Passing the Buck to AI: How Individuals' Decision-Making Patterns Affect Reliance on AI

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Psychological research has identified different patterns individuals have while making decisions, such as vigilance (making decisions after thorough information gathering), hypervigilance (rushed and anxious decision-making), and buckpassing (deferring decisions to others). We examine whether these decision-making patterns shape peoples' likelihood of seeking out or relying on AI. In an online experiment with 810 participants tasked with distinguishing food facts from myths, we found that a higher buckpassing tendency was positively correlated with both seeking out and relying on AI suggestions, while being negatively correlated with the time spent reading AI explanations. In contrast, the higher a participant tended towards vigilance, the more carefully they scrutinized the AI's information, as indicated by an increased time spent looking through the AI's explanations. These findings suggest that a person's decision-making pattern plays a significant role in their adoption and reliance on AI, which provides a new understanding of individual differences in AI-assisted decision-making.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**; • **Computing methodologies** → **Artificial intelligence**.

Additional Key Words and Phrases: Human-AI Interaction, Decision-Making Pattern, AI-Assisted Decision Making, Information-seeking

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1 INTRODUCTION

Conversational AI tools like ChatGPT provide new ways for individuals to obtain information that can support their decision-making. With their widespread availability and advanced capabilities, people increasingly use these tools to ask for nutrient suggestions [48], medical advice [41], or personal financial recommendations [29]. Despite their extensive capabilities, current conversational AI tools supported by large language models (LLMs) have been found to generate inaccurate and biased information in various domains including politics, law, and medicine [6, 17, 27, 48, 52, 59].

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Reliance on these tools without caution could therefore lead to misinformed decisions and contribute to the spread of misinformation [23].

To mitigate these risks and inform interventions, research in Human-AI interaction (HAI) has focused on factors related to AI systems that affect users' reliance, such as accuracy and transparency [11, 36, 54, 55, 66, 67, 69]. Other research has explored how individual differences are correlated with varying behaviors in HAI. For example, researchers have shown that attitudes toward, and reliance on, AI vary across different demographics and personality traits [7, 34, 39, 43]. However, a research gap remains in understanding how people's decision-making patterns might influence their use of and reliance on AI.

To address this gap, this paper explores how individuals' decision-making patterns impact whether people rely more on their own knowledge or on knowledge offered by an AI—in our case ChatGPT. When decisions have to be made, who seeks out the suggestions offered by ChatGPT? Who is more susceptible to this information despite the risks? And how are these choices related to individuals' decision-making patterns?

Our work builds on a well-established decision-making framework proposed by psychologists Irving Janis and Leon Mann [44], which has been widely validated with individuals from various countries [3, 15, 16, 18, 49]. Mann et al. [44] have found that people cope with decision-related stress differently, from vigilantly searching for information on their own to deferring decision-making to others. These decision-making patterns can be closely mapped to current interactions with AI systems: the amount of information individuals search during decision-making may impact how much information they need when evaluating AI suggestions; whether individuals defer decision-making to others in *human-human* interactions could influence their reliance on AI during *human-AI interactions*.

To explore whether individual decision-making patterns predict a person's AI-assisted decision-making tendencies, we preregistered[1] and conducted an online experiment (n=810) in which we asked participants to decide whether statements about food are facts or myths, letting them choose whether they wanted to seek ChatGPT's decisions and explanations. To increase the stakes, participants were told to put together a pamphlet that should only include factual nutrition statements, and to imagine that the pamphlet will be shared with an organization that focuses on improving children's health.

Our results show that people differ in their interaction with ChatGPT depending on their individual decision-making pattern. Concretely, the higher a participants' tendency to be a vigilant decision-maker, the more time they spent looking through ChatGPT's explanations, underlining their tendency to scrutinize information before deciding. Conversely, the higher a participants' tendency for buckpassing, the more likely they were to choose to see ChatGPT's decisions, the less time they spent looking at its explanations for the decision, and the higher their self-reported reliance on ChatGPT. These findings indicate that, in general, buckpassers are less likely to question information provided by an AI, making them more susceptible to misinformation in AI responses than decision-makers who score low on buckpassing or high on vigilance.

Overall, our work contributes (1) new empirical insights into how people differ in their interactions with AI, implying that parts of the population may be more vulnerable to the risks of AI; (2) design implications for AI tools that go beyond one-size-fits-all, including suggestions for leveraging the benefits of AI technologies while mitigating their risks; (3) a new, publicly available dataset (available at [URL omitted]) with the demographics, decision-making patterns, and AI interactions of 810 participants, which can be used by researchers for replicating and extending our analyses.

[1] See our preregistration on the Open Science Framework: https://osf.io/z9527/?view_only=ea63631787a74b3c8edd7a8ddc2dbd6b

2 RELATED WORK

In this section, we first describe prior studies on AI-assisted decision-making to provide some background on common terminology. This section also sets the stage for our subsequent exploration of factors that have been found to influence human-AI interaction—in particular trust and reliance—and how decision-making patterns may be a missing, but important piece in the puzzle.

2.1 Studies of AI-assisted Decision-Making and Terminology

AI-assisted decision-making, also known as human-AI decision-making, broadly refers to scenarios where AI provides suggestions to help humans make decisions [12, 38]. To investigate the effectiveness of providing AI suggestions, recent research has examined users' trust and reliance behaviors such as *overall AI reliance*, *appropriate reliance*, *over-reliance*, and *under-reliance*. Overall AI reliance measures users' reliance behaviors in AI-assisted decision-making despite the desirability of such reliance. Users' trust and reliance on systems are often captured via objective measures such as the agreement of an individual's final decision and an AI's suggestion in decision-making tasks [9, 10, 42, 46, 50, 68] or switching from one's decision to the suggestion of an AI [9, 46, 68]. Subjective measures such as perceived reliance and trust are also often used in prior studies [7, 10]. Generally, *appropriate reliance* is desired because it means that users only adopt the AI's suggestions if they are correct. In contrast, *over-reliance* (when users adopt the AI suggestions despite it being inaccurate [7]) and *under-reliance* (where users fail to adopt the correct AI suggestions [64]) are undesirable. Studies examining these user behaviors often employ experimental designs in which AI suggestions are integrated into the collaboration process, either automatically presenting the AI suggestions before or after the users make their decisions [9, 12, 40, 42, 46, 68]. As such, the measurement of reliance is often limited to this kind of experimental design, focusing on agreement with AI's decision or switching. However, to examine whether AI suggestions are effective, it is also critical to understand whether and how people consider them, which might not be universal among individuals. Thus, our study extends the prior behavioral metrics for reliance and takes into account whether and how people choose to see AI suggestions.

2.2 Factors that Influence Trust and Reliance on AI

Recent studies have found a variance in individuals' trust in, and reliance on AI suggestions and several factors related to system design and individual characteristics. In terms of system-related factors, evidence from empirical studies identified the effects of design and performance of AI systems such as the accuracy of the AI and whether the AI provides a reason for its decision [7, 39, 54, 55, 67]. Regarding user characteristics, evidence from survey studies suggests that users' attitudes towards AI systems vary across demographics, including age, education levels, and knowledge about AI [2, 13, 26, 43]. For example, in a study on individuals' acceptance of ChatGPT, older individuals were found to be less willing to accept ChatGPT compared to younger individuals [43]. Araujo et al. [2] found that education levels and knowledge about AI and algorithms are positively associated with users' perceived usefulness and fairness of AI. In addition, personal traits have also been found to play a role in users' adoption of suggestions from AI systems: Chong et al. [13], for instance, found that self-confidence directs individuals' decisions to accept or reject suggestions from the AI. Focusing on individuals' Big-Five personality traits (including openness, conscientiousness, agreeableness, neuroticism, and extraversion), Cai et al. [8] found that individuals who scored high in conscientiousness—a tendency related to self-control and responsibility—have higher trust in AI systems that offer both human-requested and system-initiated suggestions. Faruk et al. [22] found students from India and Thailand who scored high in openness (being open to new experiences) are more likely to use ChatGPT. Meanwhile, they found negative effects of agreeableness (being cooperative, friendly) and neuroticism (high tendency toward negative feelings) on students' usage of ChatGPT. Our study extends this line of work by focusing on the effects of individual decision-making patterns in AI-assisted decision-making.

2.3 Decision-Making Theories and Individual Patterns

Social science scholars have developed different theories explaining the mechanisms behind individuals' decision-making. Rational Choice Theory, rooted in economics, posits that individuals calculate the utilities of all options to make decisions. Challenging this proposition, Simon [57] has argued that people often seek satisfactory rather than optimal choices due to their limited capacity to evaluate numerous options. Schwartz et al. [56] proposed that people tend to either have a tendency of maximizing or satisficing: maximizers tend to assess options carefully and choose one that provides maximum benefit later on, while satisficers tend to settle for an acceptable decision. Mann et al. [44]'s theory takes into account individuals' emotions and stress-coping patterns in their decision-making process. Their four decision-making patterns were derived from a survey study and are described as (i) vigilance (making decisions only after a comprehensive search of information), (ii) hypervigilance (approaching decisions in a hurried and anxious way), (iii) buckpassing (avoiding decisions or deferring to others), and (iv) procrastination (putting off the decision). See Table 1 for an overview and example scale items.

