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# Mindfulness, creative self-efficacy, and communal-agentic orientation in human–AI decision-making with implications for adaptive AI design

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**Abstract**
Human decision-making is increasingly augmented by artificial intelligence (AI), yet individuals vary in whether they revise their judgments after receiving AI-generated input. We examined how trait mindfulness and creative self-efficacy (CSE), together with communal-agentic personality orientations, relate to decision revision following AI input. Data from 549 UK-based professionals were analysed using binary logistic regression, with revision of the initial budget allocation (change versus no change) as the outcome. The mindfulness × CSE interaction was significant, indicating that the association between mindfulness and decision revision varied by CSE. The pattern was positive at lower CSE and negative at higher CSE, although neither median-split simple slope reached conventional significance. CSE showed no independent main effect. Communal-femininity moderated the association between mindfulness and revision, whereas the hypothesised mindfulness × CSE × communal-femininity interaction was trend-level and is treated as suggestive. Because the outcome captured any revision rather than movement toward the AI recommendation, the findings concern the likelihood of reconsidering an initial decision after AI input, not acceptance of AI advice or improvement in decision quality. These results refine understanding of individual differences in human–AI decision revision and identify testable considerations for adaptive AI design.

## Introduction

Artificial intelligence (AI) systems are increasingly integrated into human decision-making processes across domains such as healthcare, finance, and creative work[1–4]. While AI recommendations can improve decision accuracy and consistency, individuals show substantial variability in whether they accept, modify, or reject such advice[1]. Previous studies have documented *algorithm aversion*[1,5,6], where people tend to prefer human over algorithmic recommendations, even when the latter performs better[7]. However, *algorithm appreciation* i.e. the tendency to favor AI input, emerges when algorithms are perceived as highly accurate[2,8], tasks are objective or high-stakes[9], users lack confidence in their own judgment[10], or when AI outputs are transparent and explainable[11]. These opposing tendencies highlight a fundamental question in human–AI interaction: which psychological characteristics predict whether individuals revise their decisions after AI-generated advice?

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AI systems are not perfectly reliable and may fail in systematic, context-dependent ways, which makes calibrated reliance a core requirement for valid human–AI decision-making[12,13]. Users can diverge in two maladaptive directions: underreliance, in which AI recommendations are discounted even when informative, and overreliance, in which users defer to algorithmic output despite conflicting evidence or task-specific constraints[14]. These patterns are consequential because they shape both decision accuracy and the distribution of responsibility in AI-supported judgments, where accountability typically remains with the human decision-maker.

Understanding the individual differences that shape how individuals respond to AI input is critical for both theory and application[15]. From a theoretical perspective, identifying the cognitive and personality mechanisms that underlie advice-taking can inform models of adaptive decision-making in human–machine systems[6,9,16]. From a design perspective, such insights can guide the development of AI interfaces that dynamically adjust their recommendations to users' cognitive styles and confidence levels[2,3,17].

In the present study, we focus on two individual-difference variables: mindfulness and creative self-efficacy, as predictors of decision revision following AI input. This extends prior work on trait-based predictors of decision quality and adaptive behavior[2,9,10,18,19].

Mindfulness is defined as a dispositional tendency to attend to present-moment experience in a nonjudgmental and accepting manner[10]. It has been associated with enhanced metacognitive awareness, reduced reliance on heuristics, and improved cognitive flexibility[11,20]. Theoretically, mindfulness may support more deliberate and context-sensitive processing of external information, including algorithmic input. For example, mindful individuals have been shown to be less prone to decision biases such as the sunk-cost fallacy[11], suggesting a greater willingness to revise prior judgements in response to new evidence. On this basis, we hypothesise that individuals higher in mindfulness will be more likely to revise their initial decisions after AI input.

Creative self-efficacy (CSE) refers to an individual's belief in their ability to generate creative ideas and solutions[17,21]. Rooted in Bandura's self-efficacy theory[22], CSE captures domain-specific confidence in navigating tasks that require originality, insight, or innovation. While general self-efficacy reflects a broad sense of personal competence, CSE is more directly relevant in contexts requiring adaptive thinking under uncertainty such as evaluating algorithmic recommendations[2,3,23]. Individuals high in CSE are more likely to trust their own creative judgment and persist in solving problems autonomously[17,22]. In contrast, those low in CSE may doubt the quality of their ideas and seek external guidance, including that provided by AI[2,3]. We therefore hypothesize that individuals with higher CSE will rely more strongly on their internal judgement and will be less likely to revise their decisions after AI input.

We propose that mindfulness and CSE interact in shaping advice-taking behavior. Drawing on interactionist personality frameworks i.e. the cognitive-affective processing system[9,10,16], we argue that mindfulness may moderate the influence of self-efficacy on decision revision after AI input. For example, individuals low in CSE may be more likely to revise their decisions after AI input when they are also high in mindfulness, as mindful awareness could enhance recognition of their uncertainty and increase thoughtful engagement with external input[10,11]. Conversely, among high-CSE individuals, mindfulness may reinforce selective engagement with AI, leading them to consider the recommendation without necessarily adopting it[17]. We hypothesize that mindfulness will increase the likelihood of decision revision among low-CSE individuals but have limited influence on those with high CSE.

