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AI Usage and Disclosure: Effects on Peer Perceptions of Creativity in Multidisciplinary Teams

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ABSTRACT

As generative Artificial Intelligence (AI) becomes increasingly integrated into collaborative creative work, questions remain about how AI usage and disclosure shape interpersonal evaluations of creativity. This study examines how a team member's reputation for AI usage and the disclosure of AI assistance affect their peers' perception of their creativity in a collaborative environment. Using a vignette-based 2×2 within-subjects factorial design, a multidisciplinary sample (N=37) evaluated teammates across four conditions varying two independent variables: the teammate's established AI usage habit (frequent vs. rare) and their disclosure of the idea's origin (AI-generated vs. Human-generated). Perceived creativity served as the primary dependent variable. Results indicate a significant creativity discount associated with frequent AI use and explicit AI disclosure. A significant interaction revealed that disclosure mattered more for rare AI users, who gained substantially from claiming human generation, than for frequent users, whose creative reputation was discounted regardless of what they disclosed. The highest creativity ratings were assigned to a teammate described as a rare AI user who attributed the idea to human origin. These findings highlight a tension between AI transparency and the maintenance of creative credibility within team environments.

Keywords: LLM; Generative AI; AI Disclosure; Perceived Creativity; Algorithm Aversion; Peer Perception; Collaborative Teams.

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INTRODUCTION

Generative Artificial Intelligence (AI), especially large language models (LLMs), have been rapidly transforming creative workspaces by assisting in tasks such as brainstorming and idea generation (Folorunso et al., 2025; Dhanuka, 2025). Organizations are increasingly integrating LLMs into their innovation processes to produce novel insights. For example, Doshi and Hauser (2024) show that providing writers with access to generative AI-generated ideas leads to stories that are rated as more creative, better written, and more enjoyable, with particularly strong improvements observed among less creative writers.

Creativity or a creative act has traditionally been perceived as a "human act that gives rise to something new" (Vygotsky, 2004), requiring originality or novelty (Runco & Jaeger, 2012). Accordingly, a study by Cunningham et al. (2025) shows that when creative products (like artwork) are labelled as machine generated, audiences rate them less positively than when labelled human made. In the same study, participants explicitly preferred "human" art; pieces believed to be made by an AI were judged as of lower artistic merit, even though their perceptual processing was similar. This suggests an innate bias: public perception of AI is negative in domains of personal or emotional expression.

A key question is how disclosure of AI usage or assistance affects colleagues' perceptions of one's creativity. Existing literature such as the study from Cunningham et al. (2025) and Folorunso et al. (2025) has begun to explore how disclosure of AI shapes the evaluation of its creations, but this has been done mostly from an audience or consumer perspective. Less is known about peer perception in collaborative settings. When a person and an AI jointly produce an idea, the question of how peers assign creative credit is one of co-creation: the contribution is no longer attributable to a single human author, and teammates must decide how much of the creativity belongs to the person versus the tool. Understanding these peer attributions is therefore a prerequisite for understanding how human–AI co-creative teams function. In multidisciplinary teams such as those present at CERN's IdeaSquare where diverse expertise and backgrounds converge, members often supplement brainstorming with AI suggestions. We lack clarity on how team members judge each other's creative contributions when a person uses AI.

This study aims to measure peer judgements of a teammate's creativity under varied levels of AI disclosure. Examining disclosure is important as generative AI tools are increasingly adopted in collaborative creative work (Folorunso et al., 2025; Doshi & Hauser, 2024), raising new questions about how transparency shapes interpersonal evaluations that did not exist in purely human-driven team settings (Schilke & Reimann, 2025).

THEORETICAL BACKGROUND

Attribution theory posits that observers distribute credit for an outcome based on available information (Weiner, 1985; Raj et al., 2023). A central component is Kelley's (1973) discounting principle, whereby the perceived role of any one cause is reduced when other plausible causes are present. When evaluating a novel idea, people implicitly ask "Who (or what) deserves credit for this innovation?" An undisclosed use of AI might allow the idea's originator to receive full creative credit, whereas acknowledging AI could signal that part of the creativity came from the machine. If the person has been known to rely on AI, colleagues may view the person's own contribution as smaller. This is supported by He et al. (2025), who found that knowledge workers consistently assigned AI less credit than a human partner for equivalent creative contributions. In effect, AI disclosure could act as a "creativity discount," lowering one's perceived originality or authenticity.