According to Janis and Mann [31], all four decision-making patterns are in the repertoire of individuals, but people tend to rely on one of these patterns more than on others. Importantly, Mann et al. [44]'s decision-making patterns have been widely validated with participants from various countries and demographics [3, 15, 16, 18, 49] and have been shown to be relevant in real-world decision-making scenarios [1, 5, 35]. Moreover, Mann et al. [45] revealed that individuals' reliance on decision-making patterns (especially buckpassing) varies between East Asian and Western cultures. Together these studies suggest that people vary in their approach to decision-making.

Decision-making patterns have been found to affect individuals' decision outcomes. In the context of economic choices, research shows that when given a time constraint, maximizers tend to browse more options and change their decisions before making the final purchase than satisficers [14]. Adopting Mann et al. [44]'s decision-making categories, Kim et al. [35] found that individuals' decision-making patterns are linked to their quality of life, including physical and psychological. These findings shed light on the impact of decision-making patterns on individuals' lives, which could also be manifested in the context of AI-assisted decision-making. Jugovac et al. [32] has examined how maximizers and satisficers differ in their interactions while providing AI recommendations, however, they found no effect. Our study extends this line of work by adopting the framework from Mann et al. [45], studying how users' behaviors differ when they are faced with uncertain information and have the option to defer to the AI.

3 METHODOLOGY

3.1 Hypotheses

We developed our hypotheses based on the decision-making patterns by Mann et al. [45] (summarized in Table 1). Importantly, these decision-making patterns emphasize whether people delegate decision-making to others and how they search for information under decision stress. As such, we believe these decision-making patterns are likely predictive of behaviors that we commonly see when humans interact with an AI, such as relying on an AI to seek further information or overrelying on an AI to avoid making one's own decision.

Table 1. Decision-Making Patterns, Descriptions, and Example Statements from the Melbourne Decision-Making Questionnaire

Decision-Making Pattern	Description	Example Item
Vigilance	This pattern refers to a rigorous information search, such as when a person tries to evaluate different alternatives before making a decision.	"I consider how best to carry out the decision."
Hypervigilance	This pattern refers to a frantic way of making decisions to relieve emotional stress.	"After a decision is made I spend a lot of time convincing myself it was correct."
Buckpassing	This pattern refers to a tendency to leave decisions to someone else.	"I prefer that people who are better informed decide for me."
Procrastination	This pattern refers to a tendency to put off making decisions.	"I waste a lot of time on trivial matters before getting to the final decision."

Overall, we hypothesize that decision-making patterns could affect individuals' interactions with AI suggestions. Specifically, by **AI suggestions**, we refer to the recommended decisions from the AI (**AI decisions**) and its text-based justifications for its recommendation (**AI explanations**). Our study imagines scenarios where people encounter information online that may be right or wrong and use an AI tool like ChatGPT to assess its credibility. When using an AI, people can seek the AI's decision and, if needed, the AI's explanations for the decision. We speculate these AI suggestions are used differently across individuals with varying decision-making patterns, as outlined in Table 2. For vigilant decision-makers who tend to conduct a comprehensive search of information and evaluate it rigorously, we hypothesize that they are more likely to seek the AI's suggestions for additional information even if they already have an answer. However, as they also tend to be more confident in their own decisions [45], they might not necessarily prioritize the AI's decision over their own.

People who exhibit hypervigilant decision-making behaviors tend to search for information frantically, but not rigorously, before arriving at a decision. Thus, we hypothesize they will quickly seek information from the AI (i.e. see AI's decision and explanations) without spending much time evaluating the information. As they experience high emotional stress and are less confident in their own decisions [45], they would be more likely to rely on the AI's decision to reach their decisions.

We further hypothesize that people who exhibit a buckpassing tendency will seek out the AI's suggestions to avoid making any decisions themselves, leading to a high reliance on AI. As a result, they would not consider AI's suggestions as much, leading to less time spent on AI explanations.

We did not include *procrastination* in our hypotheses because this would require leaving participants with potentially infinite time, which we did not deem feasible. However, procrastination has been shown to be correlated with behaviors or buckpassing and hypervigilance [4], and all three decision-making patterns are considered forms of defensive avoidance [31].

3.2 Experiment Design

To examine our hypotheses, we designed an online study (preregistered at link) that includes (i) a questionnaire and (ii) a task requiring participants to decide on the factuality of a series of nutrition statements while having the option to seek out AI suggestions (**AI decision** and **AI explanations**). We generated AI decisions and explanations using ChatGPT before the study (rather than having participants interact with ChatGPT live) to ensure consistency of response quality.

Table 2. We develop our hypotheses based on individuals' decision-making patterns, focusing on their behavioral characteristics related to information search.

Decision Making Pattern	Hypotheses	Notation
The higher people score on vigilance,	the *more* likely they are to choose to see AI decisions.	H1a
	the *more* time they spend seeing AI explanations.	H1b
	the *lower* they report their reliance on AI to be.	H1c
The higher people score on hypervigilance,	the *more* likely they are to choose to see AI decisions.	H2a
	the *less* time they spend seeing AI explanations.	H2b
	the *higher* they report their reliance on AI to be.	H2c
The higher people score on buckpassing,	the *more* likely they are to choose to see AI decisions.	H3a
	the *less* time they spend seeing AI explanations.	H3b
	the *higher* they report their reliance on AI to be.	H3c

The study was approved by our Institutional Review Board and launched in English on the volunteer-based online study platform [AnonymousOnlineLab][2]. We encouraged honest participation by informing participants in advance that they would receive personalized result—their own decision-making patterns and performance on evaluation food facts and myths—at the end of the study.

Nutrition Statements for the Main Task: We used 30 nutrition statements and their accuracy (i.e., fact or myth) from Florença et al. [25] who had curated a list of popular food (mis)-conceptions from online sources. In their study with 503 participants, several of these statements were inaccurately classified as facts or myths by participants, and even by participants working in areas related to nutrition, suggesting that the statements have a range of difficulty. Among the 30 statements, 9 nutrition statements are facts and 21 are myths. One example false statement (a myth) is "Pregnant women should be eating for two", while an example true statement (a fact) is "Dairy products should be consumed in between two and three portions per day". The full list of statements with fact/myth labels is in the Supplementary Materials.

AI Suggestions (AI Decisions and Explanations): We generated AI decisions and explanations for each nutrition statement using ChatGPT[3] in July 2023, prompting ChatGPT in the format of "`[Nutrition Statement]. Is this fact or myth?`" After the model generated an answer to the prompt, we asked it to shorten its answer to less than four sentences by prompting "`Rewrite it in less than 4 sentences.`" Based on nutrition statements from Florença et al. [25], ChatGPT produced incorrect answers for three out of the 30 statements (two false facts and one false myths). We used ChatGPT's decision whether the statement is a fact or a myth as the *AI Decision* and the rest of the information it provided as the *AI Explanation*.

We then chose 21 accurate AI suggestions (each comprising a decision and explanation), the 3 inaccurate AI suggestions that ChatGPT provided, and further inverted 6 suggestions to become false, resulting in 21 accurate and 9 inaccurate AI suggestions. From these two pools of statements, we randomly sampled 6 statements with accurate AI suggestions and 4 with inaccurate AI suggestions. We included more accurate than inaccurate AI decisions in our experiment to be faithful to the real-world performance of AI models (i.e., ChatGPT provided accurate responses to

[2] name changed to preserve anonymity
[3] https://chat.openai.com/

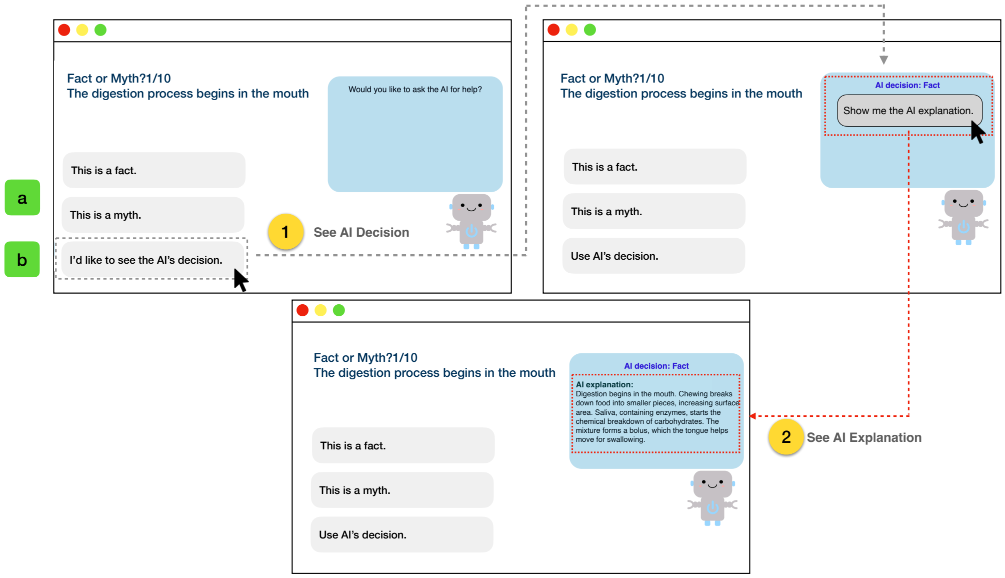

Fig. 1. The study interface and workflow for each statement. Participants first read one statement at a time. They could then decide whether the statement is a fact or myth (a). If participants decided at this point, they could move on to the next statement. Alternatively, participants could choose to reveal the AI's decision (1) showing ChatGPT's decision (b). Participants could then decide to choose fact or myth or use the AI decision. They could also choose to see AI's explanation to reveal the AI explanation before making their decision (2).

most of the 30 nutrition statements). To generate inaccurate AI explanations for these 6 statements, we prompted ChatGPT with "`What are some arguments people would use to support this statement as a fact/myth: [Nutrition Statement]`." and also asked it to shorten its answer to have fewer than four sentences.