In addition to these cognitive traits, we examine the potential moderating role of gender-linked personality orientations, conceptualized using the communal–agentic framework[24–26]. Drawing on social role theory[27], we distinguish between communal traits (e.g., warmth, empathy, cooperativeness), traditionally associated with femininity, and agentic traits (e.g., assertiveness, independence, dominance), traditionally associated with masculinity. This dimensional approach enables the study of gender-role orientations as continuous psychological dispositions, offering a more precise account of behavioural differences rather than binary sex-based comparisons[24,25,27]. This interpretation is in line with Bakan's agency-communion framework which describes agency as striving for individuality and mastery, and communion as striving for connection and sharing[24,28]. Prior research suggests that individuals higher in communal traits are more receptive to external perspectives, while those higher in agentic traits prioritize autonomy and self-direction[24,25,29]. These traits have also been shown to influence how individuals process persuasive messages and social cues, particularly in cognitively demanding contexts[29].

In Hofstede's taxonomy, the United Kingdom (UK) is typically characterized by strong individual agency, alongside enduring gender-role associations in which communal traits are linked to relational roles and agentic traits to assertiveness and independence[30,31]. This cultural backdrop offers important context for how UK participants may interpret communal versus agentic orientation, and it supports the broader premise that social-motivational orientations shape how algorithmic input is understood and incorporated into decision-making.

Related cross-cultural findings further suggest that individuals from collectivistic (communal) cultures report greater increases in decision confidence and creative self-efficacy when supported by AI, compared to individuals from individualistic (agentic) cultures[4]. This supports the broader premise that social-motivational orientations shape how algorithmic input is interpreted and applied. However, the interaction of gender-linked trait orientations with mindfulness and CSE in AI-assisted decision-making remains unexplored[16]. We hypothesize that communal-agentic orientations will moderate the mindfulness × CSE interaction with an amplified effect among communal-oriented individuals especially when they are both mindful and lower in CSE.

## Hypotheses

- *H1*: Higher mindfulness will increase the likelihood of revising decisions after AI input.
- *H2*: Higher CSE will decrease the likelihood of revising decisions after AI input.
- *H3*: Mindfulness and CSE will interact to predict decision revision, such that mindfulness will increase the likelihood of revision among individuals low in CSE.
- *H4*: Communal-agentic trait orientation will moderate the mindfulness × CSE interaction, such that the interaction will be stronger among individuals higher in communal traits.

Figure 1 presents the conceptual framework summarizing the hypothesized relationships among mindfulness, creative self-efficacy, gender-linked trait orientation, and decision revision following AI input.

**Fig. 1** Conceptual framework.

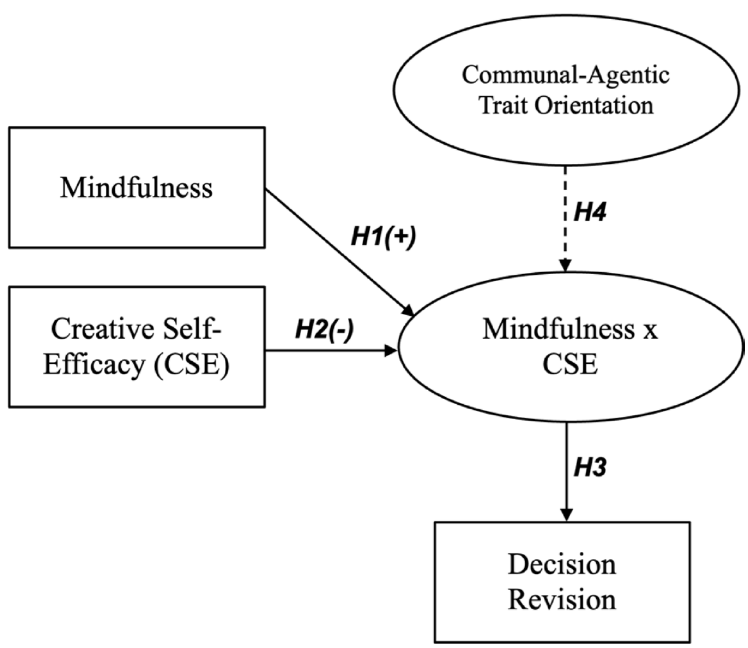

**Table 1** Descriptive statistics of main variables.

| Variable | M | SD | Min | Max |
|---|---|---|---|---|
| Mindfulness | 3.86 | 0.84 | 1.73 | 6.00 |
| CSE | 3.93 | 0.63 | 3.00 | 5.00 |
| First response | 2.69 | 0.98 | 1.00 | 4.00 |
| Second response | 2.59 | 0.78 | 1.00 | 4.00 |

**Table 2** Binary logistic regression predicting decision revision.

| Predictor | Coefficient | SE | z | *p* |
|---|---|---|---|---|
| (Intercept) | 0.09 | 1.43 | 0.16 | 0.873 |
| CSE | −0.19 | 0.17 | −1.19 | 0.234 |
| Mindfulness | −0.03 | 0.16 | −0.22 | 0.826 |

## Results

To examine the conditions under which individuals revised their decisions after AI input, we analysed the effects of mindfulness, creative self-efficacy (CSE), and gender-role traits on decision revision. The results did not support H1 or H2 as independent main effects. H3 was supported by a significant mindfulness × CSE interaction, although the median-split simple slopes were not independently significant. H4 received partial support: the mindfulness × communal-femininity interaction was significant, whereas the hypothesised three-way interaction was trend-level.

### Descriptive statistics and initial response patterns

A total of 549 participants completed the study. Of these, 393 (71.6%) did not revise their response after AI input, while 156 (28.4%) revised it; descriptively, 65 (11.8%) increased and 91 (16.6%) decreased their ratings. Descriptive statistics are presented in Table 1.

A McNemar–Bowker test indicated that the distribution of first and second responses differed, $\chi^2(6)=44.28$, $p<.001$. This omnibus result establishes that response distributions changed across the two measurement points; it does not indicate that revisions moved toward the AI recommendation.

