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RECIPROCAL HUMAN-AI LEARNING IN CROWDSOURCED DESIGN: ALGORITHM AVERSION, TACIT KNOWLEDGE, AND ETHICAL TRANSPARENCY

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ABSTRACT

The fast integration of generative artificial intelligence in digital design has altered the use of AI systems from an automated tool to a partner. With this change, there is limited empirical research that can explain how adaptive human-AI interaction can lead to a better creative outcome, especially in crowdsourced design settings. This paper explores how reciprocal human-AI learning (RHML) influences creative synergy and considers the mediating and moderating roles of ethics, transparency, and algorithm aversion, respectively. A 2 x 2 factorial controlled experiment was carried out with 320 subjects with design backgrounds who completed an AI-assisted creative task under a simulated crowdsourced design condition. Expert raters assessed creative, productive outputs, and validated questionnaires assessed psychological constructs. The analysis was done using the factorial ANOVA and moderated mediation analysis with PROCESS. The findings reveal that RHML has a great effect on enhancing creative synergy ($F(1,316) = 28.74$, $p < .001$). RHML also decreases aversion to algorithms, which partly mediates its beneficial influence on the results of creativity. Moreover, ethical disclosure puts a lot of force in the correlation between RHML and creative synergy (interaction $F(1,316) = 12.63$, $p < .001$). The results prove that successful human-AI cooperation in creative systems is based not only on technological ability but also on psychological acceptance and clear governance mechanisms. The research paper provides empirical support to the study of hybrid intelligence and has design implications in the use of AI-assisted creative platforms.

Keywords: Reciprocal human-AI learning, creative synergy, crowdsourced design, algorithm aversion, ethical transparency

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1. INTRODUCTION

The creation of creative work in digital design environments has recently been revolutionized by the development of generative artificial intelligence. AI-assisted tools are being used more and more to create visual concepts, explore alternative design solutions, and facilitate faster iteration prototyping in areas like graphic design, fashion, architecture, and media production. Rather than being strictly automated systems, however, these technologies are slowly emerging as collaborative partners working in tandem with human designers during the creative process. This shift has triggered increasing academic interest in hybrid intelligence, in which human creativity and algorithmic computation are combined to arrive at results through a synergy that they would never have been able to produce on their own (Dellermann et al., 2019).

Crowdsourced design platforms are thus a very pertinent environment to study this interaction. Online design communities, open innovation, and digital marketplaces allow the distributed to work together on creative tasks while increasingly relying on AI-assisted design tools. In such environments, human designers provide contextual understanding, aesthetic judgment, and domain expertise, and AI systems provide idea exploration and computational experimentation. Ideally, such interactions can generate creative synergy, where the combined, sometimes complementary interaction between human intuition and algorithmic computation can generate more innovative solutions than either could produce alone. However, effective human-AI collaboration is not guaranteed. One of the main obstacles to this comes from algorithm aversion, a psychological preference to distrust or reject algorithmic recommendations, especially after seeing errors, or when the way a decision is taken seems "spooky" (Dietvorst et al., 2015). In the case of creative areas, this resistance may be even more pronounced since designers tend to relate creative results with personal authorship and professional identity. With algorithmic suggestions out of their creative process, designers may be reluctant to accept the use of AI systems when they may deem them as opaque and intrusive. Another factor that affects the collaboration between humans and AI is ethical transparency. Transparent AI systems ensure the ability to communicate about how outputs come to be generated, the kind of data sources being used, and the kind of contribution from an algorithm. Greater transparency may help to enhance trust and decrease uncertainty, and boost willingness to engage with AI-assisted tools. In the context of collaborative creative environments, transparency will also support the understanding of the relationship between the creativity of human individuals and that of machines.