3.3 Study Procedure

Our online study, directed at intrinsically motivated volunteer participants, was advertised with the question "What is your decision-making style?" Participants were able to receive personalized results at the end of the study. As they entered the study page, we explained the goal of the experiment and that they would be asked to judge a set of nutrition statements. Participants could proceed to the experiment only if they consented. Participants were then asked to fill out a demographic questionnaire including questions about their age, gender, education levels, and country. We also inquired about their knowledge of nutrition ("How would you describe your knowledge of nutrition compared to the general public?" with the answer options being: "Very limited", "Limited", "Average", "Above average", and "Expert") and assessed their perception of the accuracy of AI-generated information ("To what extent do you believe that conversational AI (e.g. ChatGPT) provides correct information?" with answer options "I don't know what ChatGPT is", "It never provides anything correct", "It provides correct information sometimes", "It provides correct information usually", and "It always provides correct information.").

Next, participants were asked to complete the Melbourne Decision-Making Questionnaire (MDMQ) [44] (see Supplementary Materials), with 10 questions being shown before the main tasks and the remaining 7 questions being shown after the main task (all in random order) to reduce the perceived questionnaire length.

Main task: The main task showed participants 10 nutritional statements (6 accurate and 4 inaccurate decisions, drawn from the larger set of 30 statements using stratified random sampling). For each statement, participants were asked to assess whether it was a fact or myth while being provided options to use AI assistance (see Figure 1). To encourage participants to make cautious decisions about these statements, we introduced the following scenario:

> *Imagine your manager asks you to put together a nutrition pamphlet to share with an organization that focuses on improving children's health. To do so, you will need to evaluate 10 nutrition-related statements and determine if they are facts or myths. You will have access to an AI that can assist you with these assessments. However, please keep in mind that the AI's suggestions may not always be entirely accurate or definitive. Whether to use the AI's decision is completely up to you.*

We mentioned the limited performance of AI assistance to ensure participants knew that not all information presented to them was factually correct, in line with current state-of-the-art conversational AI systems which do not always output accurate information [19]. Informing participants about the imperfection of decision aid is often used in prior work assessing users' trust and reliance on automated support systems [21]. While it might prime participants to refrain from seeking AI suggestions, it could also encourage participants to critically evaluate AI suggestions rather than accept them blindly.

If participants chose "I'd like to see the AI decision," they were provided two additional options: to see an AI explanation or to immediately accept the AI decision (without seeing an explanation). This design was motivated by our hypotheses: *see AI decisions* is designed to observe whether users prefer to refer to the AI's decision before making their own. Subsequently, we offer the option to *see AI explanations* to investigate whether some users may want to further investigate and seek additional details.

After an AI decision is revealed, participants could select *Use the AI decision* to indicate they accept the AI decision; however, this design revealed its limitations as participants barely selected this option based on our analysis of results which we discuss later. For each statement, we recorded the time they took to evaluate the AI's decision and explanations before final decision-making.

At the end of the study, participants were asked to assess their reliance on AI during the study via the question "How much did you rely on the AI in your decisions for food facts and myths?". Participants could select from a five-point scale with 1 being 'Didn't rely on it at all' and 5 being 'I relied on it all the time'.

The experiment ended with a page showing participants their decision-making patterns, how many nutrition statements they judged correctly versus incorrectly, and which statements they got wrong. We further debriefed participants by stating that we used ChatGPT for the AI-generated content during the experiment and that only some of the nutrition statements and explanations were correct.

3.4 Metrics

We operationalize individuals' interactions with AI suggestions via a combination of clicking behaviors, reading time, and self-reported reliance:

- **See AI Decision** is a binary variable that indicates whether participants select the option "I'd like to see the AI's decision" (1 in Figure 1) for each statement. This variable measures whether participants seek more information from the AI during the task. For each participant, we also calculated the percentage of statements they see AI decisions (**Frequency of See AI Decision**).

- **See AI Explanations** is a binary variable indicating whether participants selected the option "Show me the AI explanation" (2 in Figure 1) for each statement. This measures whether people seek more information from the AI in the task after seeing the AI decision. For each participant, we also calculated the percentage of statements they see explanations out of the 10 statements they see (**Frequency of See AI Explanations**).
- **Time Spent Seeing AI Explanations** is a continuous variable that measures the time it takes participants to select a final evaluation of a statement after they choose to see the AI explanation. We will only examine this variable for participants who select a response after they click "See AI Explanation".
- **Perceived AI Reliance** measures individuals' self-reported reliance on AI assistance in the study based on their responses to the question "How much did you rely on the AI in your decisions for food facts and myths?" We coded levels 1 to 5 (1 for "Didn't rely on it at all", 5 for "I relied on it all the time"). We adopted a one-item measurement approach to examine individuals' perception-based reliance on AI based on prior study design [10]. The item was adapted to focus specifically on our nutrition task, assessing participants' reliance explicitly during the study.

We examined the effects of decision-making patterns while considering the demographic covariates (age, gender, education levels) as well as the following variables:

- **Vigilance, Hypervigilance, Buckpassing**: Based on participants' answers to the **Melbourne Decision Making Questionnaire (MDMQ)** [44] on a 3-point scale ("True for me" (score 2), "Sometimes true for me" (score 1), "Not true for me" (score 0)), we obtained the total score for each of their decision-making dimensions. Each decision-making pattern has its own independent subscale, consisting of a unique set of question statements distinct from those used in the other subscales. Therefore, while we excluded procrastination in our hypotheses and did not administer that portion of the MDMQ, this should not impact the validity of measuring buckpassing, vigilance, and hypervigilance. The maximum score for hypervigilance is 10, and for vigilance and buckpassing, it is 12. The vigilance and buckpassing subscales consist of 6 items each, while the hypervigilance subscale consists of 5 items.
- **Domain Knowledge** is based on participants' self-reported knowledge level of nutrition compared to the average public. We categorized participants into three groups ("Below Average", "Average", "Above Average") due to the imbalance of individuals among the five subgroups ("Very Limited" (41), "Limited" (92), "Average"(351), "Above Average"(300), "Expert" (27)). When participants reported their knowledge levels as "Above Average" or "Expert", their domain knowledge was coded as "Above Average". We categorized "Very Limited" and "Limited" to be "Below Average". Note that we treated this variable as nominal since we were uncertain about whether the increase of likelihood to see AI suggestions and perceived AI reliance would be the same from "Below Average" to "Average" compared to from "Average" to "Above Average".
- **Perception of AI** of participants were coded as "High" and "Not high" based on their perception of the accuracy of conversational AI before participating in the experiment. If they selected "It provides correct information usually" or "It always provides correct information", it was coded as "High", otherwise it was coded as "Not high".

3.5 Participants

Participants in our study were 917 volunteers recruited via the online study platform [AnonymousOnlineLab][4] between August 2023 and April 2024. The platform was chosen to allow us to recruit diverse participants of various ages and

[4]Name omitted for anonymity.

education levels to ensure a broad spread of decision-making styles. Participation on [AnonymousOnlineLab] is open to anyone without signing up; we therefore obtained a waiver of parental consent from our IRB so that minors were able to take our study. To reduce the risk of participants mistaking factually incorrect nutrition information as correct, the study instructions clearly stated that not all nutrition statements are factual and that the goal is to test how much participants know about nutrition. As part of this debrief, participants were also told which of the nutrition statements they wrongfully assumed to be true at the end of the experiment.