Bauer et al. (2025) find that when creators anticipate their AI use will be revealed, they reduce their creative involvement, investing less effort in prompting and identifying less with the result, perceiving it as a less authentic expression of themselves. Building off this, if a teammate says "AI helped me," others might similarly see the idea as less purely the person's own work and subsequently view the person as "less creative". Raj et al. (2023) directly investigated disclosure effects; they found that labelling creative text as AI-generated did not change evaluations for most stories, but caused significantly lower ratings for personal, first-person poems. Similarly, Yang and Xu (2025) showed that disclosure of AI involvement in a creative product leads audiences to judge it as higher in originality but lower in depth, credibility, and attractiveness. Knowledge of AI use shifts how novelty and value are weighed.

Additionally, biases against AI, often attributed to algorithm aversion, suggest that people assume or perceive human creativity as inherently superior or more genuine compared to machine-generated content (Castelo et al., 2019; Cunningham et al., 2025). Castelo et al.’s (2019) research on algorithm aversion indicates that people often prefer human over algorithmic contributions, even if the latter is objectively better.

At the same time, research requires nuance regarding an idea's origins. When an idea is more technical or abstract, people may not care much if AI was involved (Raj et al., 2023). On the other hand, when the idea is personal or emotional, disclosure of AI use tends to matter much more. This context-dependency suggests that the domain and nature of creative work moderate how AI disclosure affects peer perceptions.

Measurement considerations also shape our approach. Creativity is multifaceted (originality, feasibility, aesthetics, etc.), but asking peers explicitly whether they perceive their peer to be creative can be tainted by various confounding factors. By using adjectives that describe creative personality (e.g., "innovative," "imaginative"), peers indirectly quantify how creative they perceive the teammate to be. This aligns with past work highlighting personal creativity traits rather than just idea novelty (Runco & Johnson, 2002) and avoids priming participants with AI-specific language in the creativity measure itself.

Adjective-based measures of creative personality, such as the Gough Creative Personality Scale (CPS), offer a validated approach to quantifying perceived creativity (Gough, 1979; Zampetakis, 2010). While the CPS is traditionally used for self-assessment, the Adjective Check List framework from which it derives was explicitly designed for both self-report and observer ratings (Gough & Heilbrun, 1965). Asking participants to describe others using adjectives has been widely used in personality and creativity research. For example, Runco and Johnson (2002) analysed parents' and teachers' adjective-based trait descriptions of children's creativity, and Williams and Best (1983) highlighted the versatility and cross-cultural applicability of adjective-based instruments like the Adjective Check List, making the adjective format particularly suitable for peer ratings. This approach provides a standardised method for peers to rate a teammate's creativity without directly asking "Is this person creative?", a question that might be influenced by social desirability or demand characteristics.

In conclusion, the theoretical literature converges on a tension between AI's creative utility and the biases it triggers in observers. Building on attribution theory, algorithm aversion, and evidence that AI disclosure shifts perceptions of creative ownership, we derive three hypotheses. We expect that frequent AI users will receive lower peer creativity ratings than rare users (H1), that disclosing AI assistance will further reduce perceived creativity relative to claiming human generation (H2), and that these effects will interact such that the benefit of claiming human generation will be greater for rare AI users than for frequent AI users, whose creative reputation is already discounted by their known habits (H3).

METHOD AND DATA

This study used a quantitative, survey-based experimental design to assess how a teammate's use and disclosure of AI assistance affect peer perceptions of their creativity, structured to isolate these variables while controlling for potential biases. Participants were instructed to pay full attention throughout the survey to ensure data quality.

The study employed a 2×2 factorial design that manipulated two independent variables: the teammate's established AI usage habit (frequent vs. rare AI user), and their disclosure of the specific idea's origin (claimed AI-generated vs. claimed entirely human-generated). Each condition was presented as a short, third-person narrative vignette in which the interdisciplinary team setting and the contribution of a "good idea" were held identical; only the teammate's name, professed AI habit, and disclosure statement varied. This ensured that any observed differences in perception could be attributed directly to the manipulated variables.