The current research on AI-assisted creativity focuses mainly on the technical aspects of generative systems or the attitudes of users towards AI outputs. Nevertheless, there is a lack of empirical research on the effects of adaptive learning interactions between humans and AI in collaborative creativity, especially in crowdsourced design settings. This paper, thus, explores the impact of reciprocal human-AI learning on creative synergy and explores the mediating effect of algorithm aversion and the moderating effect of ethical transparency. At the same time, empirical research on the types of reciprocal human-AI learning interacting with psychological resistance, such as algorithm aversion and governance conditions

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such as ethical transparency, is still limited, especially in the context of crowdsourced design environments. As a result, the socio-technical mechanisms for determining whether human-AI collaboration increases or limits creative performance are still not well understood. Most of the current studies either focus on the technical capabilities of generative AI or study user perceptions without testing out the causal mechanisms. As a result, the psychological and socio-technical processes that make for effective human-AI collaboration on distributed creative platforms are still not well understood. In order to fill this gap, the study examines the role of reciprocal human-AI learning in generating positive effects on collaborative creative tasks in situations when designers engage in communication with AI-assisted design systems. Besides, the psychological process behind this relationship is also assessed by testing whether the relationship is mediated by algorithm aversion, which indicates the resistance of designers to algorithmic suggestions in creative decision-making. The contextual role of ethical transparency is also taken into account in the research, as it is tested whether transparent communication about AI processes, data sources, and algorithmic contributions reinforces the impact of reciprocal learning on creative performance. The combination of these relationships in one empirical study aims to provide better insight into how adaptive human-AI interaction, psychological acceptance of algorithmic support, and transparent system design jointly contribute to the development of collaborative creativity in crowdsourced digital design environments.

2. LITERATURE REVIEW

The findings of the study reveal the challenges faced by educators in implementing an integrated curriculum in music education, such as resistance from administrators and colleagues, limited resources, time constraints, and the need for collaboration. The document also includes examples of the sources of data used in the study, such as articles, theses, and YouTube videos, to support the theme analysis for the research questions.

2.1 Theoretical Foundations of Human-AI Creative Collaboration

Emerging scholarship implicates a mounting concern arising in crowdsourced design environments: there is an often-inadvertent possibility for the expansion of tools that use AI to help with tasks or processes, to put a strain on tacit human knowledge and creative autonomy if the collaborative interaction is not well structured. Creative design activities involve a lot of experiential judgement, contextual interpretation, and intuitive decision-making, which are types of tacit knowledge that are hard to translate into algorithmic systems. When AI systems take the lead in the ideation process and do not take meaningful input from humans, it can mean that the reciprocal relationship of learning between the designers and AI may worsen. In an attempt to address this problem, Wardi et al. propose the Integrated Reciprocal Human-AI Socio-Technical Framework (RHML) that stresses the two-way learning process between human expertise and algorithmic systems. Within this framework, the Polanyi Paradox can be thought of as an explanation for the challenge of reducing the human mind into sets of computational rules, and that algorithm aversion is an aspect of psychological resistance that can deter users from

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interacting with the suggestions produced by AI. Governance mechanisms and ethical transparency are thus placed as an important form of safeguard for the preservation of human agency within systems that are supportive of creativity through AI (Wardi et al., 2025). This view is in line with the wider socio-technical research on the effects of transparent governance structures on trust, coordination, and collaboration in human-AI teams (Vossing et al., 2022; Sqalli et al., 2023).

