Framing Effects of AI Unemployment Information

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Abstract

The advancement of artificial intelligence technology has raised concerns about future unemployment, and information encountered when learning about "AI unemployment" may influence individuals' perception of AI threat. Through seven experiments, this article investigates the effects of two digital information frames regarding "AI unemployment" on AI threat perception, as well as their underlying mechanisms and boundary conditions, and subsequent impacts on support for AI research and development and job evaluation criteria. Results reveal that, compared to factor framing, probability framing reduces individuals' AI threat perception (Experiments 1-7); the mechanism involves the mediating role of judgments regarding the likelihood of "AI unemployment" occurrence, wherein probability framing leads individuals to perceive "AI unemployment" as less likely to happen, thereby reducing AI threat perception (Experiments 2-5); this effect is moderated by tolerance for ambiguity, such that the threat-reducing effect of probability framing is primarily observed among individuals with high tolerance for ambiguous information (Experiment 5); furthermore, under the influence of probability framing, individuals also demonstrate greater support for policies related to AI research and development, with AI threat perception serving as a mediator (Experiment 6); concurrently, individuals influenced by probability framing also exhibit more positive willingness to recommend jobs requiring frequent interaction with AI (Experiment 7). The findings differentiate the effects of the two digital information frames on AI threat perception, providing novel evidence for prior research exploring the antecedents of AI threat.

Full Text

The Information Framing Effect of "AI Unemployment"

Abstract

The advancement of artificial intelligence (AI) technology has sparked widespread public concern about future unemployment. The information people encounter while learning about "AI unemployment" may influence their perception of AI threat. Through seven experiments, this paper examines how two numerical information frames regarding "AI unemployment" affect AI threat perception, explores the underlying mechanisms and boundary conditions, and investigates subsequent impacts on support for AI research and development policies and willingness to recommend jobs in industries with high AI exposure. Results show that, compared to a factor frame, a probability frame reduces people's AI threat perception (Experiments 1-7). The mechanism involves the mediating role of subjective likelihood judgments: probability frames lead people to form judgments that AI unemployment is less likely to occur, thereby reducing AI threat (Experiments 2-5). This effect is moderated by individual ambiguity tolerance, such that the probability frame's reduction of AI threat primarily manifests among individuals with high tolerance for ambiguous information (Experiment 5). Additionally, influenced by the probability frame, people demonstrate greater support for AI-related policies, with AI threat serving as a mediator (Experiment 6). Simultaneously, those influenced by the probability frame show stronger willingness to recommend jobs requiring frequent AI interaction (Experiment 7). These findings distinguish the effects of two types of numerical information frames on AI threat, providing new evidence for research exploring the antecedents of AI threat.

Keywords: technological unemployment; information processing; probability judgments; AI threat; ambiguity tolerance

Artificial Intelligence (AI) has been hailed as "the most important general-purpose technology of our era" (Felten et al., 2021). From programming to disease diagnosis, image generation to everyday conversation, AI's human-like performance across numerous domains has attracted extensive media coverage, leading the public to recognize its vast application potential (Metz, 2022; Roose, 2022; Savage, 2020; Strogatz, 2018; Verma, 2022). Statistics show that since 2022, major U.S. publications have published one AI-themed article for every 200 articles on average, compared to one per 1,150 articles in 2012 (Santoro & Monin, 2023). However, as public exposure to AI technology increases, associated social issues have intensified (Brynjolfsson & McAfee, 2017). For instance, strikes against automation have frequently occurred in food, transportation, and retail industries across Europe and America, while the EU has implemented strict access regulations to limit AI deployment in production. Recent events such as Duolingo (the world's largest language learning community) introducing AI products and laying off thousands of translators, along with professional artists launching the "No To AI Generated Images" movement, have triggered widespread public skepticism and vigilance toward AI (Hsu, 2022; Iza World of Labor, 2019; Nemo, 2018; Sparrow, 2007; Złotowski et al., 2017). In these incidents, the conflict between AI and humans centers on potential competition in the workplace, making "AI unemployment" a focal topic of public discourse (Wike & Stokes, 2018).

AI unemployment falls under the category of technological unemployment, referring to large-scale job losses caused by AI technology' s substitution effect on human labor, its impact on traditional employment structures, and its displacement of job opportunities (Schlogl & Sumner, 2018). As AI technology remains in the developmental stage from "weak AI" to "strong AI," AI unemployment is generally considered a forecast about future employment conditions (许丽颖, 喻丰, 2020; Makridakis, 2017). However, starkly divergent perspectives persist regarding whether and on what scale AI unemployment will occur. Based on market adjustment and compensation mechanisms, optimists argue that AI, like previous transformative technologies, will create more new jobs while eliminating old ones (Makridakis, 2017; Padalino & Vivarelli, 1997). Conversely, considering that AI development aims to create machine intelligence that simulates human intelligence, others predict that AI' s substitution effect will outweigh its creation effect (Frey & Rahbari, 2016).

Similar to theoretical predictions, surveys on AI unemployment have yielded inconsistent conclusions. McKinsey Global Institute' s calculations indicate that 51% of paid positions in the U.S. will be gradually replaced by AI within 20 years (Chui et al., 2016), with the figure reaching 77% in China (范长煜, 邓韵雪, 2022). However, survey results on AI' s substitution effect show that the actual rate of "machine replacement" that has occurred is only 0.18%–0.34% in the U.S. (Acemoglu & Restrepo, 2020) and approximately 2.5% in China (程虹 et al., 2018). Other studies have found that AI introduction in Spanish manufacturing created 10% new positions overall (Koch et al., 2021), while AI adoption in non-manufacturing sectors resulted in a 0.2% decrease in employment and a 0.37% decline in wage levels (Acemoglu & Restrepo, 2020).

These discrepancies reflect the uncertainty in public understanding of "AI unemployment" and suggest that attitudes toward AI unemployment and AI itself may be shaped by relevant information (Blanas et al., 2019; Dauth et al., 2018). For most people, media reports on the industries affected by AI unemployment and the scale and probability of its occurrence serve as the primary source of information (Morikawa, 2017). Information framing effects may exist in this process, whereby different presentations of the same event, selectively highlighting certain features, elicit different responses (Levin et al., 1998). Therefore, even identical content about AI unemployment, using the same objective data, may provoke vastly different public reactions when placed in specific information frames, particularly regarding "AI threat" —the discomfort, anxiety, and fear arising from AI (Gray et al., 2024; McFarland, 2014; Złotowski et al., 2017).

Like general threat perception, AI threat perception reflects psychological perception rather than being based on sufficient objective facts (Gray et al., 2024), which explains why AI threat is already widespread across cultures and regions despite the currently unclear actual impact of AI on employment (Lingmont & Alexiou, 2020; Yam et al., 2023). For example, a 2015 survey found that nearly 30% of U.S. respondents feared being replaced by AI (McClure, 2018), while a 2019 domestic survey showed that approximately 46% of respondents expressed varying degrees of concern (李佩, 2019). Although AI threat formation is not entirely rational, it influences how and to what extent people adopt AI technology and affects personal career planning decisions and behaviors (Dekker et al., 2017; McClure, 2018).