We excluded any participants who did not complete the study or affirmed they had taken the study before. To reduce the risk of including participants who were not truthfully responding to the task (i.e., those exhibiting satisficing behavior [33]), we also excluded participants who consistently selected either the option "True for me" or "Not true for me" for all questions in the decision-making questionnaire. After examining the distribution of participants' total time spent completing the study (included in the Appendix), we decided to remove participants whose study completion times were outliers—either extremely short or extremely long—and unlikely to represent a serious attempt at completing the tasks. On average, participants took 9 minutes to finish the study (Median = 468 seconds, SD= 297 seconds). Thus, we eliminated participants who completed the study in less than 240 seconds minutes (N=18) or more than 1200 seconds (N=54), accounting for participants who did not seek AI suggestions and those who reviewed all suggestions. In total, we excluded 107 participants, resulting in a final sample of size 810.

The final set of participants reported being from 69 countries, with the majority from the United States (44%), followed by the United Kingdom (9%), Canada (8%), India (5%), Germany (3%), and Australia (3%, all others $\leq$ 3%). Half of our participants reported pursuing or having obtained a college education, approximately 29% of participants reported pursuing or obtaining a high school education; with the rest reporting to pursue or having obtained a graduate education. Our study participants were between 12 to 90 years of age (M = 31, SD = 14). A detailed breakdown of demographics for participants is shown in Table 3.

4 ANALYSES AND RESULTS

4.1 Descriptive Statistics

This section presents our sample characteristics and key variables, as a form of robustness check in line with prior work Mann et al. [45] and Florença et al. [25]. Then we present detailed analysis results on (1) Effect of Decision-Making Patterns on Seeing AI Decisions (H1a, H2a, H3a), Effect of Decision-Making Patterns on Seeing AI Explanations (H1b, H2b, H3b), and Effects of Decision-making Patterns on Perceived AI Reliance (H1c, H2c, H3c).

Variance in Decision-Making Patterns and Measurement Reliability. The full summary statistics of decision-making patterns for the different demographics are shown in the Appendix (Table 9). On average, our study participants scored 9.41 (SD = 2.31) out of 12 on vigilance, 4.25 (SD = 2.61) out of 10 on hypervigilance, and 4.56 (SD = 3.03) out of 12 on buckpassing. Each subscale reaches a satisfactory level of internal reliability. Cronbach's alphas for each subscale is 0.74 (vigilance), 0.81 (buckpassing), and 0.74 (hypervigilance). [5] (Cronbach alphas were 0.80,0.87,0.74 from Mann et al. [45]). The mean and standard deviation of our measures fall within a similar range compared to those observed in Mann et al. [45] across different countries. Participants' hypervigilance has significantly positive correlation with their measure of buckpassing ($r = 0.59, p < 0.001$), which aligns with prior studies [24, 44]. Additional factor analysis

[5]Cronbach's alpha measures internal consistency and reliability of a scale, ranging from 0 to 1. Values from 0.70-0.90 are recommended to be acceptable values [60].

Table 3. Sample sizes of study participants across different demographics in terms of participants' education levels, gender, age group, self-reported knowledge of nutrition, and their perception of the accuracy of AI-generated information.

	N
Overall	
Overall	810
Education	
<=High School Education	231
Pursuing or Have obtained college education	403
Pursuing or Have obtained graduate education	176
Gender	
Female	409
Male	363
Non-binary/No-disclosure	38
Age Group	
Less than 18	106
18-24	264
25-34	189
35-44	107
45-55	82
Above 55	62
Nutrition Knowledge	
Very limited	41
Limited	92
Average	351
Above Average	300
Expert	26
Perception of AI	
I don't know what conversational AI (ChatGPT) is.	64
It never provides anything correct.	8
It provides correct information sometimes.	346
It provides correct information usually.	378
It always provides correct information.	14

confirms that these three different decision-making patterns are identified with the same corresponding question items from Mann et al. [45]. Details regarding factor loadings and a corresponding diagram are included in the Appendix. These similarities suggest the reliability of our measure of decision-making patterns and the robustness of our samples.

Variance in Participants' Frequency of Seeing AI Decisions and Explanations. We first verified if there was variance in participants' interactions with AI suggestions before we identified the respective underlying factors. We found that the frequency of seeing AI suggestions varied across participants, with the average participant choosing to see the AI's decision 30% of the time ($M = 30\%, SD = 26\%, Min = 0\%, Max = 100\%$) and the AI's explanations 23% of the time ($M = 23\%, SD = 23\%, Min = 0\%, Max = 100\%$).

Participants' Overall Performance. On average, participants accurately evaluated 70% of the statements ($M = 70\%, SD = 14\%$). The performance of our participants is significantly correlated with participants in Florença et al. [25] ($r = 0.58, p < 0.001$), indicating that most of our participants exhibit a similar knowledge pattern regarding common food myths and facts.

Performance did not significantly differ across the different decision-making styles.

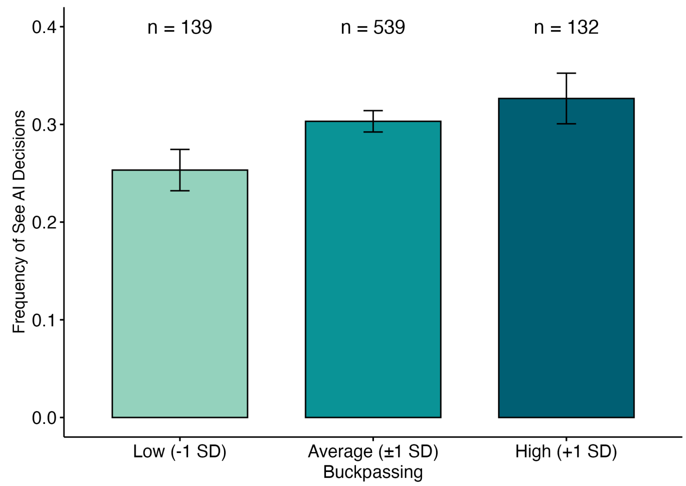

Fig. 2. Overview of Frequency of See AI Decisions with Different Levels of Buckpassing: Participants with varying levels of buckpassing show differences in how often they view AI decisions. "Low" and "High" buckpassing refer to scores that are more than one standard deviation below and above the average, respectively. "Average" buckpassing refers to scores that are within one standard deviation of the average. Each bar represents the average frequency, with error bars indicating the confidence intervals. On average, those who score low in buckpassing view AI decisions 25% of the time, while those who score high view them 33% of the time.

4.2 Effect of Decision-Making Patterns on Seeing AI Decisions

To examine the effect of decision-making patterns on individuals' likelihood to see AI decisions (**H1a, H2a, H3a**), we fit a series of mixed-effects logistic regression models for our binary dependent variables (i.e., whether a participant decided to see the AI decision and the AI explanation for each statement). We included participants' individual decision-making scores (for *vigilance, hypervigilance, buckpassing*) as fixed effects, with participant and nutrition statement as random effects (**Model 1** in Table 4) to account for variation across nutrition statements and individual differences. Neither hypervigilance nor vigilance showed a significant effect, suggesting that **H1a** and **H2a** are not supported. Buckpassing had a significant positive effect on the likelihood of people seeing AI decisions ($\beta = 0.062, p < 0.05$), supporting **H3a**. We also show an overall frequency of seeing AI decisions across different levels of buckpassing among our participants in Figure 2.

Additionally, we built a model (**Model 2**) that controls for demographic covariates since prior research suggests that individuals' demographics factors such as age, education levels, domain knowedge [2, 36, 43] influence their trust and reliance on AI. The details of this model are summarized in Table 4. The positive effect of buckpassing remains marginally significant after controlling for participants' age, education, domain knowledge, and perception of an AI ($\beta = 0.048, p = 0.06$).

4.3 Effect of Decision-Making Patterns on Seeing AI Explanations

To test **H1b**, **H2b**, and **H3b**, we first examined whether participants chose to see AI explanations, which was true for 548 out of 811 participants. Per **Model 3** in Table 4, there is no significant effect of decision-making patterns on individuals' tendency to see AI explanations. We included the results of the model with only decision-making measures as fixed effects in the Supplemental Materials.

Table 4. Mixed-effects logistic regression results predicting participants' tendency to seek AI suggestions (See AI Decision and See AI Explanations). Regression analysis with only variables related to decision-making patterns indicates a statistically significant effect of buckpassing on one's likelihood to see AI's decision. When including demographic variables, the regression analysis shows that participants' education levels, self-reported domain knowledge, and perception of AI-generated information have significant effects on participants' tendency to seek AI suggestions. Reference groups are less than college education, domain knowledge (Above average), and perception of AI (Not high).