The literature on human-AI collaboration seems to generally converge around three themes, which are related, yet not the same: First, research on reciprocal learning and socio-technical design stresses that for work to be effective this requires mutual exchange of knowledge as well as a carefully designed work. RHML conceptualizes the concept of collaboration as a dynamic learning process through which human feedback and adaptation of algorithms developed through an iterative process (Wardi et al., 2025). Empirical research has shown that sound collaboration structures enhance role clarity and trust in hybrid teams, and these in turn facilitate creative performance (Jain et al., 2022; Vossing et al., 2022). Second, transparency, explainability, and ethics research emphasize how important the user-friendliness of AI processes is. Functional transparency and user-centered explainability bring more accountability and enhance the ability of users to interpret algorithmic recommendations (Hosain et al, 2023). Ethical frameworks governing its application also further underscore principles of transparency, fairness, safety, and accountability as important principles for the responsible application of AI (Sqalli et al., 2023). However, the transparency can have complex responses; humans disclosing algorithmic uncertainty can sometimes undermine user confidence in AI (Vossing et al., 2022). Third, algorithm aversion research and interaction design research indicate that people often have an aversion to algorithmic advice, and that this is especially true in areas that deal with creativity and judgment. However, interaction design practices like conversational interfaces and joint task duties can help to counter algorithm aversion by motivating people to think of AI systems as inventive partners instead of automated take-choice establishments (Zhang, 2025; Le et al., 2025; Jain et al., 2022). Despite these advances, there are still several important research gaps. Existing studies often focus on studying reciprocal learning, algorithm aversion, and ethical transparency independently; they lack insight into the joint impacts of these learning mechanisms on collaborative creativity in crowdsourced design environments. In addition, there is still little empirical evidence on how tacit knowledge exchange works amid human-AI design collaboration. Addressing these gaps, the present study is interested in proposing an integrated model that explores how reciprocal human-AI learning enhances creative synergy (H1), reduces algorithm aversion (H2), and how algorithm aversion negatively affects creative synergy (H3). Furthermore, algorithm aversion is proposed as a mediating mechanism linking RHML and creative outcomes (H4), while ethical transparency is expected to strengthen the positive relationship between RHML and creative synergy (H5). These relationships form the conceptual foundation of the framework tested in this study.

2.2 Reciprocal Human-AI Learning and Creative Synergy

The use of artificial intelligence has changed the digital design space very fast, where AI is not merely a calculating mechanism but a co-creator of designs. The

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initial discourse on AI in design was more about automation and efficiency, where algorithms helped designers to expedite production activities or produce alternative design options. Later scholarship, however, considers AI as a component in hybrid intelligence systems, with people and intelligent machines communicating with each other to generate knowledge and creative outputs (Dellermann et al., 2019). This is because in those systems, the complementary strengths in both agents lead to creativity. Humans add contextual analysis, aesthetic judgment, and tacit experiential knowledge, whereas AI systems add computational exploration, pattern recognition, as well as quicker exploration of design alternatives (Amabile and Pratt, 2016; Rafner et al., 2023).

Empirical studies are showing that human-AI environments of collaboration can augment creative exploration. However, experiments on generative design systems have demonstrated that interacting designers with AI tools generate more design solutions than working designers alone (Mao et al., 2023). On the same note, research on co-creative systems indicates that AI-based proposals may lead to divergent thinking when they present designers with new patterns and design opportunities (Deterding et al., 2017). The benefits mentioned are not necessarily the results of the introduction of AI into the creative processes, though. The success of AI-assisted creativity is determined by the cognitive exchanges between people and algorithms. In the case when AI acts as a static recommendation engine, the interaction is usually superficial. On the contrary, more significant collaborative processes can be established in the relationship between human users and AI systems through dynamic learning. This view is consistent with the socio-technical systems theory, according to which technological innovation is the result of the interrelation between social actors and infrastructures based on technology (Bostrom & Yudkowsky, 2014). According to this system, creativity is not generated through human cognition or algorithmic ability, but it is the interplay of the two factors in a common design context.

2.3 Tacit Knowledge and Reciprocal Knowledge

Crowdsourced design faces two ongoing challenges with reciprocal human-AI learning: the challenge of transforming tacit human knowledge into algorithmic structures dubbed the Polanyi Paradox, and psychological resistance to AI use termed algorithm aversion. Collectively, these issues make the workflow complex and cause the question of ethical openness and trust in AI-assisted design spaces. Recent work suggests that the Reciprocal Human-AI Learning (RHML) approach can be used in response to these constraints, focusing on the human-to-intelligent systems learning interactions as two-way learning interactions. By relying on feedback and adopting an adaptive approach to the system, RHML seeks to enhance collaborative learning and maintain human creative agency (Wardi et al., 2025; Sen, 2025). In this view, the Integrated Reciprocal Human-AI Socio-Technical Framework emphasizes the necessity to convert tacit design knowledge into mutual collaboration and work routines while dealing with the aversion to algorithms, which can be caused by too much automation. Balance and ethics consequently serve as a control mechanism to preserve trust and accountability during human-AI designed collaborations (Wardi et al., 2025).