This paper examines whether the process of learning about AI unemployment is influenced by information framing, whether such framing effects manifest as differences in AI threat perception, and how these differences subsequently affect attitudes toward AI technology and personal employment decision-making. Additionally, we investigate whether this information framing effect is influenced by specific individual characteristics. Through seven primary experiments, this study examines the effects and mechanisms of information framing regarding "AI unemployment" on AI threat perception and provides practical insights for AI governance issues related to information dissemination.

1.1 Factor-Based and Probability-Based Information Framing Effects

People complete decisions and behaviors through information conveyed by objects (Betsch et al., 2015; Brewer et al., 2004; Diener & Richardson, 2007). However, human cognitive processing determines that only partial information can be acquired, leading to potential differences in understanding the same object—this possibility forms the basis for information framing effects (Anderson, 1965). Information framing effect refers to the phenomenon where different information presentation methods lead individuals to make different choices; that is, a decision problem can be described in two linguistically different but substantively equivalent ways, resulting in significantly different choice outcomes (Tversky & Kahneman, 1981). Due to different highlighted information, information framing effects have various classifications, including valence frames that reflect feature information (e.g., pros and cons of an event; Wong, 2020) and numerical frames that reflect quantitative information (e.g., probability of an event; Chernev & Gal, 2010).

Previous research has primarily focused on gain-loss valence frames (Levin et al., 1998). According to prospect theory, gain-loss frames cause different perceptions of a target by emphasizing its positive or negative features, triggering favorable or unfavorable associations in memory (Kareklas et al., 2012). A classic gain-loss framing effect is the "beef problem": when a hamburger is described as "containing 25% fat" versus "containing 75% lean meat," people perceive the former as less healthy, show lower choice preference, and weaker purchase intention (Levin et al., 1998; 文桂婵 et al., 2011). Kim and Song (2022) investigated people's reactions to AI under gain-loss frames, describing an AI that successfully completes 8 out of 10 tasks and fails 2 as either "AI with 80%

success rate" or "AI with 20% error rate." Influenced by the information frame, people placed greater trust in the "80% success rate AI."

Although valence frames are widely applied, they are uncommon for describing "AI unemployment." On one hand, the term "unemployment" easily triggers unfavorable associations; on the other hand, AI unemployment often involves "numerical" and "categorical" information that is not easily assigned valence. For example, "51% of positions will be replaced" (Chui et al., 2016) or "Securities, law, insurance, and accounting are high-risk occupations for AI replacement" (Felten et al., 2021). Such presentations are closer to factor-probability numerical frames than to gain-loss frames emphasizing positive versus negative features (Karmarkar & Kupor, 2023).

A factor frame emphasizes several manifestations of a target event (Tversky & Koehler, 1994). For example, compared to the general statement "AI will replace 77% of human jobs in the future,"a factor frame would state: "AI will replace 77% of human jobs in the future, including service, manufacturing, and agriculture."A probability frame highlights the probability details of each manifestation (Baron, 2014): "AI will replace 77% of human jobs in the future, including service (24%), manufacturing (26%), and agriculture (27%)." Research in persuasion has shown that factor frames elevate risk assessment levels; when people learn about several types of traffic accidents, the frequency of seatbelt use increases (Brewer et al., 2004). Karmarkar and Kupor (2023) found that describing an infectious disease using a factor frame increased preventive behaviors, while using a probability frame for the same disease produced opposite results.

Factor-probability frames cause behavioral differences because they alter people' s subjective judgments of event likelihood (Morewedge & Kahneman, 2010). Under factor frames, various manifestations of an event are treated as additional evidence proving the target' s existence, and cumulative evidence leads people to judge its likelihood as high (Redelmeier et al., 1995; Rottenstreich & Tversky, 1997). Probability frames, by emphasizing probability details of each manifestation, lead people to process information through averaging operations, with the result of averaging sub-probabilities being lower perceived likelihood (Anderson, 1965; Chernev & Gal, 2010; Lynch, 1979; Weaver & Garcia, 2018). In other words, factor frames activate an "addition" calculation process, while probability frames activate an "averaging" calculation process, leading individuals to make different judgments about event likelihood (Karmarkar & Kupor, 2023).

Therefore, when learning about AI unemployment, does exposure to factor versus probability frames lead to differences in judging AI unemployment likelihood, and do these differences trigger varying levels of AI threat? This is the primary question this study seeks to answer.

1.2 AI Threat and Its Behavioral Consequences

AI threat represents a specific form of psychological threat (Gray et al., 2024; Złotowski et al., 2017). According to social identity theory, people categorize themselves as belonging to the human group, in contrast to AI as belonging to a non-human group. Group members have motives to protect their group' s interests and distinctiveness. When a group' s interests or distinctiveness are violated by an outgroup, group conflict arises and creates threat perception (Brewer, 2001; Jackson, 1993; Tajfel & Turner, 1986). Following Riek et al.' s (2006) classification, threats are divided into realistic threat and symbolic threat: realistic threat endangers a group' s survival, economic interests, or political rights (Campbell, 1966), while symbolic threat damages a group' s identity characteristics or moral values (Stephan et al., 2015).

Złotowski et al. (2017) applied the same classification to AI threat. AI realistic threat specifically refers to AI' s potential to cause unsafe consequences for humans and compete for existing resources, such as compressing human living space and encroaching on human economic interests. AI symbolic threat refers to AI' s imitation of human intelligence blurring the boundary between humans and machines, such as AI demonstrating creativity comparable to humans or intervening in moral decision-making and religious affairs (Samuel, 2020; Vincent, 2022). Multiple studies have shown that AI threat perception is universal across regions, cultures, and ideologies (Dang & Liu, 2021; Gnambs & Appel, 2019; Yam et al., 2023).

Increased AI threat perception typically leads to deteriorated human-machine relationships. Although some surveys have found that AI threat increases employees' willingness to train their skills (Innocenti & Golin, 2022), the purpose is to avoid being replaced by AI (Di Tella & Rodrik, 2020). More evidence points to negative outcomes, such as technophobia among individuals (McClure, 2018), decreased AI usage intention (Huang et al., 2021), distrust of AI (Lin et al., 2022), and opposition to using tax revenue for robot research and development (Yogeeswaran et al., 2016). In workplace contexts, AI threat not only intensifies employees' perceived unemployment risk but also alters their evaluation criteria for jobs, potentially leading to suboptimal decisions in career choices. For example, job seekers prefer positions emphasizing interpersonal interaction and creativity (Rotman, 2013), while jobs with low skill requirements and high task homogeneity are less likely to enter individuals' career plans (Jørgensen & Navrbjerg, 2001).

It should be noted that numerous achievements in medical and economic fields have demonstrated that human-AI collaboration outperforms both human-only cooperation and fully automated operations. This 良性 cooperation requires people to place sufficient trust in AI (Tang et al., 2022; Waardenburg et al., 2022); however, AI threat undermines the foundation of trust (Alaiad & Zhou, 2013; Correia et al., 2016; Paetzel et al., 2020). If factor and probability frames create different levels of AI threat, can lower AI threat perception lead to greater support for AI research and development policies and increase individuals' willingness to choose (or recommend) jobs requiring frequent AI interaction? These are also questions this study seeks to explore.