As illustrated in Figure 1, these two factors create four conditions. Two are congruent, with disclosure matching the known habit: Alex (Scenario A), a frequent user who disclosed AI assistance, and Jordan (Scenario B), a rare user who claimed human generation. Two are incongruent: Morgan (Scenario C), a rare user who claimed AI origin, and Mark (Scenario D), a frequent user who claimed human origin.

Disclosure		AI usage habits: frequent	AI usage habits: rarely uses
	with AI	Scenario A Alex	Scenario C Morgan
	without AI	Scenario D Mark	Scenario B Jordan

Fig. 1. 2×2 experimental design. Four scenarios crossing AI usage habit (frequent vs. rare) with disclosure (AI-generated vs. human-generated claim). Scenario names indicate congruent (A, B) vs. incongruent (C, D) information.

To control for order effects, the four experimental scenarios were counterbalanced using a 4×4 Latin square design, ensuring each scenario appeared equally often in each ordinal position across participants. Perceived creativity was the primary dependent variable, measured using the complete 30-item Gough Creative Personality Scale from the Adjective Check List (Gough, 1979). The scale consists of 18 adjectives indicative of creative personality (e.g., capable, clever, confident) and 12 contraindicative adjectives (e.g., cautious, commonplace, conservative). Participants rated each teammate by selecting which adjectives applied to them, with scoring calculated as the number of positive items checked minus the number of negative items checked. Additionally, participants rated each teammate on various attributes using a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree) for qualitative analysis. As a validity check, the CPS score for each teammate was correlated with a direct single-item creativity rating ("[name] is creative," 1–7) drawn from the same Likert block. Participants also reported their own AI usage frequency, which was later used to examine whether participants' personal AI habits moderated their evaluations of teammates. Demographic questions were placed at the end of the survey to reduce the risk that group-based priming could influence participants' evaluations, as making social categories salient prior to experimental tasks can activate associated stereotypes and bias subsequent judgements (Steele & Aronson, 1995).

Data was collected via an online survey. Of the 56 responses received, 37 were complete and included in the final dataset, with the remaining 19 excluded due to incomplete responses. The sample consisted primarily of university students. The multinational recruitment is reflected in responses from several countries, with the largest contingents from Iran, the Netherlands, and Spain. This diversity extends to professional backgrounds, with the most common fields of study being Engineering, Computer Science, and Industrial Design.

Data were analysed using a two-way repeated measures ANOVA to assess the impact of AI usage habit and disclosure on perceived creativity. Prior to the main analysis, counterbalancing effectiveness was assessed by testing whether presentation order interacted with the experimental manipulations. A sensitivity analysis indicated that the final sample of 37 participants provided 80% power ($\alpha = .05$, two-tailed) to detect within-subjects effects of Cohen's $d_z \approx 0.47$ (partial $\eta^2 \approx .18$) or larger.

RESULTS

The main analysis yielded significant results for both main effects and their interaction. There was a significant main effect of the teammate's habit, with rare AI users being perceived as significantly more creative than frequent AI users ($F(1, 36) = 38.92$, $p < .001$, $\eta^2p = .52$). There was also a main effect of disclosure, where ideas claimed to be human-generated received higher creativity ratings than those claimed to be AI-generated ($F(1, 36) = 12.41$, $p = .001$, $\eta^2p = .26$). Crucially, these main effects were qualified by a significant habit × disclosure interaction effect ($F(1, 36) = 9.31$, $p = .004$, $\eta^2p = .21$; see Figure 3). This interaction indicates that the effect of disclosure on perceived creativity was different depending on the teammate's known AI usage habits. As shown in Figure 2, the highest creativity scores were attributed to Jordan ($M = 3.51$), the rare AI user who claimed his idea was human-generated. In contrast, the lowest scores were given to Alex ($M = 0.24$), the frequent AI user who disclosed using AI. The interaction (Fig. 3) reveals the nuances of disclosure: claiming an idea was human-generated provided a significant boost in perceived creativity for the rare AI user (Jordan), elevating him far above all others. However, for the frequent AI user, the same claim (Mark, $M = 0.38$) resulted in a score that was only marginally better than disclosing AI use (Alex, $M = 0.24$), and dramatically lower than the rare user's score.