	Dependent variable:		
	See AI Decision		See AI Explanations
	Model 1	Model 2	Model 3
	Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)
Buckpassing	0.062^{**} (0.025)	0.048^{*} (0.025)	0.032 (0.026)
Hypervigilance	−0.001 (0.029)	−0.021 (0.029)	−0.029 (0.030)
Vigilance	0.015 (0.027)	0.014 (0.026)	−0.007 (0.027)
Age		-0.015^{***} (0.005)	-0.016^{***} (0.005)
Pursuing or Have obtained college education		0.071 (0.149)	0.104 (0.153)
Pursuing or Have obtained graduate education		0.624^{***} (0.185)	0.631^{***} (0.190)
Domain_Knowledge (Average)		0.594^{***} (0.136)	0.406^{***} (0.139)
Domain_Knowledge (Below Average)		0.500^{***} (0.187)	0.108 (0.193)
Perception of AI (High)		0.256^{**} (0.121)	0.080 (0.124)
Constant	-1.697^{***} (0.315)	-1.695^{***} (0.387)	-1.704^{***} (0.399)
Observations	8,100	8,100	8,100
Akaike Inf. Crit.	8,411.871	8,379.897	7,455.465
Marginal R^2 / Conditional R^2	0.006 / 0.470	0.033 / 0.469	0.020 / 0.469
Note:			*p<0.1; **p<0.05; ***p<0.01

Next, we examined the effect of decision-making patterns on how much time people spend reviewing AI explanations, if they choose to see them. On average, participants spent 14 seconds seeing AI explanations ($M = 14.34, SD = 10.73$). We used a linear mixed-effects regression model, considering that each participant could have their own reading speed and each statement has different lengths of AI explanations. Per Table 5, buckpassing has a statistically significant negative effect on individuals' time spent evaluating AI explanations ($\beta = -0.40, p < 0.05$). For one additional score of increase in buckpassing dimension, the time users spend on seeing explanations decreases by 0.4 seconds. This suggests individuals who score higher in buckpassing tend to spend less time evaluating AI explanations before they make their final decisions. On the contrary, vigilance has a statistically significant positive effect on participants' time spent evaluating AI explanations ($\beta = 0.53, p < 0.05$). For one score of increase in vigilance dimension, the time users spend on reading explanations increases by 0.53 seconds. These results support our hypotheses **H1b** and **H3b**, but not **H2b**.

4.4 Effects of Decision-making Patterns on Perceived AI Reliance

To test **H1c**, **H2c**, and **H3c**, we constructed an ordinal logistic regression model while controlling for participants' demographic covariates including age, education level, domain knowledge, and perception of AI. Ordinal logistic regression is often used to predict dependent variables that can be ordered in a natural way such as *mild, moderate, severe* [28]. Per Table 6, our result indicates the effect of buckpassing on perceived AI reliance is statistically significant ($OR = 1.09$, 95% CI$[1.03, 1.15]$, $p < 0.05$). For one score of increase in buckpassing, the odds of having more self-perceived

Table 5. Linear mixed model predicting individuals' time spent evaluating AI explanations: participants' buckpassing and vigilance tendency significantly affect the time they spent reading AI's explanations if they chose to see them.

	Dependent variable:
	Time Spent Seeing AI Explanation (Seconds)
Buckpassing	-0.401^{**} (0.197)
Vigilance	0.528^{**} (0.206)
Hypervigilance	0.291 (0.223)
Age	0.054 (0.038)
Domain_Knowledge (Average)	−0.162 (1.035)
Domain_Knowledge (Below Average)	4.173^{***} (1.454)
Pursuing or Have obtained college education	0.026 (1.160)
Pursuing or Have obtained graduate education	−0.066 (1.431)
Perception of AI (High)	0.885 (0.931)
Constant	6.950^{**} (2.864)
Observations	1,542
Marginal R2 / Conditional R2	0.023 / 0.232
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6. Ordinal Logistic Regression Model for Perceived Reliance on AI (reference levels are high school education, domain knowledge-above average, perception of AI-low). Significance levels:p<0.001***, p<0.05**, p<0.1*

Predictors	**Odds Ratios**	**CI**
Buckpassing	1.09^{**}	1.03 – 1.15
Hypervigilance	0.97	0.91 – 1.03
Vigilance	0.98	0.93 – 1.04
Pursuing or Have obtained college education	1.21	0.89 – 1.64
Pursuing or Have obtained graduate education	1.60^{*}	1.08 – 2.37
Age	0.99	0.98 – 1.00
Domain Knowledge (Average)	1.86^{***}	1.40 – 2.47
Domain Knowledge (Below Average)	1.46	0.98 – 2.17
Perception of AI (High)	1.41^{**}	1.09 – 1.82
Observations	810	
R^2 Nagelkerke	0.056	

reliance on the AI increases by 9%, suggesting that people who score high in buckpassing are more likely to rely on AI when making their decisions. Figure 3 shows the distribution of response in terms of level of reliance related to individuals' buckpassing tendency. Noteworthily, 12% of people who received a low buckpassing score reported to rely on the AI "all the time" (rating of 5) or most of the time (rating of 4), while 20% of those who received a high buckpassing score reported the same.

No effect of vigilance or hypervigilance is observed. Hypotheses **H1c** and **H2c** are therefore not supported, while **H3c** is supported.

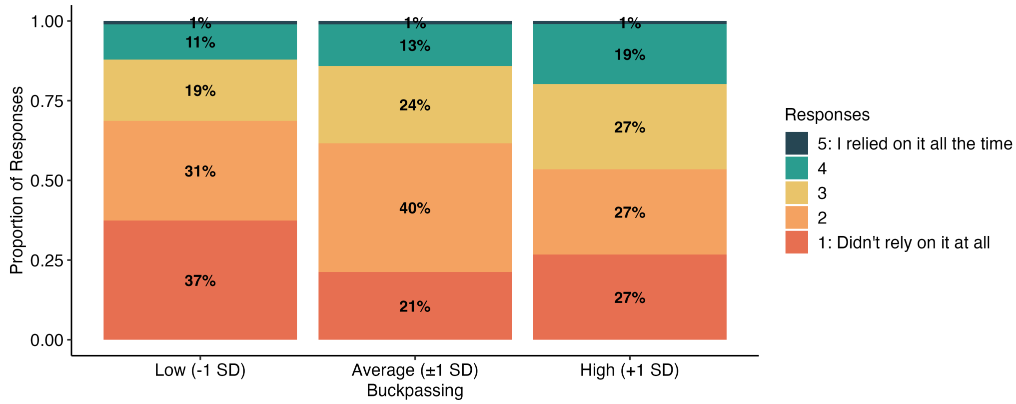

Fig. 3. Perceived AI Reliance Variations Across Different Levels of Buckpassing: individuals who score high in buckpassing report a higher reliance on AI.

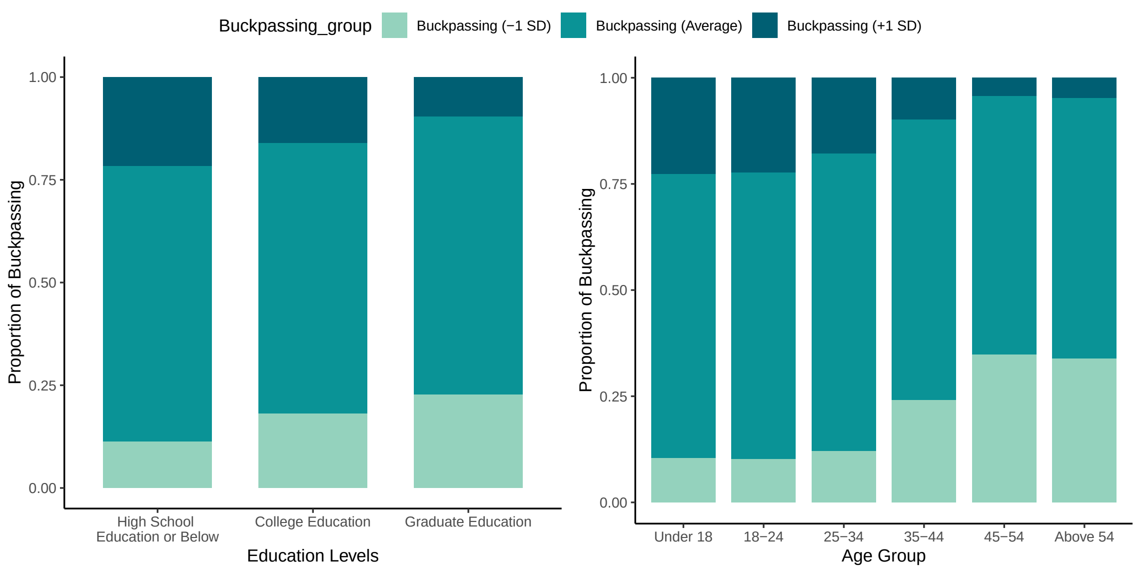

Fig. 4. Examining the demographic distribution of buckpassing tendency: participants who have a high school education or below score higher in buckpassing (23% in high buckpassing level); participants who are aged under 18 and in their early 20s also tend to score higher in buckpassing.

4.5 Who tends to score high in buckpassing?

Our analysis indicates that a buckpassing tendency significantly influences participants' use of AI suggestions and reliance on AI. Thus we further explore the demographic distribution of buckpassing scores among our participants to gain insights into which demographic groups exhibit a higher buckpassing tendency. Figure 4 shows the distribution of buckpassing levels among different education levels and age groups. Age is treated as a categorical variable in this descriptive analysis to obtain a more granular understanding of age group differences. Teenagers and young adults in our sample tend to score higher in buckpassing compared to participants who are aged above 35. Participants who obtain a lower level of education (high school education or below) also exhibit a higher buckpassing tendency compared to those with a higher level of education (pursuing or having obtained college or graduate education).