1.3 The Influence of Ambiguity Tolerance on Information Framing Effects

Information framing effects reflect how information guides people, and the strength of these effects is also associated with individual characteristics (Lauriola et al., 2005). Big Five personality traits—extraversion, conscientiousness, and neuroticism—all influence the degree to which individuals are affected by information frames and the resulting decision preferences (Levin et al., 2002; Rusting & Larsen, 1998). Individual differences in numeracy or understanding of mathematics and probability also manifest as differences in information framing effects; individuals with strong numeracy skills are better able to identify valence information in numbers than those with weak skills and are thus less influenced by information frames (Peters et al., 2006; Stanovich & West, 1998). Additionally, personal experience with target events affects cognitive processing in decision-making; individuals more familiar with described objects are less susceptible to information frames, while those lacking relevant experience often exhibit framing effects due to high uncertainty in decision situations (Hoch & Ha, 1986). Finally, cognitive closure need in cognitive style also influences susceptibility to framing; individuals with high cognitive closure need tend to make quick decisions and process information heuristically, making them more vulnerable to information frames (Kruglanski, 1989).

In the specific context of AI unemployment, there is considerable uncertainty regarding unemployment scale, intensity, and development trends, making information received by individuals "ambiguous" (Złotowski et al., 2017). Simultaneously, in workplace practice, individuals cannot exhaust all occupational information before making decisions, making AI threat perception judgments "timely" (Xu & Tracey, 2014). We therefore propose that information framing effects based on AI unemployment may also be related to ambiguity tolerance as a personal trait.

Ambiguity tolerance is the degree to which individuals accept ambiguous situations, reflecting a trait tendency to tolerate ambiguous, uncertain information that is novel, inconsistent, and complex (Furnham & Ribchester, 1995), and is associated with the urgency of resolving uncertainty intrusions (Webster & Kruglanski, 1994). Individuals with low ambiguity tolerance experience stress when facing incomplete information and respond quickly to avoid ambiguous stimuli, while those with high ambiguity tolerance perceive such situations as interesting, accepting complex and inconsistent information (Furnham & Ribchester, 1995). When describing "AI unemployment" with different information frames, ordering them by amount of information (and thus ambiguity) from most to least ambiguous yields: general statement (AI will replace 77% of human jobs in the future), factor frame (AI will replace 77% of human jobs in the future), and probability frame (AI will replace 77% of human jobs in the future, including service (24%), manufacturing (26%), and agriculture (27%)). Due to characteristics of individuals with low ambiguity tolerance—susceptibility to heuristic processing, tendency to process information in extreme ways in uncertain environments, and excessive anxiety about the future (Dugas et al., 1998; Grenier et al., 2005)—they may show similar reactions to all three frames. In contrast, individuals with high ambiguity tolerance, who exhibit more self-exploration and environmental exploration behaviors and have higher career decision-making efficacy (Xu & Tracey, 2015), may be more susceptible to information frames due to their detailed processing of uncertain information. We hypothesize that information framing effects in learning about AI unemployment exist primarily among individuals with high ambiguity tolerance.

1.4 Research Overview

In summary, this study investigates the effect of factor-probability frames on AI threat perception through seven experiments. Experiment 1 finds that people exposed to probability frames (versus factor frames) perceive lower AI threat when learning about AI unemployment. Experiment 2 examines the mediating mechanism of likelihood perception, showing that probability frames lead people to judge AI unemployment as less likely, thereby reducing AI threat. Experiment 3 excludes the influence of specific probability values, replicating results from Experiments 1 and 2. Experiment 4 further tests the probability framing effect, demonstrating that even when informed of larger predicted AI unemployment scales, people still perceive lower AI threat under probability frames. Experiment 5 tests the moderating role of ambiguity tolerance, showing that probability frames reduce AI threat primarily among individuals with high ambiguity tolerance. Experiments 6 and 7 further explore the framing effect' s impact on subsequent behaviors, revealing that probability frame influence leads to greater support for AI technology R&D policies and stronger willingness to recommend jobs requiring frequent AI interaction.

Experiment 1

Experiment 1 examines the effect of information frames on AI threat perception. Using a single-factor three-level between-subjects design with information frame type as the independent variable, the dependent variables are AI threat perception and judgments about the likelihood of large-scale AI unemployment. The study investigates whether people exposed to probability frames perceive lower likelihood of large-scale AI unemployment and lower AI threat compared to general descriptions and factor frames.

2.1 Participants

A priori analysis using G*Power 3.1 (Faul et al., 2007) was conducted with effect size f = 0.2, significance level $\alpha = 0.05$, and statistical power = 0.9, yielding a required total sample size of 322. Participants were recruited online through the Credamo platform. The final sample consisted of N = 322 participants (136 male, 186 female), aged 18-67 years (Mage = 32.16, SDage = 10.28). Participants were randomly assigned to three experimental conditions: general condition (N = 111), factor condition (N = 106), and probability condition (N = 105), and received small cash compensation.

2.2 Procedure

All participants first passed attention checks to ensure they understood job classification content and that China' s job classifications are similar to most other countries. The attention check questions were: "Classifying human work into logistics, manufacturing, installation and maintenance, construction and metallurgy, agriculture, office administration, sales, service, healthcare, education and arts, computer, and financial management is a universal standard worldwide, and our country is no exception. To confirm you have read this information, please answer: Is China' s industry classification different from most countries?" and "For most countries, agriculture, manufacturing, and service are the most common job types, and our country is no exception. To confirm you have read this information, please answer: In our country, are agriculture, manufacturing, and service as common as in most countries?"

After passing attention checks, all participants viewed a fictional forecast about future AI unemployment: "It is projected that by 2033, AI will replace 58% of human jobs." This figure was selected for two reasons: first, following Karmarkar and Kupor's (2023) research methodology; second, this value falls between actual Chinese and U.S. estimates of AI unemployment scale, making it more credible to participants (U.S. = 51%, China = 77%; Chui et al., 2016; 范长煜, 邓韵雪, 2022).

In the general condition, the supplementary explanation read: "Specifically: 58% of people' s jobs will be replaced by AI."

In the factor condition, the supplementary explanation read: "Specifically: Jobs replaced by AI will come from logistics; jobs replaced by AI will come from manufacturing; jobs replaced by AI will come from education and arts; jobs replaced by AI will come from office administration; jobs replaced by AI will come from sales; jobs replaced by AI will come from financial management; additionally, jobs replaced by AI will also come from other industries."

In the probability condition, the supplementary explanation read: "Specifically: About 8% of jobs replaced by AI will come from logistics; about 7% from manufacturing; about 9% from education and arts; about 8% from office administration; about 9% from sales; about 7% from financial management; additionally, about 10% of jobs replaced by AI will come from other industries."

After reading the materials, participants judged the likelihood of AI unemployment occurring on a scale from 0 (completely impossible) to 100 (completely possible). They then completed the AI threat perception measure using a 7-point Likert scale with 10 items (Cronbach' s $\alpha = 0.93$). Sample items include: "In the long run, AI technology poses a direct threat to human safety and well-being" ; "The increasing prevalence of AI technology in daily life poses a threat to human safety" ; "Recent technological advances challenge the essence of humanity" (Złotowski et al., 2017). Finally, all participants reported their gender and age.

2.3 Results

ANOVA with information frame as the independent variable and perceived likelihood and AI threat as dependent variables revealed a significant overall effect of information frame on AI threat perception, $F(2, 319) = 5.43$, $p = 0.005$, $p^2 = 0.03$, 95% CI [0.00, 0.08]. Post-hoc Bonferroni tests showed that participants in the probability condition perceived lower AI threat than those in the single-factor condition ($p = 0.023$) and multi-factor condition ($p = 0.001$). No significant difference in AI threat perception existed between the single-factor and multi-factor conditions ($p = 0.333$).

