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Judge’s Advice Utilization: Whose Advice is More Persuasive, AI or Human?

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Short Paper

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Abstract

In recent years, especially with the development of Generative AI, more and more people seek advice from AI application when they make important decisions like career choice. The trend raises an important question: Do judges prefer to rely on human or AI advice in different advising scenarios? Although this topic has been discussed variously in research on algorithm appreciation and algorithm aversion, there are still some gaps need to be filled. Based on belief revision theory and the judge-advisor system, this study attempts to explore how advice strategy types (clinical vs. actuarial) and feedback inconsistency will affect judges' perceived advice utilization when the advisor is different (Human vs. AI). To achieve this objective, a scenario-based online experiment will be carried out to collect data and test our research model.

Keywords: AI advisor, advice utilization, judge-advisor system, belief revision theory

Introduction

Artificial intelligence (AI) is commonly defined as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks" (Kaplan & Haenlein, 2019). With the advancement of Generative AI, algorithmic guidance is becoming more accessible and affordable. Previously, AI-generated advice was mainly applied to enterprises, such as production management and marketing decisions. Yet presently, AI advice is expanding its reach to provide professional assistance to individual judges, including career choices, financial investment decisions, and college admission advices.

A notable example of AI consultancy is in the field of career advice. The global market for career and educational counseling, as estimated by Verified Market Research, is projected to reach USD 4,803 million by 2030, a significant increase from the estimated value of USD 2,230 million in 2021. The ongoing development of society has led to a gradual increase in the number of industries and employment categories, resulting in career decisions becoming a regular and challenging issue. This challenge is particularly significant for judges transitioning from education to the workforce. Due to their limited knowledge and experience, judges in transition may encounter difficulties in making informed career decisions. Seeking advice from domain experts can facilitate better decision-making. Furthermore, the emergence of AI offers judges an alternative to human advisors, addressing the challenges faced by traditional career counseling services in delivering widespread and cost-effective career decision support. AI are being employed as decision-support advisors, while humans retain ultimate decision-making right. Many applications like LinkedIn, Mya Systems, Leap.ai can provide AI-based career advices that helps individuals navigate their career paths. These AI-based applications can offer resume and interview feedback, job matching based on skills and preferences, and personalized career guidance.

However, the utilization of AI-based career counseling remains limited at present. Given the increasing demand for career counseling and the limitations of traditional counseling models, it is crucial to assess the suitability of AI in advisory scenarios. Research on algorithm aversion and algorithm appreciation explored the impact of AI advice. However, there is no consensus on which advisor is better, and few studies consider subjective tasks. The existing studies on AI consultancy, such as financial investment advice (Northey et al., 2022), may not be directly applicable to career counseling, as career decisions are more personalized and subjective. Unlike financial investment advice, which aims to maximize monetary rewards and relies heavily on past data, career counseling is a complex and subjective decision-making process. Therefore, this study will investigate judges' preference for algorithmic versus human advice when making career decisions.

So far, studies on judges' attitudes towards AI advice have focused on factors such as task objectivity (Logg, 2017), AI transparency (You et al., 2022), expert power (Hou & Jung, 2021). Advice strategy types (clinical vs. actuarial) and feedback inconsistency are crucial advice characteristics. However, there is no consensus in existing research regarding the relative effectiveness of different advice strategies, nor has there been sufficient investigation into how the advice strategies employed by AI algorithms impact judges. Additionally, the influence of feedback inconsistency on AI-generated advice has been largely overlooked in current research. Thus, our research questions are as follows:

RQ1*: Which advice strategy (clinical vs. actuarial) is more effective for different advisors (AI vs. Human)?*

RQ2*: When the advice feedback is different from the initial ideas of judges, can AI dampen the negative effect of feedback inconsistency on perceived advice persuasiveness?*

To address the research questions, we have adopted the belief revision theory as the theoretical basis of this paper. We constructed a research model based on the advice and advisor characteristics of the judge–advisor system. To test our research model, we plan to design a 2 (Advice strategy type: Clinical vs. Actuarial) × 2 (Advisor type: Human expert vs. AI) scenario-based online experiment.