5 DISCUSSION

Individuals' decision-making patterns have been shown to influence their decision outcomes and quality of life [20, 35], underlining the importance of understanding how people vary in making decisions. However, despite the increasing role of AI in decision-making contexts, how individual cognitive decision-making processes influence the use of AI technology has been unknown. Our study offers evidence of this influence; we discuss our findings and consider their implications for designing AI systems and explainable AI research below.

Decision-making Patterns as Important Factors in AI-assisted Decision-making. In this work, we extend the current understanding of factors behind individuals' reliance on AI. Consistent with our hypotheses, we found that people who tend to defer decision-making patterns to others (score high in buckpassing) are more likely to seek out suggestions from an AI and report relying on it, though they spend less time reading AI's explanations. While the difference can be described as a small to medium effect—those who score low on buckpassing viewed the AI's decisions 25% of the time versus 33% for those who scored high on buckpassing—this difference can be profound when AI decision-making tools are frequently used. The difference may also gain importance with the number of decisions to be made as decision fatigue sets in [12] or as task difficulty or uncertainty increases [53, 64], leading to a higher likelihood of overreliance.

Prior work has identified individual-related factors that affect individuals' trust and reliance on AI including personal traits and demographic characteristics. In addition to personality and self-confidence [8, 13], our work suggests that individuals' decision-making patterns could affect individuals' interactions with AI systems. We encourage future work to examine these factors in various kinds of human-AI interactions. In addition, prior HCI research shows that individuals' trust and reliance vary by their age, education levels, and perception of AI [2, 43]. Our work extends this by showing that individuals' buckpassing tendency has a marginal effect on AI use when accounting for these demographic covariates. While the significance of the effect decreases after controlling these factors, it is probably due to the correlation between these demographic factors and decision-making patterns (see correlation matrix table in the Appendix).

What might explain these findings is the stress level and confidence people experience while making decisions. Mann et al. [44]'s work has indicated that these decision-making tendencies can be seen as different kinds of coping mechanisms during decision conflict. Individuals with a strong buckpassing tendency often experience high psychological stress during decision-making tasks, while vigilant decision-makers experience a lower level of stress [44]. Experiencing high psychological stress while making decisions might propel people to seek out an immediate relief by turning to AI suggestions. Mann et al. [45] also identified that individuals who score high in buckpassing tend to have a lower confidence in their own decision-making. This could potentially propel participants in our study to seek AI's suggestions when they were not confident about making the decisions themselves. Interestingly, we did not observe any effect of vigilance or hypervigilance on participants' tendency to see AI suggestions. This might be due to the low variance of participants on vigilance ($SD = 2.31$) and hypervigilance ($SD = 2.61$) compared to buckpassing pattern (3.03). However, we observed participants who score high in vigilance spent significantly more time seeing AI explanations. This suggests that an increased vigilance goes hand in hand with careful reading of any explanations people are provided, likely as a tool for evaluating whether the AI's decision can be reasonably trusted.

Benefits and Risks of AI-assisted Decision-making for People with Different Decision-Making Patterns. AI-assisted decision-making could yield both positive and negative outcomes for people with a tendency for buckpassing. On the one hand, the rise of AI systems could ease the burden of information seeking and processing for individuals to make effective decisions, if the performance of these systems is reliable. As evidenced by prior work, making decisions with the help of AI could lead to more accurate decisions when the AI has high advice accuracy and quality [61, 65] (though there are some exceptions where this was found not to be the case [30, 62]). AI assistance can also lower mental demand [7]. With highly reliable AI systems, AI suggestions could help relieve the decision-making stress experienced by people with a buckpassing tendency. On the other hand, given the current risks of AI hallucinations, where AI generates unfaithful or nonfactual content [6], and AI overconfidence [71], where AI outputs sound confident yet are inaccurate [71], buckpassers are more susceptible to overreliance on AI, potentially resulting in misleading decisions and negative decision outcomes.

The benefits and risks of AI-assisted decision-making might be exacerbated for some people and groups, as our study and other research show that decision-making patterns vary across demographics. Consistent with prior findings [24], our study suggests that buckpassing tendency is more prevalent among younger people (especially individuals under 18) and people with high school education or below. This warrants greater intervention to guide these populations in their usage of AI systems. Prior work from Mann et al. [45] indicates that people from East Asian countries (e.g., Japan, Hong Kong) exhibit a higher buckpassing tendency compared to people in Western countries (e.g., USA, Australia, New Zealand). East Asians have also been found to have a lower decision-making self-esteem, which is generally in line with a preference for making decisions in a group [45]. These demographic groups may seek out information from the AI more often, benefiting more from AI systems that have high accuracy but also facing greater risks of overreliance.

5.1 Implications for Designing AI Systems and Explainable AI Research

The variations in people's decision-making patterns, and in particular in people's tendency to be vigilant or pass the buck warrant more caution in the design and implementation of AI systems. How do we cultivate appropriate reliance on AI systems given these decision-making patterns? Prior work has investigated several interventions that could help mitigate inappropriate reliance, which we consider together with the implications of our findings below.

Delay AI suggestions for buckpassers to reduce tendency of deferring decision-making to AI. Our findings show that those prone to deferring decisions to others are also more likely to rely on the AI. The relatively short time they spent looking at the AI evaluations, compared to participants who scored low in buckpassing, further suggests that buckpassers may not think for themselves in these situations; the immediate access to the AI suggestions (as is most common in human-AI studies and AI decision-support systems in various contexts [9, 12, 40, 42, 46, 68]) seems to be an easy way to lower cognitive effort, which then results in an overreliance on the AI. Buçinca et al. [7] found that cognitive forcing functions—forcing people to make their own decisions *before* seeing an AI's suggestions—can effectively reduce their overreliance.Hence, delaying the option to seek AI assistance could be especially beneficial for buckpassers, encouraging them to form an opinion themselves before seeing the AI's suggestions.

Note that in our study, the impact of decision-making patterns on the accuracy of people's decisions was negligible. This was likely due to the relatively easy task, which meant that even when heavily relying on the AI, participants didn't have significantly worse decision outcomes. However, the increased reliance on the AI that we saw in our buckpassing participants suggests that delaying the AI suggestions is crucial in high-stake decision-making tasks. AI designs should therefore detect who may be prone to buckpassing behavior, such as by detecting people's decision-fatigue using their cursor entropy as suggested in [51] or the amount of time they tend to spend reading AI-generated explanations). Cognitive forcing functions could then be applied in a personalized manner and reactive to an individual's decision-fatigue to reduce overreliance.

Adopt presentation formats of AI explanations that ease cognitive load and decision stress. Our study found that buckpassers tend to spend less, and vigilant people more time, when reviewing AI explanations, posing challenges to the design of AI explanations. The format of AI explanations in our study was text-based and lengthy. This format might induce further cognitive load and stress for buckpassers, resulting in their reduced time investment in AI explanations. Prior research found if decisions are made under high cognitive load, it can lead to higher overreliance on AI [70]. Thus, identifying presentation formats of AI suggestions that reduce cognitive load and decision stress may enourage buckpassers to evaluate AI explanations carefully.

Chen et al. [12] found that for individuals who rely on their intuition in decision-making, providing example-based scenarios as AI explanations can effectively calibrate appropriate reliance on AI. Psychology research on cognitive load theory (CLT) and e-learning has identified various information presentation techniques to reduce individuals' cognitive load [37, 58, 63]. Mousavi et al. [47] found that presenting information in both audio and visual format leads to less cognitive load than in visual format alone. As such, designers could consider showing AI explanations to users in both visual and audio formats to lower their cognitive load. Redundant information is also shown to increase individuals' cognitive load and experts and novices have different perceptions of redundancy [58]. In AI suggestions, designers should personalize information based on individuals' domain knowledge level and avoid providing information that is commonly known among domain experts.

Provide users with diverse options for presentation type of AI suggestions. Despite the effectiveness of interventions in cultivating appropriate reliance on AI, research in explainable AI has focused on explanations for binary decision-making tasks; however, the information that conversational AI systems, such as ChatGPT, provide often use one-size-fits-all presentation format. The varied amount of time investment could result in a different level of caution when processing information from ChatGPT. While these lengthy paragraphs might suit the information-seeking habits of vigilant people, they might not be processed carefully by individuals who tend to be buckpassers. As such, developers should consider providing features that enable users to select their own preferred presentation format based on their own information-seeking habits. For example, if users may adjust the length of text and amount of details (i.e. summary of references or concrete examples) used in AI suggestions, vigilant individuals may choose to obtain more comprehensive information whereas buckpassers could request brief explanations.