The overall effect of information frame on likelihood perception was also significant, $F(2, 319) = 11.05$, $p < 0.001$, $p^2 = 0.07$, 95% CI [0.02, 0.12]. Post-hoc Bonferroni tests indicated that participants in the multi-probability condition perceived lower likelihood of AI replacing human jobs than those in the single-factor condition ($p < 0.001$) and multi-factor condition ($p < 0.001$). No significant difference in likelihood perception existed between the single-factor and multi-factor conditions ($p = 0.396$) (see Table 1). Controlling for gender and age in this and subsequent experiments did not change the significance or direction of results.

Table 1 Mean values and standard deviations of threat and likelihood across different information frame conditions

Condition	Likelihood Perception	AI Threat
Multi-probability	M (SD)	M (SD)
Single-factor	M (SD)	M (SD)
Multi-factor	M (SD)	M (SD)

2.4 Discussion

Experiment 1 tested differences in AI threat and AI unemployment likelihood caused by information frames. Results showed that when people saw the scale prediction of AI unemployment (58%), compared to general descriptions and factor frame descriptions, those influenced by the probability frame—even though the sum of specific probabilities across industries (58%) matched the prediction—perceived lower AI threat and lower likelihood of AI unemployment occurring, thus supporting Hypothesis 1.

Since the general and factor conditions showed no significant differences in AI threat or likelihood perception, the framing effect primarily manifested in the probability condition. Compared to the general condition, the factor and probability conditions contained more information, so subsequent experiments focused comparisons between the factor and probability conditions. These results extend previous findings on factor-probability numerical framing effects (Karmarkar & Kupor, 2023), demonstrating that information frames affect both likelihood perception and AI threat perception during learning about AI unemployment.

Experiment 2: The Mediating Role of Likelihood Perception

Since Experiment 1 showed that probability frame influence leads people to judge AI unemployment as less likely and perceive lower AI threat, Experiment 2 examines whether differences in AI threat caused by information frames originate from differences in perceived likelihood—that is, whether lower subjective likelihood of job replacement by AI leads to lower AI threat perception.

3.1 Participants

Experiment 2 used a single-factor two-level between-subjects design. A priori analysis with G*Power 3.1 (Faul et al., 2007) was conducted with effect size f = 0.2, significance level $\alpha = 0.05$, and statistical power = 0.9, yielding a required total sample size of 266. Participants were recruited online through the Credamo platform. The final sample consisted of N = 266 participants (114 male, 152 female), aged 18-67 years (Mage = 33.18, SDage = 11.57). Participants were randomly assigned to two experimental conditions: factor condition (N = 135) and probability condition (N = 131).

3.2 Procedure

Consistent with Experiment 1, participants first passed attention checks. After viewing predictions about future AI-induced unemployment scale, participants read supplementary explanations in either the factor or probability condition. Likelihood perception and AI threat measures were identical to Experiment 1 (Cronbach' s $\alpha = 0.94$). Considering that participants' views and knowledge about algorithms might differ and affect AI threat perception, participants also reported their algorithm familiarity ("How familiar are you with algorithms?"), knowledge ("Compared to the average Chinese person, how much do you think you know about algorithms?"), and liking ("How much do you like algorithms?") (Bartneck et al., 2009; Leo & Huh, 2020; 许丽颖 et al., 2021). Finally, all participants reported their gender and age.

3.3 Results

ANOVA on AI threat across the two information frame conditions showed that participants in the probability condition (M = 4.27, SD = 1.38) perceived lower

AI threat than those in the factor condition ($M = 4.86$, $SD = 1.33$), $p < 0.001$. This result replicates Hypothesis 1.

Bootstrap analysis (PROCESS Model 4; Hayes, 2013) with information frame type as the independent variable (factor condition coded as 0, probability condition as 1), perceived likelihood of AI unemployment as the mediator, and AI threat as the dependent variable (5,000 samples, 95% confidence interval) revealed a significant mediating effect of likelihood perception (indirect effect $b = -0.27$, $SE = 0.07$, 95% CI = [-0.40, -0.15]). As shown in Figure 1 [Figure 1: see original paper], compared to the factor condition, people influenced by the probability frame judged AI unemployment as less likely and consequently perceived lower AI threat, supporting the hypothesis that likelihood perception mediates the relationship between information frame and AI threat.

Furthermore, after controlling for participants' AI familiarity, the mediating effect of AI unemployment likelihood perception between information frame and AI threat remained significant (indirect effect $b = -0.25$, $SE = 0.06$, 95% CI = [-0.38, -0.14]).

Figure 1. Mediating role of perceived likelihood of "AI unemployment" (Information frame: 0 = factor frame, 1 = probability frame; * $p < .05$, ** $p < .01$, *** $p < .001$)

3.4 Discussion

Experiment 2 validated the mediating role of perceived likelihood through mediation analysis. Results showed that compared to the factor frame, people influenced by the probability frame judged AI unemployment as less likely, leading to lower AI threat perception. This finding further demonstrates the important influence of information frames on subjective likelihood perception (Eagly & Chaiken, 1993). In subsequent experiments, we will modify experimental conditions to examine the stability of the likelihood mediation effect.

Experiment 3

Experiment 3 serves two purposes. First, it aims to exclude the influence of probability values on subjective likelihood. In previous experiments, although the sum of probabilities across seven industries in the probability condition was 58%, the specific AI unemployment scale for each industry ranged from 7% to 10%. One alternative explanation is that the low probability values for each industry led people to judge AI unemployment as less likely. Therefore, we adjusted experimental materials to exclude this alternative hypothesis. Second, Experiment 3 reintroduces measurement of subjective likelihood of AI unemployment to continue testing the mediating role of likelihood perception in the effect of information frame on AI threat.

4.1 Participants

Experiment 3 used a single-factor two-level between-subjects design. A priori analysis with G*Power 3.1 (Faul et al., 2007) was conducted with effect size f = 0.2, significance level $\alpha = 0.05$, and statistical power = 0.9, yielding a required total sample size of 266. Participants were recruited online through the Credamo platform. The final sample consisted of N = 266 participants (108 male, 158 female), aged 19-57 years (Mage = 29.66, SDage = 7.59). Participants were randomly assigned to two experimental conditions: factor condition (N = 133) and probability condition (N = 133).

4.2 Procedure

After passing attention checks to ensure understanding of basic job types, all participants viewed a prediction about future domestic AI unemployment scale: "It is projected that by 2033, AI will replace 58% of human positions."

Participants in the factor condition saw the supplementary explanation: "Specifically, replaced positions will come from the service industry; replaced positions will also come from industries other than service."

Participants in the probability condition saw: "Specifically, 28% of replaced positions will come from the service industry; 30% of replaced positions will come from industries other than service."

Subsequently, participants completed the same AI unemployment likelihood judgment and AI threat measure as in previous experiments (Cronbach' s α = 0.92). Finally, all participants reported their gender and age.

4.3 Results

ANOVA on AI threat perception across the two information frame conditions showed that participants in the probability condition (M = 4.24, SD = 1.23) perceived lower AI threat than those in the factor condition (M = 4.71, SD = 1.16), $p < 0.001$. This result replicates the hypothesis that information frame affects AI threat.