### Main effects of mindfulness and creative self-efficacy

A binary logistic regression was conducted to assess whether mindfulness and CSE predicted decision revision (Change = 1; No Change = 0). Neither mindfulness nor CSE had a statistically significant independent association with revision. The model converged with a residual deviance of 861.76 and an AIC of 873.76. Key results are summarized in Table 2.

### Interaction effects: mindfulness × CSE

Introducing an interaction term between mindfulness and CSE improved model fit (AIC = 869.18). The mindfulness × CSE interaction was significant ($p=.034$; Table 3).

In the interaction model, the mindfulness coefficient is conditional on CSE being at its standardized mean and should not be interpreted as an unconditional main effect. The significant mindfulness × CSE term ($p=.034$) indicates that the association between mindfulness and revision varied by CSE.

To further investigate the significant interaction between CSE and mindfulness, a subgroup analysis was conducted. The self-efficacy measure was split into two subgroups: high CSE and low CSE, based on the median CSE score. A logistic regression model was applied to both subgroups to assess the effect of mindfulness on the likelihood of change.

**Table 3** Binary logistic regression predicting decision revision with interaction term.

| Predictor | Coefficient | SE | z | *p* |
|---|---|---|---|---|
| (Intercept) | −14.84 | 7.13 | −2.02 | 0.043 |
| CSE | 1.50 | 0.81 | 1.81 | 0.070 |
| Mindfulness | 3.91 | 1.83 | 2.09 | 0.037* |
| CSE x Mindfulness | −0.45 | 0.21 | −2.12 | 0.034* |

*$p$<.05 indicates statistical significance.

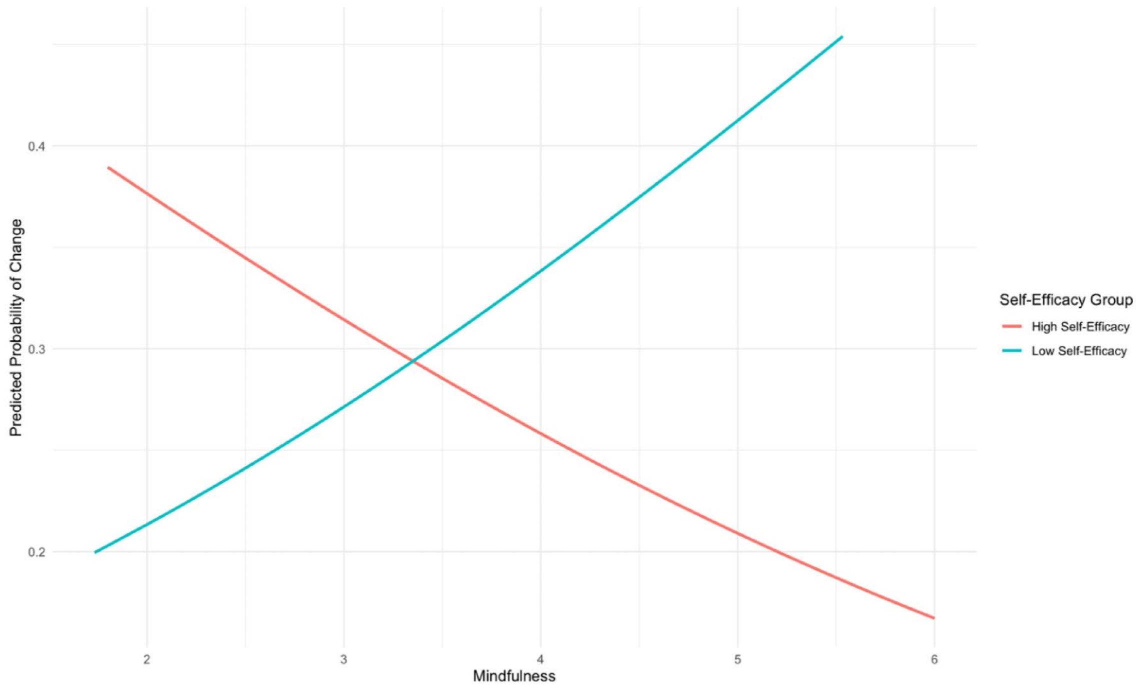


**Fig. 2** Visual representation of subgroup analyses: effect of mindfulness on change in response

Neither simple slope reached conventional significance. In the low-CSE subgroup, the association between mindfulness and revision was positive but non-significant (β = 0.317, SE = 0.199, z = 1.592, $p$ = .111). In the high-CSE subgroup, the association was negative and trend-level (β = −0.276, SE = 0.151, z = − 1.820, $p$ = .069). These subgroup estimates describe the direction of the interaction but do not establish a reliable effect of mindfulness within either subgroup. Because median splits reduce power and discard continuous information, the interaction term from the continuous model is the primary inferential result.

Figure 2 displays the estimated interaction. The plotted pattern is positive at lower CSE and negative at higher CSE; it is presented descriptively and should not be interpreted as evidence that either subgroup-specific slope is independently significant.

## Main effects of gender-linked traits

To examine whether gender-linked personality traits predicted decision revision, we incorporated trait scores from the Personal Attributes Questionnaire (PAQ)[32]. The instrument represents agentic-masculinity and communal-femininity as orthogonal continuous dimensions[24,25,32,33]. Participants were not assigned to categorical gender-role groups; PAQ_M, PAQ_F, and PAQ_MF scores were analysed as continuous predictors.