6 LIMITATIONS AND FUTURE WORK

We acknowledge several limitations of this study. Firstly, the observed behaviors in the design of this study may not generalize to other domains. Our study was designed to capture participants' collaborative decision-making behavior with an AI in a task that required them to accurately identify whether a set of nutrition statements were facts or myths. Choosing nutrition as a domain has the advantage that the study was broadly accessible to diverse participants, but inaccuracies have naturally less severe consequences than tasks in, e.g., the medical domain. We additionally chose to conduct an online study with volunteer participants who were offered personalized performance feedback in exchange for study completion. This usually means participants are intrinsically motivated to do well; however, the consequences of mistaking a nutrition statement as true when it was false (and vice versa) are mild when compared to a real-world situation. Future work is needed to validate the findings with tasks that carry greater consequences for participants in other real-world scenarios.

Secondly, our study did not fully capture individuals' various reliance outcomes. Prior studies on AI-assisted decision-making often investigate individuals' overreliance or underreliance on AI [11, 64]. Our design examines individuals' interactions with AI suggestions by focusing on whether they seek out AI suggestions and how they rely on the AI overall. Future studies may examine reliance outcomes together with the observed behaviors in our study to provide a holistic understanding of individuals' reliance behaviors.

Thirdly, our study design does not fully capture users' holistic experiences with AI systems, such as ChatGPT, through chatbot interfaces since users did not have a choice to see more AI explanations if they were not satisfied with the output. We chose such a design to ensure AI suggestions are consistent for each participant, yet we hope future studies could explore experiment designs that closely mimic interactions with generative AI systems. Meanwhile, our design of asking users' to indicate their adoption of AI suggestion by providing an option "Use the AI Decision" had very few engagement click despite the high reliance suggested by other measures. We suspect this occurred due to an unintuitive display of options for users to choose from or a motivation to preserve autonomy in making the final decision. In future work, we will also improve our designs of interface features that are more closely matched with users' behaviors. It's also worth noting that our design of the study does not provide the opportunity to search for information from the web. In real-world scenarios, users could potentially navigate other information sources for more information before they make their final decisions. Future work could further integrate this option to examine how users' behaviors are influenced by their decision-making patterns in a more dynamic setting. Notably, while we did not examine the effect of procrastination in our study, future work that integrates more dynamic interactions shall investigate the behaviors of individuals who tend to procrastinate in their decision-making.

Lastly, our sample primarily consisted of participants who were fluent in English and motivated to participate in our study due to our study topic. In future work, we hope to gather a larger and more diverse sample via by providing the study in other languages and various topics to follow up on the present findings. In line with this, one exciting avenue for future work is to investigate how differences in decision-making patterns across countries and cultures impact people's reliance on an AI. For instance, Mann et al. [45] had found that people from more hierarchical cultures commonly score high in buckpassing, which could imply that there are cross-cultural differences in reliance, and potentially in overreliance, on an AI.

7 CONCLUSION

With the increasing use of conversational AI such as ChatGPT for information-seeking and decision-making, it is essential to understand how people vary in their interactions with AI suggestions in the decision-making process. Through an online study, we asked participants (n=810) to evaluate the factuality of nutrition-related statements with the option to seek AI suggestions (decisions and explanations). We found that people who tend to defer decisions to others (buckpassers) are more likely to seek AI suggestions yet spend less time evaluating these suggestions and reported a higher level of reliance on AI when evaluating nutrition information than those scoring low on buckpassing. In contrast, vigilant decision makers tended to more carefully scrutinize the AI's information than those scoring low on vigilance. Drawing insight from psychology research on decision-making, our study suggests that individuals' decision-making patterns implicate not only *human-human* interactions but also human-AI interactions. In particular, these findings expand the current research horizon of AI-assisted decision-making by underscoring the importance of individual cognitive processes. As more AI-driven systems are being developed and integrated into our everyday lives, these findings shed light on the importance of individual cognitive factors, providing new insights for the future development of AI technologies.

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This paper has no relation to authors' prior publications.

A NUTRITION STATEMENTS

Code	Statement	Nature	Presented AI Decision
S1	Drinking water during meals, contributes to weight gain.	Myth	Myth
S2	The digestion process begins in the mouth.	Fact	Fact
S3	Fruit should be eaten before meals.	Myth	Myth
S4	Egg consumption increases blood cholesterol.	Myth	Myth
S5	Drinking milk is bad for health.	Myth	Myth
S6	Eating carbohydrates at night leads to an increase in weight gain.	Myth	Fact
S7	Fat is important to the human body.	Fact	Fact
S8	Fruit should be eaten after meals.	Myth	Myth
S9	Fiber intake is important for normal bowel function.	Fact	Fact
S10	Gluten-free foods are better for health and should, there-fore, be adopted by all.	Myth	Myth
S11	Cheese consumption is bad for memory.	Myth	Myth
S12	Coconut oil is healthier than olive oil.	Myth	Myth
S13	Lactose-free foods are better for health and should, there-fore, be adopted by all.	Myth	Myth
S14	Children have different nutritional needs than those for adults.	Fact	Fact
S15	Fruits and vegetables do not contribute to weight gain.	Myth	Myth
S16	Normal potatoes are more caloric than sweet potatoes.	Myth	Fact
S17	Diet should be adapted to a person's blood group.	Myth	Fact
S18	Not having a balanced and varied diet can lead to the development of multiple diseases.	Fact	Myth
S19	The alkaline diet allows balancing the acidity in the blood.	Myth	Myth
S20	Drinking, while fasting, a glass of water with lemon helps in weight loss.	Myth	Fact
S21	Inadequate eating habits are the third risk factor for the loss of years of healthy life.	Fact	Fact
S22	Ingesting high amounts of protein helps in the faster formation of muscles.	Myth	Fact
S23	Pregnant women should be eating for two.	Myth	Fact
S24	Cold water should not be drunk.	Myth	Myth
S25	The day should always start with breakfast.	Fact	Myth
S26	Water is essential to the normal function of all organs.	Fact	Fact
S27	Soy milk is healthier than cow's milk.	Myth	Myth
S28	Orange should not be eaten at the same time as milk or yogurt.	Myth	Myth
S29	Dairy products should be consumed in between two and three portions per day.	Fact	Myth
S30	All food additives (E's) are harmful to health.	Myth	Myth

Table 7. Nutrition statements and presented AI's decisions used in the study's experiment for participants. These statements are adopted from Florença et al. [25].

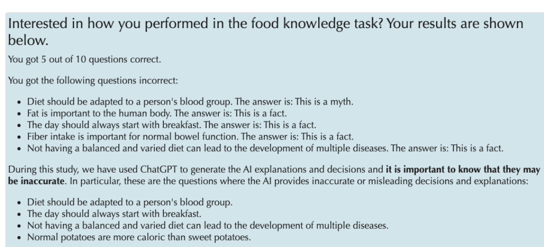
B THE MELBOURNE DECISION-MAKING QUESTIONNAIRE

Table 8. The Melbourne Decision-Making Questionnaire by Mann et al. [44], which we used in our study to assess participants' decision-making patterns. All items could be answered on a 3-point scale: "Not true for me", "Sometimes true for me", or "True for me".

Vigilance	Item
1	I like to consider all of the alternatives.
2	I try to find out the disadvantages of all alternatives.
3	I consider how best to carry out a decision.
4	When making decisions I like to collect a lot of information.
5	I try to be clear about my objectives before choosing.
6	I take a lot of care before choosing.
Buckpassing	
7	I avoid making decisions.
8	I do not make decisions unless I really have to.
9	I prefer to leave decisions to others.
10	I do not like to take responsibility for making decisions.
11	If a decision can be made by me or another person I let the other person make it.
12	I prefer that people who are better informed decide for me.
Hypervigilance	
13	Whenever I face a difficult decision I feel pessimistic about finding a good solution.
14	I feel as if I am under tremendous time pressure when making decisions.
15	The possibility that some small thing might go wrong causes me to swing abruptly in my preference.
16	I cannot think straight if I have to make a decision in a hurry.
17	After a decision is made I spend a lot of time convincing myself it was correct.

B.1 Study Design

To ensure that participants were aware of any inaccurate information we presented to them during the study, we included at the end of the study a page about their performance in the nutrition evaluation task. Specifically, we included statements where they submitted inaccurate answers and the correct answers for them as well as statements where AI suggestions were not accurate.


Interested in how you performed in the food knowledge task? Your results are shown below.

You got 5 out of 10 questions correct.

You got the following questions incorrect:

- Diet should be adapted to a person's blood group. The answer is: This is a myth.
- Fat is important to the human body. The answer is: This is a fact.
- The day should always start with breakfast. The answer is: This is a fact.
- Fiber intake is important for normal bowel function. The answer is: This is a fact.
- Not having a balanced and varied diet can lead to the development of multiple diseases. The answer is: This is a fact.

During this study, we have used ChatGPT to generate the AI explanations and decisions and **it is important to know that they may be inaccurate**. In particular, these are the questions where the AI provides inaccurate or misleading decisions and explanations:

- Diet should be adapted to a person's blood group.
- The day should always start with breakfast.
- Not having a balanced and varied diet can lead to the development of multiple diseases.
- Normal potatoes are more caloric than sweet potatoes.