Bootstrap analysis (PROCESS Model 4; Hayes, 2013) with information frame type as the independent variable (factor condition coded as 0, probability condition as 1), perceived likelihood of AI unemployment as the mediator, and AI threat as the dependent variable (5,000 samples, 95% confidence interval) revealed a significant mediating effect of likelihood perception (indirect effect b = -0.15, SE = 0.06, 95% CI = [-0.27, -0.05]). Compared to the factor condition, people influenced by the probability frame judged AI unemployment as less likely and consequently perceived lower AI threat, replicating the hypothesis that likelihood perception mediates the relationship between information frame and AI threat.

4.4 Discussion

Combined results from Experiment 3 again validated the effect of information frame on AI threat perception. Notably, when the supplementary explanation of AI unemployment was reduced from seven industries to two industries, and the unemployment probability for each industry increased from 7%-10% to 28% and 30%, people influenced by the probability frame still perceived lower AI threat. Additionally, Experiment 3 showed that the mediating role of likelihood perception remained: participants in the probability condition judged AI unemployment as less likely subjectively and consequently perceived lower AI threat.

Experiment 4

Experiment 4 aims to further verify the robustness of information frame effects on AI threat. Specifically, we seek to replicate Experiment 3' s results and advance the hypothesis: compared to the factor frame condition, participants influenced by the probability frame will still form judgments that AI unemployment is less likely and perceive lower AI threat even when reading larger predicted AI unemployment scales.

5.1 Participants

Experiment 4 used a single-factor two-level between-subjects design. A priori analysis with G*Power 3.1 (Faul et al., 2007) was conducted with effect size f = 0.2, significance level $\alpha = 0.05$, and statistical power = 0.9, yielding a required total sample size of 266. Participants were recruited online through the Credamo platform. The final sample consisted of N = 268 participants (117 male, 151 female), aged 18-59 years (Mage = 30.29, SDage = 8.21). Participants were randomly assigned to two experimental conditions: factor condition (N = 134) and probability condition (N = 134).

5.2 Procedure

Unlike previous experiments, after passing attention checks, participants in the factor condition saw the prediction: "It is projected that by 2033, AI will replace 58% of human positions." Participants in the probability condition saw: "It is projected that by 2033, AI will replace 59% of human positions." The predicted scales differed between the two groups.

Subsequently, the factor condition saw: "Specifically, replaced positions will come from the service industry; replaced positions will also come from industries other than service." The probability condition saw: "Specifically, 29% of replaced positions will come from the service industry; 30% of replaced positions will come from industries other than service."

Participants then completed AI unemployment likelihood judgments and AI threat measures (Cronbach' s $\alpha = 0.92$). Finally, all participants reported their gender and age.

5.3 Results

ANOVA on AI threat perception showed that participants in the probability condition (M = 4.19, SD = 1.21) perceived lower AI threat than those in the factor condition (M = 4.65, SD = 1.24), p = 0.002. ANOVA on likelihood judgments showed that participants in the probability condition (M = 56.82, SD = 15.45) judged AI unemployment as less likely than those in the factor condition (M = 61.96, SD = 12.35), p = 0.003. These results again support the hypothesis that information frame affects both AI threat and likelihood perception.

Bootstrap analysis (PROCESS Model 4; Hayes, 2013) with information frame type as the independent variable (factor condition coded as 0, probability condition as 1), perceived likelihood as the mediator, and AI threat as the dependent variable (5,000 samples, 95% confidence interval) revealed a significant mediating effect of likelihood perception (indirect effect b = -0.08, SE = 0.04, 95% CI = [-0.17, -0.02]), again supporting the hypothesis that likelihood perception mediates the relationship between information frame and AI threat.

5.4 Discussion

Experiment 4 again tested the effect of information frame on AI threat and replicated Experiment 3' s results: when AI unemployment probabilities in the probability condition increased from 7%-10% to 28%-30%, participants still perceived lower AI threat. More importantly, Experiment 4 found that even when the probability condition saw a larger AI unemployment scale (59%) than the factor condition (58%), they still judged AI unemployment as less likely and perceived lower AI threat. Experiment 4 also revalidated the mediating role of likelihood perception: participants in the probability condition subjectively judged AI unemployment as less likely and consequently perceived lower AI threat. Overall, Experiments 1-4 established the robust relationship among information frame, AI threat, and likelihood perception. Subsequent experiments will explore boundary conditions for the effect of information frame on AI threat.

Experiment 5: The Moderating Role of Ambiguity Tolerance

Experiment 5 investigates whether ambiguity tolerance moderates the relationship between information frame and AI threat. Theoretically, individuals with low ambiguity tolerance are susceptible to heuristic processing, struggle with comprehensive analysis, and have difficulty making prudent judgments. The question is whether information frame effects on AI threat occur only among individuals with high ambiguity tolerance.

6.1 Participants

Experiment 5 used a single-factor two-level between-subjects design. A priori analysis with G*Power 3.1 (Faul et al., 2007) was conducted with effect size f = 0.2, significance level $\alpha = 0.05$, and statistical power = 0.9, yielding a required total sample size of 266. Participants were recruited online through the Credamo platform. The final sample consisted of N = 264 participants (93 male, 171 female), aged 19-51 years (Mage = 28.80, SDage = 7.00). Participants were randomly assigned to two experimental conditions: factor condition (N = 138) and probability condition (N = 126).

6.2 Procedure

Consistent with Experiments 2 and 5, after passing attention checks, all participants viewed predictions about future domestic AI unemployment. The factor and probability conditions then saw different supplementary explanations: the factor condition' s materials indicated AI unemployment would occur across seven industries; the probability condition' s materials included both the seven industries and corresponding probability information for each. Participants then completed AI unemployment likelihood judgments and AI threat measures (Cronbach' s $\alpha = 0.91$). Subsequently, we measured ambiguity tolerance using the Chinese version of the Multiple Stimulus Types Ambiguity Tolerance Scale-II (MSTAT-II; McLain, 2009). This 13-item scale includes four dimensions: novelty (e.g., "I prefer familiar environments to new ones"), complexity (e.g., "I enjoy solving problems with complex information and unclear clues"), insolubility (e.g., "I am unwilling to solve problems requiring analysis from different perspectives"), and uncertainty (e.g., "I find it difficult to make choices when outcomes are uncertain") (Cronbach' s $\alpha = 0.87$). Finally, all participants reported their gender and age.

6.3 Results

ANOVA on AI threat perception showed that participants in the probability condition (M = 4.21, SD = 1.16) perceived lower AI threat than those in the factor condition (M = 4.60, SD = 0.99), p = 0.004. ANOVA on likelihood judgments showed that participants in the probability condition (M = 56.42, SD = 18.15) judged AI unemployment as less likely than those in the factor condition (M = 61.25, SD = 15.66), p = 0.021.

Bootstrap analysis (PROCESS Model 4; Hayes, 2013) with information frame type as the independent variable (factor condition coded as 0, probability condition as 1), perceived likelihood as the mediator, and AI threat as the dependent variable (5,000 samples, 95% confidence interval) revealed a significant mediating effect of likelihood perception (indirect effect b = -0.12, SE = 0.05, 95% CI = [-0.23, -0.02]).