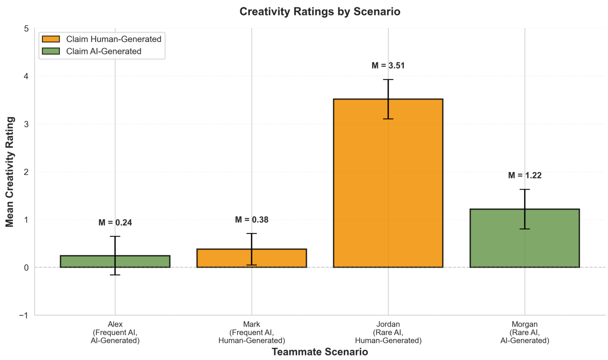

Fig. 2. Mean creativity ratings across all four scenarios. Jordan (rare AI user claiming human-generated idea) received the highest ratings ($M = 3.51$), while Alex (frequent AI user claiming AI use) received the lowest ($M = 0.24$). Error bars represent ±1 SEM.

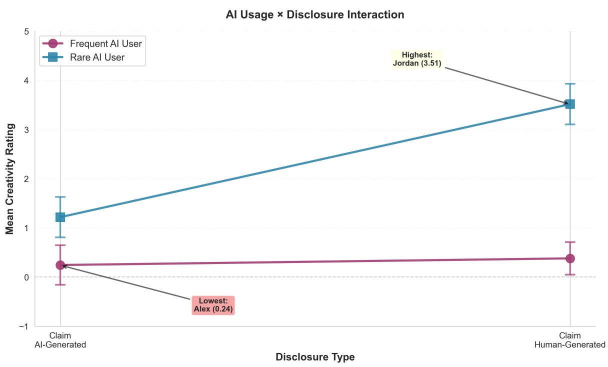

Fig. 3. Interaction between AI usage habit and disclosure on perceived creativity. The effect of disclosure differed significantly by AI usage habit ($F(1, 36) = 9.31$, $p = .004$, $\eta^2p = .21$). For rare AI users, claiming human generation substantially boosted creativity ratings. For frequent AI users, this claim provided minimal benefit. Error bars represent ±1 SEM.

To assess whether the Gough Creative Personality Scale functioned as intended when used for peer rather than self-evaluation, CPS scores were correlated with participants' responses to the direct seven-point "[name] is creative" item within each scenario. The two measures were positively associated across all four scenarios, significantly so for Mark ($r = .48$, $p = .003$), Jordan ($r = .42$, $p = .011$), and Morgan ($r = .51$, $p = .002$), and in the same direction for Alex ($r = .30$, $p = .077$), where the restricted range of ratings likely attenuated the coefficient. Pooled across scenarios, the association was moderate and highly reliable ($r = .55$, $p < .001$). This convergence indicates that the adjective-based CPS captured the same underlying creativity judgement as a direct rating, supporting its validity as an observer measure in this context.

To test whether the effect depended on raters' own AI habits, creativity ratings were examined by participants' reported AI usage frequency. The pattern across scenarios did not differ significantly between usage groups (Group × Scenario interaction: $F(6, 99) = 0.91$, $p = .491$, $\eta^2p = .052$), indicating that the creativity discount operated consistently whether participants used AI "Sometimes," "Most of the time," or "Always."

Mixed ANOVAs indicated that neither the AI usage effect nor the disclosure effect interacted significantly with presentation order (AI usage × Order: $p = .349$; Disclosure × Order: $p = .278$). Overall creativity ratings did vary somewhat across the four orders (order means ranging from 0.62 to 2.47), but with 8–10 participants per order these interaction tests have limited power to detect order-dependent differences; the non-significant results should therefore be read as the absence of detectable order effects on the manipulations rather than proof that order was immaterial. The main effects reported above also exceeded the sensitivity threshold ($dz \approx 0.47$), consistent with their detection at the current sample size.