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Additional exposure to knowledge management studies also underpins the significance of embedding tacit knowledge in AI-assisted processes. According to Sen (2025), to have effective collaboration, there must be mechanisms of capturing experience knowledge and contextualizing the algorithmic outputs by having structured AI-knowledge management cycles that regulate how human insights are encoded, interpreted, and refined in the digital systems. These loops make it clear that AI is not to displace human judgment but rather an interpretive partner, which is able to learn through the means of contextual responses. These methods contribute to perpetuating designer agency and keeping up the interpretative richness of creative work. Although these theoretical achievements have been received, there is a limited amount of empirical research to validate RHML in terms of real crowdsourcing settings. Researchers thus have urged the need to empirically investigate the processes of reciprocal learning in a variety of design activities and group contexts (Wardi et al., 2025).

Simultaneously, the ethical issues of algorithmic power and epistemic injustice are still influencing the discussion of AI-aided creativity. In case of inadequate application of the principles of transparency, accountability, and participatory design, algorithmic systems can unconsciously favor automated outputs in comparison to human insight, thus overlooking the knowledge of the designer. The solution to this threat should be the implementation of relational and participatory strategies of AI design that anticipate procedural ethics and preserve human dignity in collaborative systems (Bozkurt, 2025). On the same note, design pedagogy studies focus on promoting authorship, open data behaviors, and good governance in the context of integrating AI into the creative domain (Caglayan, 2025; Asrifan et al., 2024). All this shows that there is a need to implement objective mechanisms that involve reciprocity, trust, and ethical responsibility in human AI cooperation. To fill these gaps, the current research addresses the subsequent research question: How do tacit knowledge sharing, mutual learning dynamics, and ethics-based transparency affect collaborative creativity in crowdsourced design contexts (Wardi et al., 2025; Sen, 2025; Bozkurt, 2025; Caglayan, 2025; Asrifan et al., 2024).

2.4 Algorithm Aversion and Creative Results

The process of becoming suspicious or averse to algorithm-based suggestions is called algorithm aversion, and it is especially likely to occur when algorithms are viewed as addressing issues without human interpretation and other contextual factors (Dietvorst et al., 2015). Studies on human decision-making have continued to show that human advice is generally favored over algorithmic advice in situations where an algorithm based on its predictive power is better than human advice under predictive accuracy. In artistic situations, algorithm aversion can be very powerful since it is customary to relate creativity to the originality of human beings and their instincts. Designers find artificial intelligence-generated ideas to be formulaic, impersonal, or not in the spirit of genuine creative purpose. Therefore, they can be reluctant to accept algorithmic contributions to their work even when they help explore creativity. Nevertheless, previous research indicates that algorithm aversion is preventable when users have permission to engage in and adjust algorithm outputs. People will be more ready to use algorithmic inputs when they have a feeling of control (Dietvorst et al., 2018). Such conditions are formed by reciprocal

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human-AI learning interactions, which allow the designer to actively control algorithmic outputs with feedback and refinements. In turn, RHML can mitigate the aversion to the algorithm by shifting the AI system into a partner in decision-making. Reduced algorithm aversion, in its turn, should increase the readiness of designers to use AI-generated ideas in their creative activities. Based on this reasoning, the following hypotheses are addressed as follows:
Hypothesis 2 (H2): Reciprocal human-AI learning negatively influences algorithm aversion.

Hypothesis 3 (H3): Algorithm aversion negatively influences creative synergy.

Hypothesis 4 (H4): Algorithm aversion mediates the relationship between reciprocal human-AI learning and creative synergy.