Regression analysis on AI threat examined the interaction between information frame (factor condition coded as 0, probability condition as 1) and ambiguity tolerance. Results showed a significant interaction between information frame and ambiguity tolerance on AI threat (b = -0.44, SE = 0.20, t = -2.19, p = 0.029). AI threat was significantly lower in the probability condition than the factor condition (b = -0.39, SE = 0.12, t = -3.15, p = 0.002). Ambiguity tolerance significantly affected AI threat (b = -0.65, SE = 0.10, t = -6.51, p < 0.001). The model' s adjusted $R^2 = 0.18$, $\Delta R^2 = 0.02$, F = 4.80, p = 0.03. The interaction is shown in Figure 2 [Figure 2: see original paper]. Simple slope analysis indicated that for individuals with low ambiguity tolerance, information frame did not significantly affect AI threat (b = -0.12, SE = 0.17, t = -0.67, p = 0.50). For individuals with high ambiguity tolerance, information frame significantly affected AI threat (b = -0.66, SE = 0.17, t = -3.78, p < 0.001).

Figure 2. Moderating role of ambiguity tolerance

6.4 Discussion

Experiment 5 further explored boundary conditions for information frame effects on AI threat, finding that ambiguity tolerance moderates this relationship. Among individuals with high ambiguity tolerance, those influenced by the probability frame perceived lower AI threat than those in the factor condition; among individuals with low ambiguity tolerance, no significant difference in AI threat existed between the two frame conditions. Experiment 5 also revalidated the mediating role of likelihood perception: the probability frame reduces judgments of AI unemployment likelihood, thereby leading to lower AI threat. In subsequent experiments, we will extend the impact of information frame on AI threat to examine resulting changes in attitudes and behaviors.

Experiment 6: Information Framing Effects on Support for AI Research and Development

Experiment 6 investigates behavioral changes following information frame effects on AI threat. Złotowski et al. (2017) found that higher perceived AI threat reduces support for AI R&D-related policies. We therefore test whether information frames also cause differences in AI R&D policy support through their impact on AI threat.

7.1 Participants

Experiment 6 used a 2 (information frame: probability vs. factor) $\times$ 2 (industry type: industries mentioned in materials vs. industries not mentioned) mixed design (information frame as between-subjects factor, industry type as within-subjects factor). A priori analysis with G*Power 3.1 (Faul et al., 2007) was conducted with effect size f = 0.2, significance level $\alpha = 0.05$, and statistical power = 0.9, yielding a required total sample size of 266. Participants were recruited online through the Credamo platform. The final sample consisted of N = 261 participants (110 male, 151 female), aged 18–58 years (Mage =

29.17, SDage = 7.85). Participants were randomly assigned to two experimental conditions: factor condition (N = 129) and probability condition (N = 132).

7.2 Procedure

Consistent with Experiments 2 and 5, after passing attention checks, participants viewed AI unemployment predictions. Factor and probability condition participants read different supplementary explanations and completed AI threat measures (Cronbach' s $\alpha = 0.87$). We then collected participants' support for AI R&D policies using a 5-item scale (e.g., "To what extent do you support AI research?" "To what extent do you support national funding for AI research?") (Złotowski et al., 2017).

Additionally, to examine whether information frame effects on AI threat and policy support were limited to industries mentioned in experimental materials, we asked participants two questions: "To what extent do you support advancing AI research in logistics, law, investment, administration, insurance, and other industries mentioned earlier?" and "To what extent do you support advancing AI research in construction, handicrafts, catering, arts, textiles, and other industries not mentioned earlier?" Finally, all participants reported their gender and age.

7.3 Results

ANOVA on AI threat perception, AI R&D policy support, support for AI R&D in mentioned industries, and support for AI R&D in unmentioned industries revealed that participants in the probability condition (M = 3.95, SD = 0.98) perceived lower AI threat than those in the factor condition (M = 4.59, SD = 0.87), $p < 0.001$. Probability condition participants (M = 5.25, SD = 1.01) showed higher AI R&D policy support than factor condition participants (M = 4.68, SD = 1.23), $p < 0.001$. For the seven mentioned industries, probability condition participants (M = 5.03, SD = 1.15) showed higher support for AI R&D than factor condition participants (M = 4.61, SD = 1.23), $p = 0.005$. For the seven unmentioned industries, probability condition participants (M = 4.80, SD = 1.42) also showed higher support than factor condition participants (M = 4.36, SD = 1.54), $p = 0.018$.

Bootstrap analysis (PROCESS Model 4; Hayes, 2013) with information frame type as the independent variable (factor condition coded as 0, probability condition as 1), AI threat as the mediator, and AI R&D policy support as the dependent variable (5,000 samples, 95% confidence interval) revealed a significant mediating effect of AI threat (indirect effect b = 0.13, SE = 0.06, 95% CI = [0.03, 0.26]), as shown in Figure 3 [Figure 3: see original paper].

Similar analysis with support for AI R&D in mentioned industries as the dependent variable showed a significant mediating effect of AI threat (indirect effect b = 0.14, SE = 0.06, 95% CI = [0.03, 0.27]).

Analysis with support for AI R&D in unmentioned industries as the dependent variable showed a non-significant mediating effect of AI threat (indirect effect b = 0.06, SE = 0.07, 95% CI = [-0.08, 0.21]).

Figure 3. Mediating role of perceived AI threat (Information frame: 0 = factor frame, 1 = probability frame; * $p < .05$, ** $p < .01$, *** $p < .001$)

7.4 Discussion

Building on the relationship between information frame and AI threat, Experiment 6 examined resulting attitudinal differences. Results showed that compared to those influenced by the factor frame, people influenced by the probability frame demonstrated greater support for AI R&D policies. Importantly, this supportive attitude toward AI R&D policies was limited to industries mentioned in supplementary materials. We also found that information frame effects on policy support were mediated by AI threat perception: the probability frame reduced AI threat, which in turn increased support for AI R&D policies (across industries). Experiment 6 extended the impact of information frame from individual threat perception to policy attitudes. In the final experiment, we further explore whether subsequent effects of information frame also manifest in real-world scenarios.

Experiment 7

Experiment 7 has four objectives. First, it examines whether describing AI unemployment with different information frames in a job advice-giving scenario changes occupational recommendation willingness. Second, since Experiment 6 found that information frame effects on AI R&D policy support spread to unmentioned industries, Experiment 7 tests whether similar spillover effects exist for job recommendations. Third, considering that different occupations carry varying risks of AI replacement, Experiment 7 examines the combined effects of information frame and occupational replacement risk on job recommendations. Finally, we test whether information frame effects on job recommendations are mediated by AI threat.

8.1 Participants

Experiment 7 used a 2 (information frame: probability vs. factor) × 2 (occupational replacement risk: high-risk vs. low-risk) mixed design (information frame as between-subjects factor, occupational replacement risk as within-subjects factor). A priori analysis with G*Power 3.1 (Faul et al., 2007) was conducted with effect size f = 0.2, significance level $\alpha = 0.05$, and statistical power = 0.9, yielding a required total sample size of 266. Participants were recruited online through the Credamo platform. The final sample consisted of N = 260 participants (83 male, 177 female), aged 18-66 years (Mage = 29.64, SDage = 8.49). Participants were randomly assigned to two experimental conditions: factor condition (N = 130) and probability condition (N = 130).

