indicate better performance). As a baseline check, there are no statistically significant differences between participants in the precise versus broad advice conditions during the pre-advice phase.

Consistent with expectations, precise advice significantly improves performance by the end of the with-advice phase (notably in Round 5 under centered traffic). However, once the advice is removed, participants who previously received broad advice on the short map demonstrate greater performance gains on the long map than their counterparts who received precise advice. This result provides preliminary evidence that broad advice may confer stronger long-term learning benefits, particularly in transferring skills to environments where no further advice is offered.



(a) *Centered* condition



(b) *Skewed* condition

Fig. 9. Normalized performance across rounds.

Figure 10 illustrates how participants' strategies evolve across the three phases of the study, in line with the classification and clustering process described in Section 4.2: the pre-advice phase (rounds 1–2), the treatment phase with either precise or broad advice (rounds 3–5), and the post-advice phase (rounds 6–7), where no further advice was provided. In the pre-advice phase, participants exhibit diverse and suboptimal strategies, with a significant proportion falling into the "overcharge" cluster. This behavior reflects a conservative approach, where participants consistently charge to levels far exceeding what is optimal. Additionally, some participants undercharge or adopt highly variable behaviors, underscoring the difficulty of the task without guidance. Notably, no participants demonstrate near-optimal strategies in this phase, which may be partially attributed to the complexity of the task.

During the treatment phase, the introduction of precise advice results in high compliance among participants, with many—although not all—closely following the recommended charge levels. By contrast, participants receiving broad advice display greater variability in their responses, with fewer following a strategy close to optimal.

The post-advice phase reveals stark differences in the learning outcomes associated with the two types of advice. While adherence to precise advice leads to improved short-term performance, it does not encourage deeper engagement with the underlying strategic principles of the task. In particular, among participants who received precise advice, only 34% exhibit strategies approximating the optimal policy after the advice is removed. Most revert to overcharging, drastically undercharging in the second long round, or displaying inconsistent decision-making. This suggests that precise advice, while effective in guiding immediate behavior, does not facilitate the transfer of strategic understanding to new or unsupported contexts.

In contrast, participants exposed to broad advice demonstrate significantly better retention and application of learned strategies. Of those who adhere to the advice during the treatment phase,

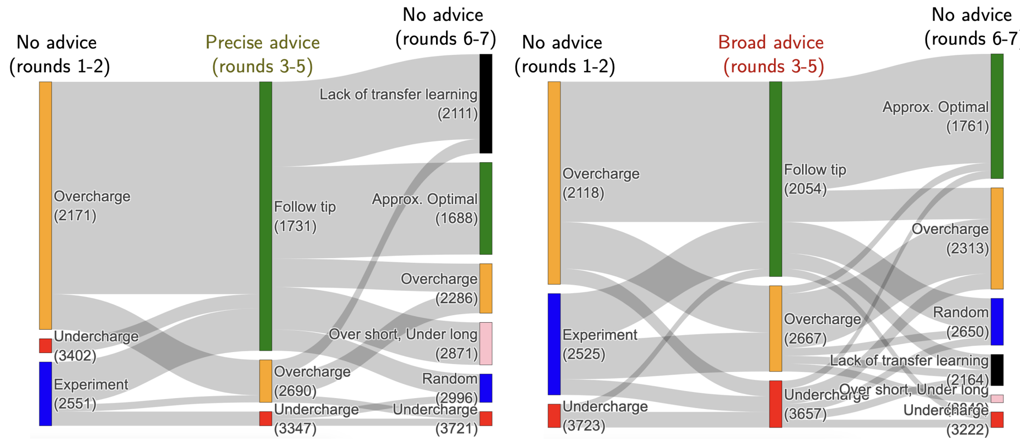


Fig. 10. Trajectory of behaviors by advice type. Numbers in parentheses indicate the average in-game time for participants in a cluster across rounds within the relevant phase.

56% continue to exhibit near-optimal strategies in the post-advice phase. This finding indicates that broad advice encourages more generalizable learning, enabling participants to adapt their decision-making to new scenarios even in the absence of explicit guidance.

6 Discussion

Our study addresses complex, sequential decision-making tasks. To understand how decision-makers behave and how their behavior changes in the face of advice (whether added or removed), we need to look at their policies (or "strategies") π. That is, rather than analyzing how decision-makers behave in one specific scenario, we need to understand how they react to a given state of the world. This is challenging, given the limited data for each decision-maker compared with the massive number of possible states a participant can find themselves in. By first simplifying the state-action pairs (s_i, a_i), classifying them into broader decision categories relative to the optimal decision c_i, then clustering the decision category sequences $\langle c_1, \dots, c_N \rangle$, we are able to approximate decision-makers' strategies, focusing on their key elements. Analyzing the textual feedback reveals that these proxy strategies are strongly aligned with participants' thinking.

Observing both the performance of the participants of our studies, as well as the resulting proxy strategies, we obtain a number of key insights. First, our results indicate that in a complex, sequential decision-making task, participants exhibit a significant degree of risk aversion. In the absence of any advice, most participants overcharge relative to the optimal, frequently even beyond what is required to finish a round, taking into account the maximum traffic.

Contrary to some recent literature, however, we find limited signs of algorithm aversion in this type of task. In particular, when receiving precise advice, which is easy to implement, we observe that most participants adhere to it closely. Hence, rather than algorithm aversion, overreliance may be a particular concern in such a setting. Again, the main countervailing force to overreliance seems to be risk aversion. In particular, we observe a significant number of participants that exhibit highly conservative charging behavior, even when they have access to precise advice.

In contrast, participants receiving broad advice exhibit more signs of underreliance. However, this seems to stem from difficulties in translating the qualitative advice into concrete actions, rather than a lack of trust in the advice itself. This observation, and potential confusion of how to integrate broad advice, is further supported by the feedback comments. That being said, those participants that are able to translate the broad advice into action seem to engage significantly more with the task and the knowledge provided by the advice about how to optimize decision-making. This engagement is visible in the behavioral changes displayed after the advice is removed.

More broadly speaking, precise advice, while easy to adhere to, doesn't seem to be helpful in forming more effective decision-making behaviors in its absence, and, thus, providing knowledge transfer and skill development. We thus intuit that it is also unhelpful to use precise advice, which doesn't require decision-makers to deeply engage with it, when skill degradation is a concern.

7 Concluding Remarks

This paper demonstrates that the precision of algorithmic advice plays a critical role in shaping human decision-making behavior in sequential tasks, both during and after the availability of AI support. While precise advice drives short-term performance improvements by simplifying decision-making, it fails to promote deeper engagement with task dynamics, resulting in limited strategy retention once the advice is removed. In contrast, broad advice, while more challenging to use, encourages exploratory behavior and fosters long-term adaptability in individuals that are capable of employing it. This can help enabling users to retain and transfer learned strategies to new environments.

Our findings have significant implications for the design of AI decision-support systems across domains such as supply chain management, transportation, and healthcare. Designers must carefully balance the trade-offs between short-term performance optimization and the preservation of human expertise. By incorporating broader, more strategic advice, AI systems can empower users to develop robust decision-making skills, ensuring that humans are able to adapt to perform well in dynamic and uncertain contexts.

Future research should explore the interplay between advice precision and other factors, such as user experience, task complexity, and the inclusion of explanatory rationales. Additionally, longitudinal studies from the field could provide further insights into how AI systems influence skill retention and decision-making adaptability over extended periods. Ultimately, this work underscores the importance of designing AI systems that not only optimize immediate outcomes but also invest in the long-term capabilities of their human collaborators.

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