This research aims to provide several contributions. The findings will enrich the existing research on advice and advisor characteristics within the judge-advisor system, particularly in the context of subjective tasks. It will extend the research on algorithmic attitudes by exploring which advice strategy and context are more suitable for AI. For practice, this study will provide useful insights for designers and organizations of AI-based counseling products, including design guidelines and modes of human-machine collaboration. It will further improve the overall favorability and organizational attractiveness of AI-based counseling products.

Literature Review

Judge–Advisor System

The judge–advisor system (JAS) is a type of advice framework often studied in advice taking research, a subset of decision-making in the social sciences (Sniezek & Buckley, 1995). In a JAS, the two primary roles are that of the judge and the advisor. The judge is the decision maker who evaluates information concerning a particular decision and makes the final judgment on the decision outcome (Bonaccio & Dalal, 2006). Judge is sometimes referred to as the advice recipient. The advisor is an individual who provides advice, information, or suggestions to the judge. Judges may revise their initial beliefs by getting input from one or more advisors and combining it with their own judgements (Sniezek & Buckley, 1995;

Tauchert & Mesbah, 2019). The characteristics in the JAS literature are categorized as judge, advisor, advice, and task (Mesbah et al., 2021).

A widely explored theme in JAS research pertains to advice characteristics that influence judges' advice utilization. Several variables have been shown to affect advice utilization, for example, quality of advice (Bonaccio & Dalal, 2006), advice types (Tzioti et al., 2014), distance between initial estimates and advice (Schultze et al., 2015). However, they were presented in the context of human advisors. With the emergence of AI advisors, it is necessary to investigate if the impact of advice characteristics on advice utilization has changed. Based on the differences between human and AI advisors, we identify advice strategy types and feedback inconsistency as the research variables.

Task characteristics influences advice utilization (Hou & Jung, 2021). While previous research in the JAS has primarily focused on objective tasks, there has been less attention paid to subjective tasks. Objective tasks involve quantifiable and measurable factors based on clear criteria (Castelo et al., 2019; Yaniv, 2004), for example, financial forecasting (Tauchert & Mesbah, 2019), estimating weight (Gino & Schweitzer, 2008), guessing quantity (Mesbah et al., 2021), predicting student grades (You et al., 2022). In contrast, subjective tasks are influenced by subjective factors and preferences, lacking specific criteria (Castelo et al., 2019; Yaniv, 2004). A few studies have investigated subjective tasks, such as music ranking (Logg et al., 2019), recommending movies and romantic partners (Castelo et al., 2019), and career choice (Dalal & Bonaccio, 2010). However, there has been little investigation into the impact of advice characteristics and AI on subjective tasks. This study can improve our understand of subjective tasks, which are both widespread and significant in daily life.

Belief Revision Theory

Advice utilization is the process in which judges selectively and systematically revise their beliefs based on advice obtained from external sources. Belief revision theory suggests that individuals will revise their beliefs in response to new cognitive information, which disrupts their existing cognitive equilibrium and form a new state of balance (Katsuno & Mendelzon, 1991). It has been increasingly applied in various fields, including psychology, artificial intelligence, and behavioral decision making. According to the belief revision theory, people's beliefs are dynamic and constantly evolving. When the advice consistent with the judge's initial belief, the revised belief will reinforce their initial thought. However, if the advice is inconsistent with or contradictory to the judge's initial belief, they will revise their initial belief to accommodate the new information.

The process of belief revision can be understood as the judges' advice utilization within the JAS framework. In the domain of behavior decision-making, belief revision has been extensively studied under the rubric of advice utilization (Miosga, 2020). Judges enhance judgment accuracy through belief revision. Kaliuzhna et al. (2012) examined how schizophrenia patients accepted advice and regarded advice utilization as belief revision. A recent study utilized the Weighting of Advice (WOA), a widely known metric advice utilization approach, to measure belief revision (Himmelstein & Budescu, 2023). Therefore, we employ advice utilization as the dependent variable to investigate judges' belief revision and explore the influence of advice and advisor characteristics on it.