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**Table 4** Univariate logistic regression results for gender traits (PAQ) subscales.

| Predictor | Estimate | Std. Error | z-value | *p*-value | Odds ratio | 95% CI |
|---|---|---|---|---|---|---|
| PAQ_M | 0.03 | 0.03 | 0.79 | 0.432 | 1.021 | (0.97, 1.08) |
| PAQ_F | 0.03 | 0.03 | 1.30 | 0.192 | 1.035 | (0.98, 1.09) |
| PAQ_MF | 0.00 | 0.02 | 0.18 | 0.858 | 1.004 | (0.96, 1.05) |

*$p$<.05 indicates statistical significance.

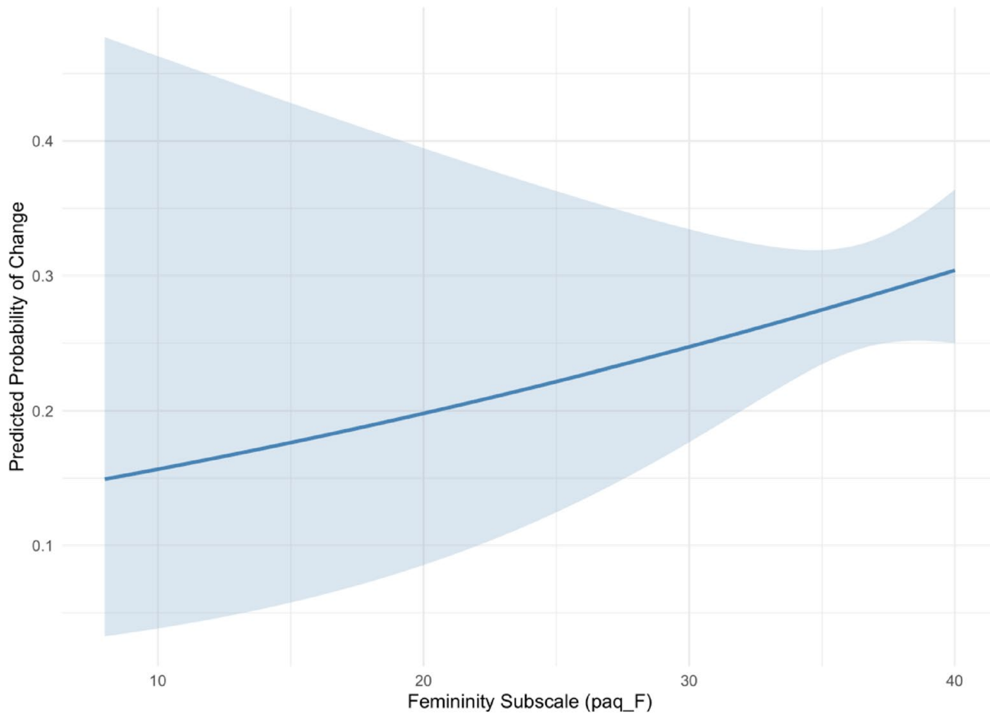


**Fig. 3** Effect of communal-femininity traits on change in response.

Univariate logistic regressions showed no statistically significant main effects of the PAQ subscales (Table 4). The positive PAQ_F estimate was non-significant and is not interpreted as evidence of an independent association. Figure 3 displays the predicted probability of decision revision as a function of communal-femininity scores.

## Subgroup analysis by participant sex

To assess whether participant-reported sex moderated the observed pattern, we conducted a follow-up subgroup analysis ($n$=549). Female ($n$=317) and male ($n$=232) participants showed broadly comparable decision-revision rates. The rate was 30.6% among female participants and 25.3% among male participants, a non-significant difference, $\chi^2(1)=1.59$, $p$ =.207, OR = 0.77, 95% CI [0.53, 1.12]. The three-category direction of change was also not associated with sex, $\chi^2(2)=2.47$, $p$ =.291. Male participants scored slightly higher on mindfulness (M = 3.97 vs. 3.78, $p$ =.006) and CSE (M = 4.00 vs. 3.88, $p$ =.027), but within-sex mindfulness × CSE coefficients were similar in direction, and the fully crossed mindfulness × CSE × sex interaction was non-significant (β = −0.066, $p$ =.732). Thus, the available analysis does not indicate that participant-reported sex accounts for the focal interaction pattern. Table 5 summarises these descriptive and inferential results.

**Table 5** Decision change and trait means by participant sex.

| Variable | Female ($n$=317) | Male ($n$=232) | Test |
|---|---|---|---|
| Change, n (%) | 97 (30.6%) | 59 (25.3%) | $\chi^2(1)=1.59$, $p$ =.207 |
| Direction of change (3 levels) | | | $\chi^2(2)=2.47$, $p$ =.291 |
| No change | 220 (69.4%) | 174 (74.7%) | |
| Increase | 59 (18.6%) | 32 (13.7%) | |
| Decrease | 38 (12.0%) | 27 (11.6%) | |
| Mindfulness, M (SD) | 3.78 (0.80) | 3.97 (0.83) | $t(548) = -2.75$, $p$ =.006 |
| CSE, M (SD) | 3.88 (0.62) | 4.00 (0.64) | $t(548) = -2.21$, $p$ =.027 |
| Mindfulness × CSE β (SE) | –0.165 (0.117) | –0.108 (0.153) | $\beta = -0.066$, $p$ =.732 (M × CSE × sex) |

Mindfulness × CSE coefficients (β) are from standardised logistic regressions within each sex predicting decision revision. $p$ <.05 indicates statistical significance.