Fig. 5. Example of result page in the study presented to participants: we included an example of our result page regarding how we debriefed participants about their performance in the nutrition evaluation task. Specifically, we included the statements where they submitted inaccurate answers and statements where AI suggestions were inaccurate.

B.2 Factor Analysis for Decision-making Patterns

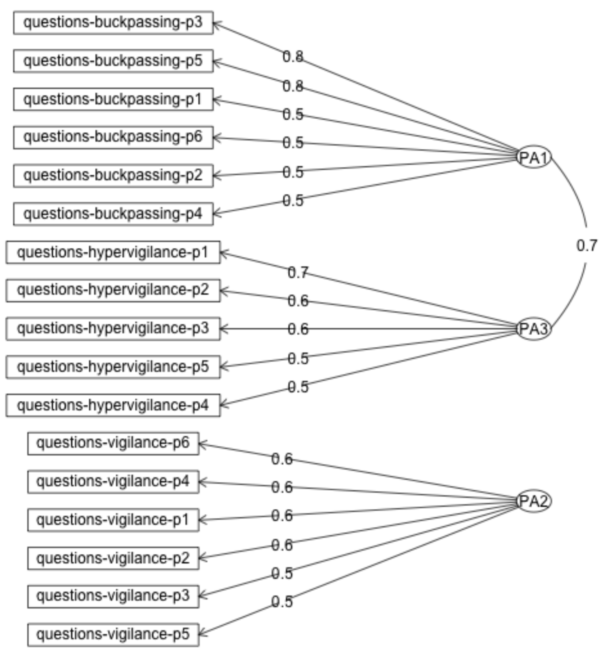


Fig. 6. Factor loading diagram confirming the three decision-making patterns based on the Melbourne Decision Making Questionnaire. Items associated with buckpassing load strongly on PA1, items related to vigilance load on PA2, and items linked to hypervigilance load on PA3, supporting the theoretical structure of the questionnaire. The inter-factor correlation between PA1 and PA3 is shown with a value of 0.7. Loadings represent the strength of the relationship between items and factors, with higher values indicating stronger associations.

C DEMOGRAPHICS INFORMATION OF PARTICIPANTS

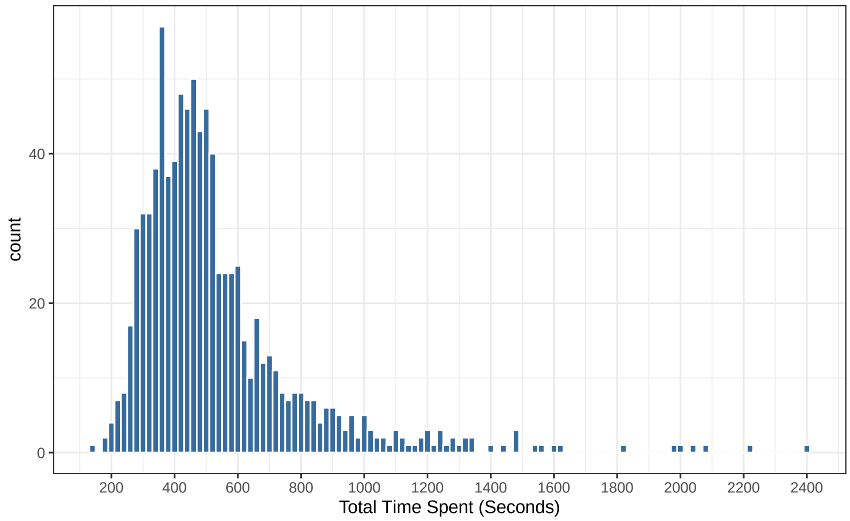


Fig. 7. Overall distribution of total time spent in the study: we selected time thresholds (240 seconds and 1200 seconds) where the number of participants significantly dropped and then filtered out participants based on these time threshold.

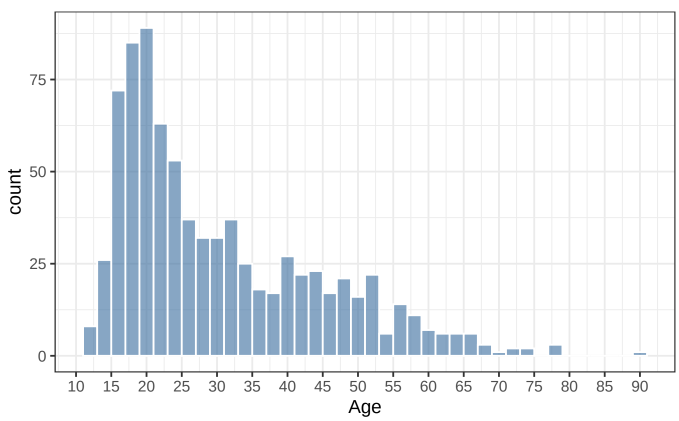


Fig. 8. Age distribution of 810 participants.

Table 9. Sample sizes as well as averages and standard deviations for each decision-making measure across different demographics. The maximum for vigilance and buckpassing is 12, whereas the maximum for hypervigilance is 10.

	N	Vigilance	Hypervigilance	Buckpassing
Overall				
Overall	810	9.41 ± 2.31	4.25 ± 2.61	4.56 ± 3.03
Education				
<=High School Education	231	9.39 ± 2.32	4.94 ± 2.55	5.25 ± 3.12
College Education	403	9.34 ± 2.34	4.12 ± 2.64	4.49 ± 3
Graduate Education	176	9.59 ± 2.2	3.64 ± 2.45	3.82 ± 2.78
Gender				
Female	409	9.43 ± 2.31	4.52 ± 2.63	4.69 ± 3.15
Male	363	9.36 ± 2.32	3.83 ± 2.47	4.33 ± 2.84
Other	38	9.66 ± 2.13	5.5 ± 2.94	5.47 ± 3.27
Age Group				
Under 18	155	9.30 ± 2.35	5.32 ± 2.43	5.59 ± 3.09
18–24	215	9.69 ± 2.22	4.64 ± 2.52	5.01 ± 2.97
25–34	174	9.32 ± 2.51	4.37 ± 2.6	4.87 ± 3.03
35–44	112	9.53 ± 2.24	3.49 ± 2.48	3.7 ± 2.78
45–54	88	9.03 ± 2.19	3.05 ± 2.45	3.03 ± 2.58
Over 55	66	9.26 ± 2.14	3.14 ± 2.42	3.39 ± 2.6

D CORRELATION MATRIX FOR ALL VARIABLES

Table 10. Correlation matrix of demographic variables. *** significance at the .001 level; ** significance at the .01 level; * significance at the .05 level; . significance at the 0.1 level.

	B	V	H	A	HE	CE	GE	DKE
Buckpassing (B)	1							
Vigilance (V)	-0.05	1						
Hypervigilance (H)	0.59***	0.05	1					
Age (A)	-0.27***	-0.05	-0.28***	1				
Less than high school education (HE)	0.14***	-0.00	0.17***	-0.35***	1			
Pursuing or Have obtained college education (CE)	-0.02	-0.03	-0.05	0.11**	-0.63***	1		
Pursuing or Have obtained graduate education (GE)	-0.13***	0.04	-0.12***	0.25***	-0.33***	-0.52***	1	
Domain Knowledge (Expert) (DKE)	-0.20***	0.07*	-0.20***	0.22***	-0.15***	0.00	0.16***	1

E ADDITIONAL REGRESSION ANALYSES

Table 11. Mixed-effects logistic regression results predicting See_AI_Explanations: no statistically significant effect of decision-making patterns is observed.

Fixed Effects	Estimate	Std. Error	z value	p-value
(Intercept)	-1.9223	0.32228	-5.965	< 0.001 ***
buckpassing	0.48502	0.31146	1.557	0.119
vigilance	-0.02133	0.32836	-0.065	0.948
hypervigilance	-0.18182	0.29880	-0.608	0.543

Table 12. Mixed-effects logistic regression result predicting whether participants correctly evaluate whether each nutrition statement is a fact or a myth: result indicates no effects of decision-making patterns. However, participants who chose to see AI decisions and see AI explanations were more likely to have incorrect responses.

Predictors	Odds Ratios	CI
(Intercept)	5.56***	2.86 – 10.79
Buckpassing	1.00	0.98 – 1.03
Hypervigilance	0.98	0.95 – 1.01
Vigilance	0.99	0.96 – 1.02
Age	1.00	0.99 – 1.00
Domain Knowledge (Average)	0.88	0.77 – 1.02
Domain Knowledge (Below Average)	0.80*	0.65 – 0.97
Pursuing or Have obtained college education	1.10	0.94 – 1.29
Pursuing or Have obtained graduate education	1.20	0.99 – 1.46
N Participant	810	
N statement	30	
Observations	8100	
Marginal R^2 / Conditional R^2	0.003 / 0.432	