2.5 Ethical Transparency in Man-Machine Interaction

The issue of ethical disclosure in mutual human-AI learning in crowdsourced design is here to stay. Wardi et al. have introduced an Integrated Reciprocal Human AI Socio-Technical Framework speculative of the anticipated 2-way learning and in which the Polanyi Paradox and algorithm aversion are assumed to act as centralizing factors; ethics is proposed as a mediating force to ensure equity, intellectual property, and free, open collaborative creative work is preserved (Wardi et al., 2025). In various spheres, researchers have emphasized that transparency, reduction of bias, and accountability are the key to reliable AI implementation and the continuation of human-AI interaction (Grover, 2025; Kumar and Sheel, 2025; Sposato, 2025). Three of these prevail: first is RHML and tacit knowledge that emphasizes the constraints of codifying tacit knowledge and how the algorithm aversion persists to generate demand for transparent interfaces and participatory design to build trust (Wardi et al., 2025; Sposato, 2025). Second, automation bias and alarm fatigue, along with the effects of AI confidence data on trust and endorsement, are demonstrated in the context of HAII research, including GI endoscopy, highlighting the need to design, train, and explain AI as a fundamental requirement (Campion et al., 2024). Third, algorithmic audits and hybrid governance are suggested as ways of synthetic ethics and governance to provide fairness and accountability, but these are mostly normative without standardized measures (Sposato, 2025; Grover, 2025; Premkumar, 2025; Kumar and Sheel, 2025). Nevertheless, this literature has not been tested empirically in crowdsourced design; even the RHML framework itself requires empirical validation (Wardi et al., 2025).

These works demonstrate the absence of empirical tests of RHML in crowdsourced design; lack of knowledge of the tacit knowledge retention in transparency interventions; and lack of measures of concrete mechanisms of transparency in actual design processes (Wardi et al., 2025; Campion et al., 2024; Sposato, 2025). The proposed research will be an empirically-tested intervention of transparency in RHML during crowdsourced design to reduce algorithm aversion and maintain tacit knowledge, which will further theory and practice (Wardi et al., 2025; Campion et al., 2024; Sposato, 2025; Grover, 2025).

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H5: Ethical transparency moderates the relationship between reciprocal human–AI learning and creative synergy, such that the positive effect of reciprocal learning on creative synergy is stronger when ethical transparency is high.

2.6 Research Gap and Contribution

Despite the recent years of a rapid increase in the number of research studies on the topic of human-AI collaboration, there are still some critical gaps in the literature. To begin with, numerous studies analyze AI creativity through the organizational prism of technology; that is, the capacity of the algorithm to achieve a specific result, but do not consider the interpersonal relationship between the human being and the AI (Dellermann et al., 2019). Second, most studies have focused on algorithm aversion in decision-making and forecasting, and little has been done to determine the effect of the psychological resistance on the creative collaboration with AI tools (Dietvorst et al., 2015). Third, the relationship between ethical transparency and accountability in algorithmic decision systems is generally discussed in studies, whereas the contribution of the former to the emergence of creative results in the human-AI design context remains under-researched (Floridi et al., 2018). Further, in previous studies, these factors are frequently studied separately as opposed to being combined in one empirical framework. The synergies between the dynamics of reciprocal learning, psychological resistance, and governance conditions on collaborative creativity are not adequately known. This gap is of particular importance when it comes to crowdsourced design spaces, where distributed designers engage with AI-assisted systems during the process of contributing to community-centric creative tasks. In order to overcome these shortcomings, the current research formulates and empirically demonstrates a composite model that investigates the effect of reciprocal human-AI learning on creative synergy, with the mediating variable being algorithm aversion and the moderating variable being ethical transparency.

2.7 THEORETICAL REFERENCES

The theoretical background of this paper is that it combines tacit knowledge theory, algorithm aversion theory, and hybrid intelligence to describe the effect of human-AI interaction on crowdsourced design collaborative creativity. All these views are used to explain the influence of human intuition, psychological reaction to algorithms, and collective interaction processes on creating something creative. The initial point of this framework is the Tacit knowledge theory. Polanyi (1966) defines that a large part of human knowledge is intuitive and experiential, which cannot be expressed in the form of rules or instructions. This tacit aspect is the foundation of the creative intuition in design practice, and in the ideation phase, designers are guided by their senses, aesthetic intuition, and experience. Nevertheless, the AI systems are usually structured in terms of their inputs and formalized instructions, and this introduces a distance between human intuitive thinking and algorithmic interpretation. This issue is often known as the Polanyi paradox, and it implies the impossibility of reducing human intuition of creativity to a form that could be processed by AI systems.