**Table 6** Interaction model: communal-femininity and mindfulness as predictors of change.

| Predictor | Estimate | Std. Error | z-value | $p$-value | Odds Ratio | 95% CI |
|---|---|---|---|---|---|---|
| PAQ_F | −0.26 | 0.14 | −1.89 | 0.058 | 0.7711 | (0.59, 1.01) |
| Mindfulness | −3.11 | 1.39 | −2.24 | 0.025* | 0.0448 | (0.00, 0.63) |
| PAQ_F x Mindfulness | 0.08 | 0.04 | 2.18 | 0.030* | 1.085 | (1.01, 1.17) |

Note. $p$ <.05 indicates statistical significance.

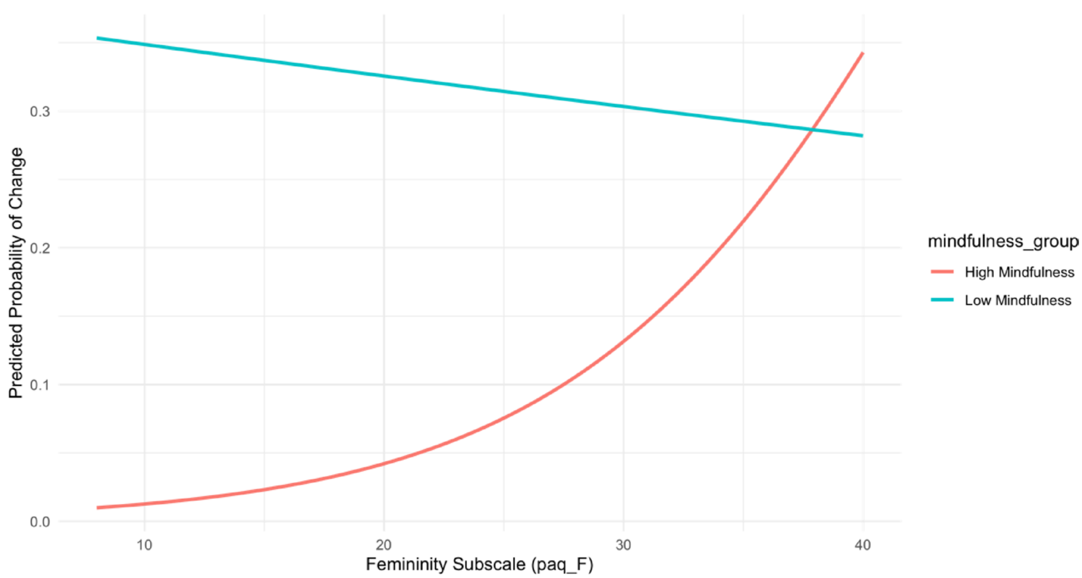


**Fig. 4** Visual representation of interactive effects: communal-femininity and mindfulness on change in response.

## Interaction effects: mindfulness × communal traits

The mindfulness × communal-femininity interaction was significant ($p$ =.030; Table 6), indicating that the association between mindfulness and decision revision varied with PAQ_F. The constituent coefficients in this interaction model are conditional effects evaluated when the other standardized predictor equals zero; they should not be compared as unconditional main effects across differently specified models. Figure 4 displays the estimated interaction.

## Interaction effects: mindfulness × communal traits × CSE

Finally, we tested the hypothesised mindfulness × CSE × communal-femininity interaction (Table 7). The mindfulness × communal-femininity term was significant ($p$ =.042), whereas the highest-order three-way term was

**Table 7** Three-way interaction model: communal-femininity, mindfulness and creative self-efficacy as predictors of change.

| Predictor | Estimate | Std. error | z-value | *p*-value | Odds ratio | 95% CI |
|---|---|---|---|---|---|---|
| PAQ_F x Mindfulness | 0.97 | 0.48 | 2.04 | 0.042* | 2.6401 | (1.02, 6.42) |
| PAQ_F x CSE | 0.37 | 0.20 | 1.84 | 0.066 | 1.4458 | (0.97, 2.11) |
| Mindfulness x CSE | 3.07 | 1.91 | 1.61 | 0.107 | 21.5465 | (0.45, 664.96) |
| PAQ_F x Mindfulness x CSE | −0.10 | 0.05 | −1.84 | 0.066 | 0.9073 | (0.82, 1.01) |

$p$<.05 indicates statistical significance.