8.2 Procedure

After passing attention checks, all participants read AI unemployment predictions, with factor and probability conditions receiving different supplementary explanations. In a fictional scenario of advising a relative or friend on job seeking, we asked participants about their recommendation levels for different occupations: "Suppose a relative or friend is facing a job search problem and asks for your advice on career direction. Temporarily ignore their professional background, and assume positions are equivalent in workload and compensation. Based on the materials, what advice would you give them about pursuing these occupations? (1 = strongly not recommend; 7 = strongly recommend)."

Occupations for evaluation were drawn from Felten et al.' s (2021) research on occupational AI exposure. Participants viewed ten occupations belonging to two categories: high exposure (administrative clerks, purchasing agents, credit reviewers, insurance sales, intermediaries/consultants) and low exposure (engineering/construction, interior design, cultural promotion, environmental planning, fitness training). After completing occupational recommendations, participants completed AI threat measures (Cronbach' s $\alpha = 0.88$) and reported their gender and age.

8.3 Results

ANOVA on AI threat perception, recommendation for low-AI-exposure occupations, and recommendation for high-AI-exposure occupations showed that probability condition participants (M = 3.93, SD = 1.05) perceived lower AI threat than factor condition participants (M = 4.39, SD = 1.03), $p < 0.001$. For low-AI-exposure occupations, probability condition participants (M = 4.85, SD = 0.87) showed lower recommendation levels than factor condition participants (M = 5.08, SD = 0.77), $p = 0.022$. For high-AI-exposure occupations, probability condition participants (M = 3.70, SD = 0.99) showed higher recommendation levels than factor condition participants (M = 3.17, SD = 0.98), $p < 0.001$.

Further repeated-measures ANOVA revealed a significant interaction between information frame and occupational AI exposure ($F = 24.03$, $p < 0.001$, $p^2 = 0.09$). As shown in the figure, for low-AI-exposure occupations, probability condition participants (M = 4.85, SD = 0.87) showed lower recommendation willingness than factor condition participants (M = 5.08, SD = 0.77, $F = 19.20$, $p < 0.001$, $p^2 = 0.07$). For high-AI-exposure occupations, probability condition participants (M = 3.70, SD = 0.99) showed higher recommendation willingness than factor condition participants (M = 3.17, SD = 0.98, $F = 5.30$, $p = 0.022$, $p^2 = 0.02$), as shown in Figure 4 [Figure 4: see original paper].

Figure 4. Interaction between information frame and AI exposure on occupational recommendation willingness (* p < .05, ** p < .01, *** p < .001)

8.4 Discussion

Experiment 7 explored information frame effects on AI threat and recommendation willingness for occupations with different AI exposure levels in an advice-giving scenario. Results showed that compared to those influenced by the factor frame, people influenced by the probability frame perceived lower AI threat. However, when facing different occupations, information frame effects on recommendation levels showed opposite trends: compared to the factor frame, the probability frame increased recommendation levels for high-AI-exposure occupations while decreasing them for low-AI-exposure occupations. Additionally, AI threat did not significantly mediate this relationship; information frame effects on occupational recommendations were not achieved through perceived AI threat.

General Discussion

This study distinguished two information frames regarding AI unemployment, systematically examined information framing effects on AI threat and employment decisions, and further investigated the roles of judgments about large-scale AI unemployment likelihood and ambiguity tolerance. Findings show that individuals influenced by probability frames experience lower AI threat (Experiments 1–7), demonstrate greater support for AI technology R&D policies (Experiment 6), and show stronger willingness to recommend occupations requiring frequent AI interaction (Experiment 7). Judgments about AI unemployment likelihood mediate the relationship between information frame and AI threat: probability frames lead individuals to judge AI unemployment as less likely, thereby reducing AI threat (Experiments 2–5). Ambiguity tolerance moderates the relationship between information frame and AI threat, with the probability frame' s threat-reduction effect primarily appearing among individuals tolerant of ambiguous information (Experiment 5).

9.1 Information Framing Effects on AI Threat

The main findings demonstrate information framing effects in the process of learning about "AI unemployment," showing that factor and probability numerical frames create different levels of AI threat. According to prospect theory, framing' s essence lies in selecting and emphasizing information, causing people to view problems from different perspectives (Kahneman & Tversky, 1979). Previous research has primarily used gain-loss valence frames, influencing attitudes, decisions, and behaviors toward targets through processing positive versus negative features (Mcelroy & Seta, 2003), finding that gain-loss frames describing AI technology create differences in AI trust (Kim & Song, 2022). However, since public understanding of AI unemployment typically comes from numerical information about whether, when, and on what scale AI will replace human labor, and since "unemployment" easily triggers negative associations, we propose that AI unemployment information may involve factor and probability numerical frames (Acemoglu & Restrepo, 2020; Koch et al., 2021; Chui et al., 2016; Shoss & Ciarlante, 2022).

Building on this, we found that probability frames describing AI unemployment lead to lower AI threat, greater support for AI technology R&D policies, and stronger willingness to recommend jobs requiring frequent AI interaction compared to factor frames. Karmarkar and Kupor (2023) found that presenting several sources of disease transmission increased risk assessment, while presenting probability details for each source decreased risk assessment. Viewing AI threat from a risk assessment perspective (regarding survival resources and identity; Gray et al., 2024; Złotowski et al., 2017), our findings align with previous research and extend the literature on information framing effects.

As human-AI relationships grow more complex with AI advancement, discussions of AI unemployment concern not only the ultimate outcomes of AI' s substitution versus creation effects (Harari, 2017) but also the information people encounter and their reactions (Yam et al., 2023). Uncertainty about AI unemployment reflects the process of understanding things from scratch and from little to much (Blanas et al., 2019; Dauth et al., 2018), where surveys, predictions, reports, and viewpoints about AI unemployment may originate from specific aspects of the overall event (Gray et al., 2024) and trigger different types of information framing effects (Tversky & Kahneman, 1981). This study tested the impact of numerical information frames, particularly on AI threat perception. The implication is that when AI unemployment becomes a public focus, external factors such as the content of media reports and information organization methods should be treated cautiously, as information selection influences attitudes, which in turn affect AI technology adoption.

9.2 Probability-Factor Frames' Influence on Subjective Likelihood Judgments

Gain-loss framing effects cause decision and behavioral differences because gain frames trigger positive associations while loss frames trigger negative associations, with different processing of valence information causing framing effects (Kareklas et al., 2012). In contrast, factor-probability framing effects operate through changes in subjective likelihood: factor frames lead individuals to understand targets through "additive summation," yielding conclusions of higher likelihood, while probability frames lead to understanding through "averaging," yielding lower likelihood conclusions (Karmarkar & Kupor, 2023).

People receive risk-related information in multiple forms from various domains. In unemployment-related contexts, interpreting such information is particularly important. People frequently encounter information series, and their subjective perceptions of risk likelihood often guide decisions about whether to take protective measures (Brewer et al., 2004; Diener & Richardson, 2007; Meadows et al., 1993). Previous research in psychology and behavioral economics has shown multiple biases in risk assessment. In this study, altered subjective judgments about AI unemployment likelihood due to specific information guidance represent a cognitive bias: providing additional probability details about AI unemployment makes people judge it as less likely, thereby changing their decision-making.