Advisor Types: Human vs. AI

The source of advice influences judges' responses to it (Önkal et al., 2009). In recent years, AI has gradually become capable of combining big data and personalized information to provide advice. AI advisors have several distinct benefits over human advisors. Firstly, AI advisors possess powerful computational capabilities, enabling them to comprehend large-scale data and the interrelationships between different data (Siemens et al., 2022). Secondly, they are more rational and objective, overcoming human cognitive biases (Schmitt et al., 2021). Thirdly, AI advisors may deliver timely and efficient guidance while also providing convenient services to a large number of judges at the same time (Belanche et al., 2019). In addition, AI advisors are more cost-effective. Based on the definition of AI advisors from previous research (Belanche et al., 2019; Roh et al., 2023), this paper defines AI advisors as digital applications that generate advices using algorithms.

Existing studies of JAS mainly investigated the impact of human, such as the number of human advisors (Budescu et al., 2003) and the expertise (Tauchert & Mesbah, 2019). Yet, research on AI advisors in the JAS literature remains limited. Additionally, algorithm aversion and algorithm appreciation represent two radically opposed viewpoints according to the research on algorithmic attitude. Research on algorithm aversion suggests that judges tend to rely more on human than AI, despite the fact that AI performs better (Jussupow et al., 2020). The current study investigated judges, especially experts, show a rejection of AI (Gaube et al., 2021). However, it is important to note that some research has examined judges' preference for using AI to perform their tasks, which represents a distinct issue from the question of whether judges prefer AI advice or human advisors' advices (Logg, 2017). Algorithm appreciation refers to the phenomenon where judges rely more on AI than human (Logg et al., 2019). In fact, AI predictions are more accurate than human in the great majority of tasks (Dietvorst et al., 2015; Grove et al., 2000).

Despite providing the same content as humans, AI advice is sometimes received differently by judges across various contexts and tasks. For example, You et al. (2022) demonstrated that in the score prediction task, participants followed algorithmic advice to a greater extent than identical human advice. Wu et al. (2021) found that participants were more receptive to identical treatment options advised by human doctors. A similar debate arises in financial decision-making scenarios (Northey et al., 2022; Tauchert & Mesbah, 2019). The majority of research supports the phenomenon of algorithm aversion. Nevertheless, recent research also suggests that people are not always opposed to AI advice. The inconsistent findings could potentially be influenced by task types (objective vs. subjective). Considering the limited research on subjective tasks, it is crucial to conduct further investigation into the utilization of AI advice in this context.

In short, there is no consensus on which type of advisor is more effective. And there is a need for context-specific investigations into judges' decision-making processes in subjective tasks. This paper aims to examine the relative effectiveness of human and AI algorithm in different advising scenarios.

Advice Strategy Types: Clinical vs. Actuarial

Advisor's advice strategies influence judges' advice utilization (Tzioti et al., 2014) . According to previous studies, there are two modes of information processing for decision making. One is more empirical, affective and intuitive, and the other is more rational, deliberative and analytical (Godek & Murray, 2008; Kahneman, 2003). Similarly, clinical and actuarial method have been extensively investigated in the domains of medical, psychological and educational training (Eastwood et al., 2012). Actuarial method is sometimes referred to as mechanical, objective, statistical. Clinical method is also known as subjective, intuitive, and expert. In this paper, the clinical strategy is defined as an approach that relies on empirical and implicit decision rules to handle data, while the actuarial strategy is defined as an approach that uses formulas and predictive models to process data.

We argue that both human and AI can provide advices using clinical or actuarial strategies. The clinical strategy for human is based on experience, intuition and implicit decision-making knowledge that has been accumulated through handling relevant tasks over time. It has a high degree of subjectivity and is widely used by experts in various fields, such as medicine. The actuarial strategy for human, on the other hand, is considered more objective as it involves making decisions using statistical tools, formulas, and predictive models. Similarly, AI can employ an actuarial strategy based on explicit mathematical formulas and statistical predictive models to produce advice with high efficiency and accuracy. And with the rapid development of deep learning and big data in recent years, AI can make decisions by emulating the cognitive processes of the human brain. In computer science research, advanced machine learning models like neural networks have demonstrated success in facilitating accurate prediction (Zellner et al., 2021). Through numerous iterations of self-learning, deduction, and generalization, AI gain algorithmic capabilities and implicit decision rules within a specific domain. Consequently, AI can use clinical strategies to provide advice.