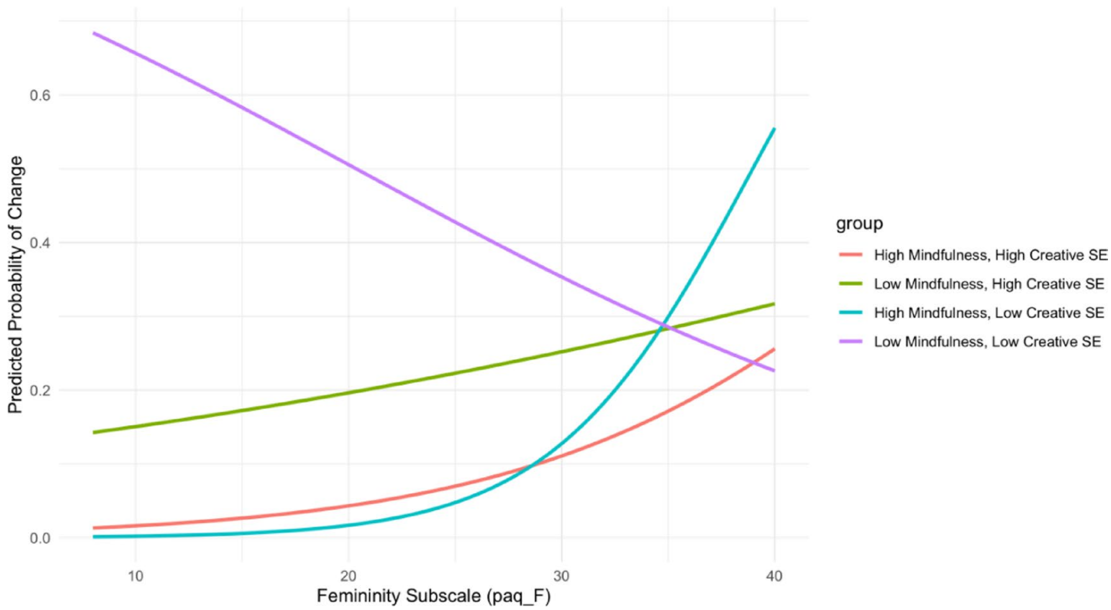


**Fig. 5** Visual representation of three-way interaction plot: communal-femininity, mindfulness and creative self-efficacy as predictors of change.

trend-level ($p$ =.066). The mindfulness × CSE term was non-significant within this model ($p$ =.107). Accordingly, the two-way moderation involving communal-femininity is supported, while the three-way pattern remains suggestive and requires adequately powered replication. Figure 5 presents the estimated probabilities for descriptive interpretation.

The wide confidence intervals for the higher-order terms indicate substantial uncertainty in their magnitude. Figure 5 is therefore used to display the model-implied pattern, not as independent evidence that the three-way interaction is established.

## Discussion

### Mindfulness and decision revision

H1 was not supported as an independent main effect: mindfulness did not significantly predict decision revision in the main-effects model. In the model containing the mindfulness × CSE interaction, the mindfulness coefficient was significant, but that coefficient is conditional on CSE being at its standardized mean. The evidence therefore supports a conditional association between mindfulness and revision rather than a general main effect. This distinction is consistent with the significant interaction and the non-significant subgroup simple slopes. Theoretical accounts linking mindfulness to reduced automaticity and cognitive flexibility remain relevant[10,11,34], but the present data do not establish the specific cognitive process underlying the interaction.

Furthermore, mindfulness is also linked to core components of creative cognition, particularly divergent thinking and cognitive flexibility. Experimental work distinguishing meditation modes shows that open-monitoring practice induces a broader, less constrained control state that reliably enhances divergent thinking performance, that is, the generation of multiple, novel alternatives rather than a single best answer[35]. Complementing this, individual-differences evidence indicates that specific mindfulness skills related to observing and attending to multiple internal and external cues are positively associated with creative performance[36]. Mindfulness has also been shown to facilitate insight problem solving, consistent with the idea that mindful awareness supports "holding" competing representations and relaxing habitual constraints that can otherwise narrow search processes[37]. At the aggregate level, meta-analytic evidence further supports a reliable positive association between mindfulness interventions and creative performance across convergent and divergent thinking tasks, with task type and intervention length moderating effect sizes[38]. Taken together, these findings provide a complementary mechanism for our results: mindful individuals may engage AI suggestions with greater cognitive flexibility and a larger hypothesis space, treating AI input as one option among multiple viable perspectives rather than as something to accept or reject reflexively.

### Creative self-efficacy: no independent effect on decision revision

Contrary to H2, creative self-efficacy did not independently predict decision revision. The main effect of CSE was non-significant in both the main-effects model and the model containing the mindfulness × CSE interaction. We therefore find no support for the proposition that confidence in one's own creative judgement, considered on its own, reduces the likelihood of revising a decision after AI input. The mechanism we had anticipated, that is, egocentric advice discounting, in which decision-makers with high domain confidence discount external input, is not supported at the level of a main effect in these data. What the data indicate instead is that CSE operates conditionally rather than independently: its role emerges only in interaction with mindfulness, as discussed below.

### Interactive effects of mindfulness and creative self-efficacy

The significant interaction indicates that the association between mindfulness and decision revision differed by level of creative self-efficacy. The direction of this difference was as predicted: positive among low-CSE participants and negative among high-CSE participants. However, neither simple slope reached conventional significance when the sample was split at the median (low CSE: $p$ =.111; high CSE: $p$ =.069). The interaction should therefore be read as evidence that mindfulness operates differently at different levels of CSE, not as evidence that mindfulness reliably increases revision among low-CSE individuals considered on their own. Median splits additionally reduce power and discard variance, and the pattern displayed in Fig. 2 is best treated as descriptive.

### Moderating role of communal vs. agentic orientation

H4 received partial support. The mindfulness × communal-femininity interaction was significant ($p$ =.042 in the three-way model), indicating that communal orientation moderated the association between mindfulness and decision revision. The hypothesised mindfulness × CSE × communal-femininity interaction was in the predicted direction but trend-level ($p$ =.066), while the mindfulness × CSE term was non-significant within that model ($p$ =.107). We therefore interpret the three-way pattern as suggestive rather than established. The results support further investigation of communal-agentic orientation in human–AI decision revision, but they do not demonstrate that any trait profile benefits more from AI advice because the outcome did not assess convergence toward the recommendation or decision quality.

### Psychological theoretical implications

From a dual-process perspective, the significant interaction is consistent with the possibility that mindfulness relates to the evaluation of AI input differently depending on CSE[9,11]. However, the present observational trait measures do not identify the cognitive process responsible for the interaction. Claims concerning reduced ego defensiveness, enhanced System 2 processing, or emotion regulation should therefore be treated as theoretically grounded explanations for future testing rather than mechanisms demonstrated by these data.