It should be noted that Experiment 1 did not find that factor frames increased perceived AI unemployment likelihood compared to general statements. Two explanations are possible: first, in both conditions' materials ("It is projected that by 2033, AI will replace 58% of human positions" ; 龚遥, 彭希哲, 2020; 李磊, 何艳辉, 2019), the single figure of 58% may have created an anchoring effect in participants' likelihood judgments; second, participants had already been exposed to reports about ChatGPT and other large language models, so the factor condition materials were not their only information source for judging AI unemployment likelihood (Kahn, 2023). Beyond this, the effect of probability frames producing lower subjective likelihood judgments than factor frames is stable: this effect persists after controlling for AI familiarity and is unaffected by the number of specific industries involved or the magnitude of predicted scale values.

9.3 The Moderating Role of Ambiguity Tolerance

Ambiguity tolerance is the range variable of individuals'acceptance of ambiguous situations when facing unfamiliar, inconsistent, complex, and uncertain stimuli, reflecting whether individuals treat uncertain situations as extreme and how they respond to uncertainty intrusions (Mclain, 1993). Ambiguity tolerance also determines whether people can accept and make rational decisions when facing difficult-to-verify information (Katsaros & Nicolaidis, 2012). Current theoretical predictions and empirical surveys on AI unemployment contain substantial room for discussion, with these controversies and inconsistent conclusions creating considerable uncertainty (Acemoglu & Restrepo, 2020; Koch et al., 2021; Chui et al., 2016). Therefore, we propose that the process of learning about AI unemployment and attitudes toward it are associated with ambiguity tolerance.

This study found that AI unemployment information framing effects exist among individuals with high ambiguity tolerance. High ambiguity tolerance individuals tend to exhibit more exploratory behaviors. Although they gather more information, make more comprehensive evaluations, and make more rational decisions, they are also more susceptible to information frames (Xu & Tracey, 2014). Conversely, low ambiguity tolerance individuals have more rigid thinking patterns, tend to prematurely select and insist on single solutions in complex situations, refuse to acknowledge that things have both good and bad features, seek certainty, and tend to avoid complex situations (Frenkel-Brunswick, 1949). Low ambiguity tolerance individuals also experience excessive worry about the future, accompanied by more severe anxiety, ultimately leading to more negative career decision outcomes (Buhr & Dugas, 2006; Dugas et al., 1998; Dugas et al., 2001; Keenan, 1978). Under multiple influences, low ambiguity tolerance individuals tend to respond to AI unemployment in single, extreme ways, making information framing effects less likely to manifest (Frenkel-Brunswick, 1949).

9.4 AI Threat Effects in Workplace Contexts

Previous research on AI (unemployment) effects in workplace contexts has yielded rich conclusions, yet exploration of the relationship between "AI unemployment" and individual work remains an area needing more investigation. Previous studies have either discussed macro-level social changes AI unemployment may cause, such as widening income gaps and industry monopolies, creating a dominance relationship where "a minority who control AI dominate a majority who do not" (Acemoglu & Autor, 2011; Lankisch et al., 2017); or examined individual-level effects of AI adoption on career decisions, such as how management relationships affect employee engagement and performance, and how introducing AI in organizational management causes employee 反感 and damages interpersonal foundations, increasing turnover intentions (Chughtai et al., 2015; Lee, 2018); or focused on attitudes toward "unemployment" in the context of AI penetration, such as people being more accepting of job replacement by AI than by humans (Granulo et al., 2019); or concentrated on emotional reactions to AI unemployment, such as unemployment anxiety, fear of reemployment, and changes in self-efficacy and well-being (Gimpelson & Oshchepkov, 2012; Liang & Lee, 2017).

This paper explored the relationship between "AI unemployment" and evaluations of industries and jobs, examining how "AI unemployment" under different information frames affects job evaluations, filling a gap in previous research. Through Experiment 7, we found that probability frame influence leads to more positive evaluations even for jobs requiring frequent AI interaction. Additionally, by comparing support for AI R&D policies across information frames, we found that probability frames increase support for AI R&D policies by reducing AI threat, with the negative predictive effect of AI threat on policy support aligning with previous research (Złotowski et al., 2017).

AI threat originates from AI technology advancement and penetration, triggering a series of reactions that may cause tangible impacts on social development and personal life. When facing the uncertain potential of "AI unemployment," people respond differently. Responses range from China' s approach of "targeting frontier fields like AI to implement forward-looking, strategic national major science and technology projects; cultivating and strengthening emerging digital industries like AI; and upgrading industries like communication equipment, core electronic components, and key software" (人民日报, 2021) to the EU' s development of AI access regulations to limit AI unemployment scale (Sparrow, 2007). Focusing on "AI unemployment" does not deny AI technology' s broad employment potential but aims to predict and mitigate risks based on possible technological developments, ensuring AI' s healthy and sustainable development in society. Revealing information framing effects of "AI unemployment" can clarify external factors such as mass media reporting and information organization methods that change AI threat, reducing the likelihood of people making suboptimal decisions.

9.5 Limitations and Future Directions

This study' s limitations and future directions are as follows. First, different industries and positions have complex interrelationships; workers in specific industries may worry about labor from other industries being displaced by AI and flowing into their own. Experiment 7 did not code participants' industries in detail nor provide finer classifications of industry types and occupational nature beyond AI exposure. Although AI exposure correlates highly with AI replacement, some industries may have low exposure but high replacement potential, such as logistics (Felten et al., 2021). Future research could conduct more detailed analyses.

Second, AI unemployment as a descriptive object carries negative connotations. Although we presented objective probability figures, AI' s replacement of human work inevitably triggers negative associations. Future research could use more neutral descriptions, such as framing AI-human labor relationships as challenges or opportunities, to comprehensively test gain-loss and factor-probability frames.

Third, research shows that beyond ambiguity tolerance, other personality factors like need for cognitive closure may affect information framing effects (Kruglanski, 1989), and some demographic variables affect AI threat perception. For example, compared to younger and higher-income individuals, older adults, lower-income individuals, and ethnic minorities experience more AI threat at work (Ghimire et al., 2020); top-level managers experience lower AI threat than front-line employees in organizational settings (Kolbjørnsrud et al., 2017); and women experience lower AI threat than men (Gallimore et al., 2019). This study did not analyze these factors in detail; future research could incorporate them.

Finally, future research could examine the relationship between information frame and AI trust. AI threat may stem from potential replacement by its functionality (Alaiad & Zhou, 2013; Paetzel et al., 2020) but may also be mitigated by trust in AI (Correia et al., 2016). Whether factor-probability numerical frames directly affect AI trust and whether they affect AI threat through AI trust are worthwhile questions.

Conclusion

This study used factor and probability information frames to describe AI unemployment, yielding the following conclusions: (1) Significant information framing effects exist for AI unemployment, manifesting in AI threat (probability frames reduce AI threat compared to factor frames), attitudes toward AI R&D policies (probability frames increase support compared to factor frames), and personal job recommendation behaviors (probability frames increase recommendation for high-AI-exposure industries compared to factor frames); (2) Factor-probability frames affect AI threat by influencing subjective likelihood judgments (factor frames increase judgments of AI unemployment likelihood, probability frames decrease them); (3) AI unemployment information framing effects primarily appear among individuals with low ambiguity tolerance.

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Note: Figure translations are in progress. See original paper for figures.