There is no unanimous view in existing research as to which strategy is better. Martin (2018) indicated that actuarial strategy is more effective when evaluating candidates. Using meta-analysis, Kuncel et al. (2013) demonstrated that actuarial methods are superior to diagnostic methods in employee selection and academic admissions decisions. Conversely, Tzioti et al. (2014) proved that in empirical decisions, human advisors' intuitive advice is more influential than actuarial advice. Similarly, Eastwood et al. (2012) investigated legal accusations and scholarship decision-making tasks, finding that participants preferred a clinical strategy over actuarial strategy employed by human advisor. In short, numerous studies have shown that actuarial strategies outperform clinical strategies. However, some studies demonstrated the advantages of clinical strategies, which remain widely used in practice, for example in medical contexts.

Despite current research has focused on identifying optimal strategy for advisors, the impact of advice strategies on judges remains relatively unexplored (Eastwood et al., 2012). In the medical field, Shaffer et al. (2013) investigated the impact on participants' perceptions when doctors used both of the strategies to make diagnostic decisions. Furthermore, there is little research on the impact of strategies used by AI. Most studies compared AI advice based on actuarial strategies with humans' advice based on clinical strategies (Önkal et al., 2009; Promberger & Baron, 2006). Some studies have also compared advices based on actuarial and clinical strategies, both of which came from human (Eastwood et al., 2012). According to our investigation, there has been limited research comparing the impact of AI and human when using both strategies. Therefore, this paper will examine the impact of advice strategies (clinical vs. actuarial) on judges when the advisor is different (Human vs. AI).

Research Model and Hypotheses

Feedback inconsistency in this study refers to the difference between advisors' advice and judge's initial beliefs in subjective tasks. Methods of belief revision strive to adhere to the principle of minimal change. It states that, amidst the contradiction between initial and new beliefs, the minimal deletion of initial beliefs should be prioritized (Johnson-Laird, 2013). It aligns with the key finding in the JAS literature, the egocentric advice discounting phenomenon. When faced with new belief input, judges tend to stick to their initial beliefs. They exhibit self-centeredness, leading to less utilize advices that deviate from their own views (Bonaccio & Dalal, 2006; Prahl & Van Swol, 2017). Judges are more easily persuaded by similar information (Feng & MacGeorge, 2010). In objective tasks, judges are more likely to follow advice that is closer to their initial estimates (Mesbah et al., 2021; Schultze et al., 2015). Therefore, we argue that feedback inconsistency negatively affects perceived advice persuasiveness. Moreover, since subjective tasks are more personalized, judges may be more likely to stick to their initial beliefs. Consequently, we propose that the impact is likely to be exacerbated in subjective tasks. Therefore, we hypothesize:

***H1**: Feedback inconsistency negatively affects judges' perceived advice persuasiveness.*

Many studies have demonstrated that actuarial strategies have higher decision accuracy than clinical strategies and have a stronger impact on individuals (Grove et al., 2000; Kuncel et al., 2013). In contrast to clinical strategies, actuarial strategies rely on well-established formulas, predictive models to provide advice (De Corte et al., 2007). Furthermore, the mathematical characteristics of the actuarial strategies ensure that the variables make conclusions based on actual projections and relationships to benefit criteria (Dawes et al., 1989). Therefore, we argue that actuarial strategies are more persuasive due to their objectivity, fairness, and clear rules. In contrast, clinical strategies may omit crucial information or improperly assess essential cues. Therefore, we hypothesize:

***H2**: Compared with clinical strategy, the advice provided by actuarial strategy will make consumers perceive higher persuasive.*