The outcome should not be interpreted as a direct measure of trust in AI. Revising an allocation after AI input may reflect consideration of the input, but it does not establish agreement with the recommendation, calibrated trust, or improved performance. The findings instead identify trait combinations associated with whether an initial decision was reconsidered. Future studies should measure perceived trust, advice weighting, and decision accuracy directly to determine how these constructs relate to revision behavior.

### Practical implications for AI adoption and design

The practical implications are necessarily provisional. The results suggest that users may differ in whether they reconsider an initial decision after AI input, but they do not justify assigning fixed user types or automatically tailoring interfaces on the basis of inferred psychological traits. A more defensible design implication is to provide all users with transparent assumptions, uncertainty information, and meaningful control over whether and how advice is incorporated. Trait-adaptive interfaces should be evaluated prospectively for accuracy, fairness, privacy, and the risk of reinforcing behavioural stereotypes before deployment.

Our findings should not be interpreted as implying that greater acceptance of AI advice is inherently desirable, nor that resisting AI advice is inherently problematic. The appropriate response to AI suggestions is context-dependent and is best framed in terms of calibrated reliance, where users integrate algorithmic input with domain knowledge, situational constraints, and their own judgment rather than defaulting to either rejection or deference. In some settings, "effective" human–AI collaboration is defined primarily by accuracy or risk reduction (e.g., safety-critical decisions), whereas in other settings it also includes solution diversity, justification quality, ethical constraints, and the ability to explore multiple viable options (e.g., complex managerial or creative decisions). From this perspective, the trait profiles identified here are most relevant for predicting whether users reconsider an initial decision after AI input and therefore where different design or training interventions may be needed to support high-quality decision processes. In practical terms, organizations may benefit from training that emphasizes critical evaluation and decision accountability, and from interface designs that maintain user agency while making uncertainty, assumptions, and trade-offs transparent, so that AI functions as decision support rather than decision replacement.

### Limitations and future research

While this study provides novel insights, several limitations must be acknowledged, which also open avenues for future research. First, the experiment examined a specific budget-allocation task, which limits generalisation to other decisions and AI systems[39,40]. Second, mindfulness, CSE, and communal-agentic orientation were measured rather than manipulated; the estimates are associational and do not establish causality[34,41]. Third, the binary outcome captured any revision after AI input but not whether the revised allocation moved closer to the AI recommendation or improved decision quality. A continuous advice-weighting measure, such as change in distance from the AI-recommended allocation, would permit a direct test of convergence. Fourth, the simple-slope subgroup analyses were not statistically significant, and the study was not powered for precise subgroup or three-way estimation; the higher-order confidence intervals were correspondingly wide. Fifth, Prolific's verified country-of-residence filter establishes UK residence rather than participants' physical location at the exact time of survey completion. Sixth, the study did not manipulate AI accuracy, explanations, or uncertainty, and it did not assess longitudinal adaptation. Replication should use adequately powered continuous moderation models, direct measures of trust and advice weighting, varied AI performance, and repeated interactions across tasks and cultural settings.

## Methods

### Study design and preregistration

This study employed a within-subject design to investigate how mindfulness, creative self-efficacy (CSE), and gender-role orientation relate to decision revision after AI input. The study was preregistered on the Open Science Framework (OSF; link blinded for peer review). Ethical approval was granted by the Institutional Review Board of the Department of Applied Psychology: Work, Education, Economy at the University of Vienna (Approval Number: 2019/A/002), which is the competent review body for research conducted by University of Vienna staff. Consistent with Austrian practice and with the Declaration of Helsinki, the responsible committee is that of the institution at which the researchers are employed and where the research is designed, conducted, stored and analysed, rather than that of the participants' country of residence. All of these activities took place at the University of Vienna.

With regard to UK-specific requirements, the study did not fall within the remit of the UK Health Research Authority or the NHS Research Ethics Service. That system governs research involving NHS patients, service users, staff, premises, tissue, or identifiable patient data. Our study involved none of these. Participants were adults in general employment, recruited through a commercial online research panel, who completed an anonymous, non-clinical online survey and a hypothetical marketing budget-allocation task. No health data were collected, no NHS resources were used, and no clinically vulnerable populations were involved. NHS or HRA approval was therefore not required.

Personal data were processed in accordance with the UK GDPR and the EU GDPR. Participation was voluntary and informed consent was obtained electronically before any data were collected, with survey logic terminating participation if consent was not granted. Participants could withdraw at any point without penalty. Compensation was set in line with Prolific's ethical payment guidelines.

### Participants and procedure

Recruitment used Prolific's country-of-residence prescreening filter, restricted to the United Kingdom. Country of residence on Prolific is not a self-declared profile field of the kind used for most demographic filters. Prolific states that, unlike other demographic attributes, age and current country of residence are verified and kept up to date automatically by the platform. Account activation additionally requires identity verification through a third-party provider, in which participants submit a valid government-issued photo identity document issued by their stated country of residence, register a mobile telephone number registered in that country, and complete verification while physically located in that country; use of a VPN or proxy during verification flags the account. This procedure establishes country of residence rather than physical location at the precise time of participation.