DISCUSSION AND CONCLUSIONS

This study investigated how a teammate's AI usage habits and disclosure of AI assistance affect peer perceptions of creativity in collaborative settings. All three hypotheses were confirmed. Teammates known to rarely use AI received consistently higher creativity ratings than frequent users (H1 confirmed; $\eta^2p = .52$), and ideas claimed to be human-generated received higher ratings than those disclosed as AI-assisted (H2 confirmed; $\eta^2p = .26$). The significant interaction further confirmed H3: claiming human generation substantially benefited rare AI users (Jordan, $M = 3.51$) but provided minimal advantage for frequent users (Mark, $M = 0.38$ vs. Alex, $M = 0.24$). This pattern suggests that once someone is perceived as a frequent AI user, peers automatically discount their creative contributions, attributing originality primarily to the tool rather than the person. In co-creative terms, this means that the perceived division of credit between human and machine is governed less by any single contribution than by the person's standing reputation as an AI user, a dynamic that any framework for human–AI co-creation will need to account for.

This pattern follows directly from attribution theory. Kelley's (1973) discounting principle holds that the perceived role of any one cause is reduced when other plausible causes are present. For a teammate known to use AI frequently, the tool constitutes a salient competing explanation for any good idea, so personal creativity is discounted regardless of what the teammate claims about a specific contribution. For a rare AI user, no such competing cause is available, and creative credit remains attached to the person; a claim of human origin then serves to consolidate an attribution that was already intact. The interaction is thus not merely an empirical curiosity but the predicted consequence of how observers apportion credit when a machine is a candidate cause.

The practical weight of this result lies in its asymmetry. For a rare AI user, claiming human origin was worth a substantial gain: Jordan (3.51) scored more than three points above the otherwise identical Morgan (1.22), who credited AI, whereas for a frequent user the same claim was worth almost nothing (Mark, 0.38, vs. Alex, 0.24). Disclosure thus mattered only for those not already marked as habitual AI users; once that reputation is established, what a person claims about any single idea does little to change how their creativity is judged.

Critically, this study measured perceptions independent of actual output quality, demonstrating that evaluative bias can persist even when AI assistance plausibly enhances creative performance. This asymmetry creates perverse incentives within collaborative contexts: when disclosure reliably lowers perceived creativity, concealment of AI use becomes a rational strategy for preserving reputational standing. This dynamic aligns with recent evidence that transparency about AI assistance can erode interpersonal trust and perceived legitimacy, even when task performance is held constant (Schilke & Reimann, 2025). Taken together, these findings suggest that well-intentioned norms of transparency may inadvertently foster information asymmetries in which honest disclosers incur reputational costs, while nondisclosure is socially rewarded. As LLMs become increasingly embedded in everyday creative and professional workflows, such perception-based penalties risk undermining collaborative integrity, distorting credit attribution, and destabilizing trust within teams. We note, however, that these implications are drawn from responses to four vignettes rated by a primarily student sample, and are best read as patterns to be tested in applied settings rather than established effects in working teams.

Several limitations warrant acknowledgment. Our sample size, while sufficient for detecting the observed large effects, limits generalizability. The Gough Creative Personality Scale is widely used for self-report rather than peer assessment, which may affect the validity of observer ratings. Additionally, our vignette-based design necessarily simplifies the complexity of real team interactions, where relationships, history, and nonverbal cues all shape peer judgements. Three further constraints follow from the design itself. Each condition was represented by a single vignette with a single name, so any effect of the specific name or wording cannot be separated from the effect of the AI manipulation. Idea quality was held constant across conditions, which isolates the AI framing but leaves open how strong the bias would be in real settings where idea quality varies. Finally, all four teammate names could be perceived as male, and the perceived gender of the person being judged is known to affect creativity ratings, so whether these effects hold across gender remains untested. Future research should develop purpose-built instruments for measuring peer-perceived creativity in AI contexts, examine how perceptions evolve longitudinally as AI becomes ubiquitous, test interventions to reduce bias, and investigate these effects in diverse organizational contexts. A between-subjects replication, in which each participant evaluates only one scenario, would further test whether these effects survive when participants cannot compare conditions directly, removing any consistency or demand pressures introduced by the within-subjects design.

This research demonstrates that peers' perceptions of a teammate's creativity are influenced by that teammate's known AI usage habits, with frequent users facing significant bias regardless of disclosure. Without deliberate intervention, the productivity gains promised by AI may be offset by social costs including attribution disputes and erosion of collaborative norms. Addressing this requires clear organizational policies, educational programs targeting algorithm aversion, and frameworks that position AI as a collaborative tool, so that transparency about AI use is not systematically penalised but instead recognised as a sign of integrity within creative teams.

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CONFLICT OF INTEREST

None to declare.

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