The source of advices influences advice discounting. Computers are considered to possess higher quality and objectivity when used as the source of information (Sundar & Nass, 2001). In recent years, AI could emerge as a more reliable source of advice. Mesbah et al. (2021) showed that in objective tasks, judges utilized advices of AI more when the advice is similar to their own estimation compared to human. Therefore, we suggest that the advantages of AI advisors over human diminish the effect of advice discounting in subjective tasks. Firstly, AI excel in data processing as they can rapidly integrate vast amounts of information, surpassing the cognitive limitations of humans (Siemens et al., 2022). They possess the ability to automatically make decisions that encompass multiple variables and effects. Secondly, AI are considered to have superior procedural fairness due to their consistent and standardized decision-making process (Schmitt et al., 2021). Furthermore, AI are thought to be less biased than human advisors, as they are not affected by emotional factors (Lee, 2018). Therefore, we hypothesize:

***H3**: Compared to human, AI will dampen the negative effect of feedback inconsistency on judges' perceived advice persuasiveness.*

Stereotypes are relatively fixed notions or beliefs about the traits of group members, which can shape judges' perceptions and behaviors. According to the stereotype content model (SCM), stereotypes are judges' unconscious desire for their own interests and survival (Cuddy et al., 2008). Hong and Curran (2019) showed that stereotypes influence value evaluation of the art. In this study, we argue that judges hold different stereotypes of human advisors and AI. Eastwood et al. (2012) demonstrated that judges perceived human advisors as more suitable to provide advice using a clinical approach. Meanwhile, some studies demonstrated that judges prefer AI to make rationality-based decisions, while they prefer human for intuition-based decisions (Logg, 2017). Therefore, we argue that judges will assume due to stereotypes that humans are better suited for clinical strategies while AI are more appropriate for providing advice using actuarial strategies. Therefore, we hypothesize:

***H4**: Compared to human, AI enhance the perceived persuasiveness of actuarial advice and weaken the persuasiveness of clinical advice*

Persuasion is a key social process that enables cooperation, social influence and attitude change. Persuasion can be understood as an attempt to shape, reinforce or change judge's behavior, feelings or thoughts about an issue, object or action (Fogg, 1988). Advice is generally considered to be a form of persuasion that influences decision-making (Feng & MacGeorge, 2010). Persuasive messages develop favorable impressions and effectively influence desired behavior (Ajzen, 2012; Oinas-Kukkonen & Harjumaa, 2009). Furthermore, subjective tasks lack clear solutions and rely more on value assessments. Therefore, we suppose that the perceived advice persuasiveness is important for judges' perceived advice utilization in subjective tasks. Therefore, we hypothesize:

***H5**: Perceived persuasiveness has a positive impact on judge's perceived advice utilization.*

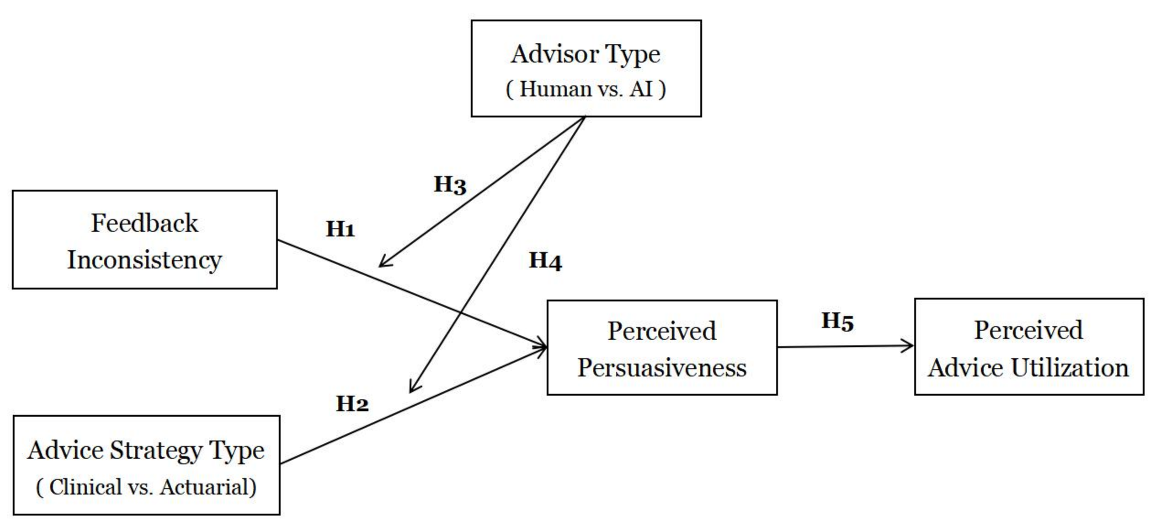

Figure 1. Research Model

Methodology

In order to empirically test our model, a 2 (Advice strategy type: Clinical vs. Actuarial) × 2 (Advisor type: Human expert vs. AI) scenario-based online experiment is designed to simulate the career decision-making context. This study will collect data from a sample of students enrolled in multiple universities, who will be randomly assigned to one of four experimental treatments. We intend to collect around 400 samples to ensure an adequate sample size, determined by comparing it with the sample sizes used in relevant previous studies (Hou & Jung, 2021; You et al., 2022). Following the completion of the experiment, participants will be asked to answer a questionnaire.

Based on the JAS research, we propose a task in which college students will seek career advice for decision-making from either an AI or a human expert. Participants will be questioned twice about their preferences for choosing a career as a civil servant, before and after receiving advice (Tzioti et al., 2014). Both the AI and the human expert will advise participant to pursue a career as a civil servant. We chose civil servant to investigate because it has a distinct career profile and is a popular target for graduate career counseling.

The degree of feedback inconsistency will be quantified by computing the difference between the initial preferences of participants and the advice provided. Perceived advice utilization will be measured using the weight of advice (WOA). It is a common measure in the JAS research and has been used in several studies (Bonaccio & Dalal, 2006; You et al., 2022).

$$\mathrm{WOA} = \frac{|\text{judge final estimate} - \text{judge initial estimate}|}{|\text{advice} - \text{judge initial estimate}|}$$

The items of questionnaire will be adapted from the existing literature. Before formal experiment, this study will use a pre-experiment to test and improve the reliability and validity of the questionnaire. Control variables, including participants' perceived task importance, prior experience with AI consulting products, career familiarity, social phobia, attitudes towards algorithmic, trusting disposition, decision-making style, educational hierarchy and grade will be collected. In addition, the questionnaire will include fundamental demographic information like age, gender, major, education level. We'll use ANOVA and structural equation modeling to analyze data collected from formal experiment.

Intended Contributions

In this study, we propose a model based on the judge–advisor system and the belief revision theory. We aim to investigate how advice characteristics and advisor types influence judges' perceived persuasiveness and advice utilization.

This study makes several important theoretical contributions. First, feedback inconsistency and advice strategy types were not thoroughly examined in the context of AI advisors. Our findings will help to advance the research of advice characteristics in JAS and their impact on belief revision. Second, there is a scarcity of literature regarding AI utilization in the context of career advice. By focusing specifically on the career consultant context, this study will enrich the existing research on AI advice utilization in subjective task settings. Third, the existing literature on algorithmic attitudes presents contrasting viewpoints. Our findings will contribute valuable insights to the ongoing debate in the algorithm aversion and algorithm appreciation literature. Through exploring the suitability of different advice strategies and contexts for AI, our research aims to shed light on the specific scenarios in which AI advice surpasses human advice in terms of performance and effectiveness.

For practice, AI providing advices as a new form is still on the way to be widely accepted. The advice characteristics need to match the advisors for the advices' efficacy, which can assist managers in allocating tasks and strategies. Firstly, AI is suitable to provide advices when the judge's initial beliefs are inconsistent with advices. Secondly, advisors need to employ matching advice strategies, which can enhance the judge's advice utilization. Additionally, when deploying AI advisors, organizations may face privacy concerns and challenges associated with the emotional intelligence of AI. Future research can explore these aspects to enhance the judges' advice utilization.

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