After quality-control and eligibility screening, 549 participants completed the Qualtrics survey. Participation was voluntary. Electronic consent was required before the survey began, and participants could stop at any point without penalty. Compensation followed Prolific's payment guidance. Study responses were analysed independently of direct identity information supplied to Prolific. After providing demographic data, participants completed trait-level measures of mindfulness, creative self-efficacy, and gender-role traits. They were then randomly assigned to a sequence of decision-making scenarios designed to test baseline judgments (without AI input) and response shifts after receiving AI-generated advice, with scenario order counterbalanced to mitigate sequence effects. In the non-AI condition, participants reviewed sales data and bar charts for four products and were asked to allocate a marketing budget based solely on their independent analysis. In the AI-assisted condition, they were shown the same data along with an AI-generated recommendation regarding optimal budget allocation and given the opportunity to revise their original decision. This design enabled us to observe whether, and how, participants' decisions changed in response to AI input. The survey concluded with a final assessment of creative self-efficacy and a full debrief. The AI-generated recommendations were provided by a text-based AI simulation using OpenAI's ChatGPT, embedded within the Qualtrics survey platform. The AI, functioning as a language model, was programmed to analyse and interpret sales data presented in chart form and generate strategic recommendations.

## Measures

*Mindfulness* was assessed using the 15-item Mindful Attention Awareness Scale (MAAS)[10]. Items (e.g., "I find myself doing things without paying attention") were rated on a 6-point Likert scale. The scale showed excellent internal consistency (α = 0.90). Higher MAAS scores reflect greater dispositional mindfulness, capturing attentional awareness and reduced automaticity.

*Creative Self-Efficacy (CSE)* was measured using the 3-item Creative Self-Efficacy scale7 and 6-item subscale of the Short Scale of Creative Self (SSCS)48. Participants rated items such as "I trust my creative thinking skills" on a 5-point Likert scale. The subscale demonstrated good reliability (α = 0.85). While the full SSCS includes a Creative Personal Identity subscale, only the CSE component was used in this study to capture confidence in generating novel solutions.

*Gender-Role Traits* i.e. communal and agentic traits were measured using the Personal Attributes Questionnaire (PAQ)[32]. The communal-femininity (PAQ_F) and agentic-masculinity (PAQ_M) subscales each consist of 8 bipolar adjective pairs (e.g., "Not at all sympathetic – Very sympathetic" for PAQ_F; "Not at all independent – Very independent" for PAQ_M). Subscale reliabilities were acceptable (α = 0.78 for PAQ_F, α = 0.75 for PAQ_M). The two dimensions were orthogonal, allowing for independent and interactional modeling of trait orientations[33].

We interpret "communal-femininity" as a continuous communal orientation that applies to individuals of any gender rather than as a fixed category[4,32,42]. The Personal Attributes Questionnaire treats masculinity and femininity as independent dimensions; its F-scale (femininity) measures a set of expressive, communal traits that are orthogonal to the M-scale (masculinity) and allows respondents to score anywhere along both dimensions[32]. This nomenclature is established in psychological research, and meta-analytic reviews of agency and communion continue to employ "agentic-masculinity" and "communal-femininity" to describe these orthogonal social-orientation dimensions[42].

*Decision Revision After AI Input* was the primary outcome. Participants were coded as Change when their second budget allocation differed from their initial allocation in either direction and as No Change when it remained identical. This binary measure captures whether a decision was revised after exposure to AI input. It does not establish that the revision moved toward the AI recommendation, represented acceptance of the advice, or improved decision quality.

The outcome captures any deviation from the participant's initial allocation; it indexes decision revision following AI input rather than movement toward the AI's recommendation. We therefore do not interpret revision as acceptance of, or agreement with, the AI's advice.

## Statistical analysis

To examine how individual traits related to decision revision after AI input, we estimated binary logistic regression models in R 4.2. The dependent variable was Change (1) versus No Change (0). Descriptive Increase and Decrease categories are reported only to show the direction of observed revisions; they were not separate outcome categories in the inferential models reported in Tables 2, 3, 4, 6 and 7.

All continuous predictors: mindfulness, CSE, and gender-role traits, were standardized before analysis. Consequently, a constituent coefficient in a model containing an interaction is conditional on the other interacting predictor or predictors being at their sample mean. We used a nested model-building strategy to test H1–H4:

- *Model 1: Main Effects (H1 & H2)*: Included mindfulness, CSE, PAQ_F (communal-femininity), and PAQ_M (agentic-masculinity) as predictors to assess whether these traits individually predicted likelihood of decision change.
- *Model 2: Two-Way Trait Interaction (H3)*: Added the mindfulness × CSE interaction to test whether mindfulness moderated the relationship between CSE and decision revision.
- *Model 3: Trait Orientation (Extension of H2 & H3)*: Included the full set of gender-role traits (PAQ_F, PAQ_M, PAQ_MF) to examine how personality orientation contributed to decision revision.
- *Model 4: Moderated Trait Interactions (Part of H4)*: Introduced two-way interactions between mindfulness × PAQ_F and CSE × PAQ_F to explore whether communal orientation influenced the individual effects of mindfulness and CSE.
- *Model 5: Three-Way Interaction (H4)*: Tested the hypothesized mindfulness × CSE × PAQ_F interaction to determine whether the combined influence of mindfulness and CSE on decision revision was amplified among individuals higher in communal-femininity traits.

All models were evaluated using Akaike Information Criterion and likelihood-ratio tests. Odds ratios and 95% confidence intervals are reported where available. Significant interactions were probed using simple slopes and predicted probabilities at ±1 SD of continuous moderators. Median-split subgroup analyses are reported as descriptive follow-ups and are not treated as the primary inferential test.

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**Data availability** The de-identified questionnaire data, analysis scripts, and preregistration file are now publicly available on Figshare at "Replication Data for: Mindfulness and creative self-efficacy in human–AI decision-making: Implications for adaptive AI design" DOI: https://doi.org/10.6084/m9.figshare.29609312.v1 under a CC-BY 4.0 licence.

## Declarations

**Competing interests** The authors declare no competing interests.



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