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The algorithm aversion theory describes the psychological obstacle that may occur in the process of human-AI interaction. It is observed that people do not trust a recommendation provided by an algorithm, especially after they realize something is wrong or when they feel that there is no transparency in how decisions are made (Dietvorst et al., 2015). This opposition can be even greater in the creative work as the designers tend to correlate creative output with authorship, identity, and self-expression. Consequently, the unwillingness to use algorithmic assistance can decrease the readiness of designers to introduce the suggestions made by AI into their creative work. The integration mechanism that deals with such challenges is offered by the theory of hybrid intelligence. Instead of focusing on AI as a substitute for human creativity, hybrid intelligence stresses a complementary interaction between human and computational cognition (Dellermann et al., 2019). Human beings play a role in providing contextual knowledge, judgment, and tacit knowledge in this view, whereas AI plays a role by providing computational power, pattern recognition, and generative exploration. Creative products arise, thus, out of integrative combining as opposed to technological replacing.

Extending such concepts, reciprocal human-AI learning (RHML) is the process of interaction that links such theoretical points of view. According to RHML, this process is a two-way learning process where designers can change their creative strategies according to AI-generated feedback, and AI systems can change their outputs according to how the user engages with them. In this process of interaction, designers can slowly transform tacit intentions into readable inputs, and AI systems can also progressively match human preferences. This interaction process has the capability of lessening psychological opposition to algorithms and enhancing the consistency between human intuition and algorithmic support, and finally increasing the synergy in creative effort between crowdsourced design settings and algorithms.

2.7.1 Conceptual Framework

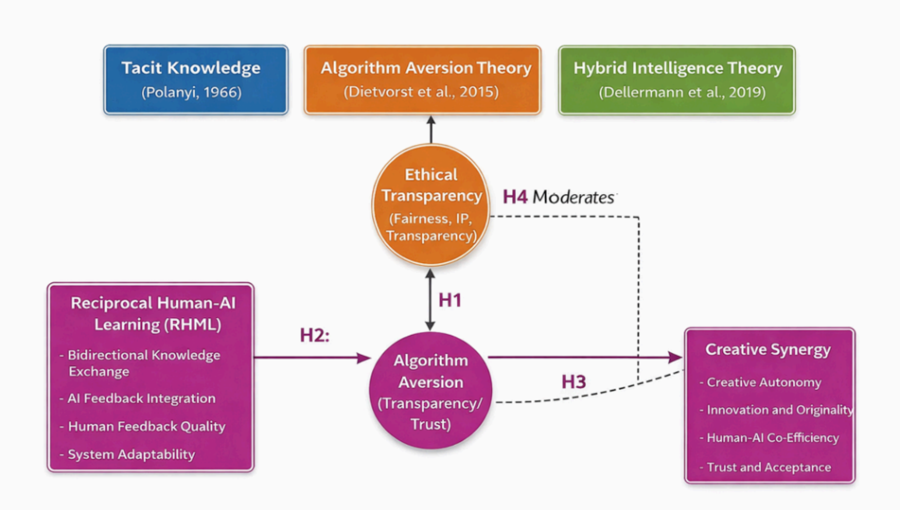

Figure 1. Conceptual framework of reciprocal human-AI learning, algorithm aversion, ethical transparency, and creative synergy in crowdsource design environments.

Figure 1 explains the conceptual framework that describes the interdependence between reciprocal human-AI learning and synergy in crowdsourced design spaces.

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Reciprocal human-AI learning (RHML) is the dynamic response between designers and AI systems with the exchange of knowledge, feedback incorporation, and system adaptability. The framework suggests that RHML maximizes creative thinking and results through generating consistent interaction between human intuition and algorithmic assistance. The algorithm aversion is placed as an intermediate factor that determines the impact of psychological resistance to algorithmic suggestions on the success of the collaboration of humans and AI. Familiarity with outputs of AI systems can lead to less distrust and increased incorporation of AI recommendations in the creative process when designers repeatedly engage with the AI systems. As a moderating variable, ethical transparency is put forward that enhances the connection between RHML and creative synergy based on the improvement of the level of trust, accountability, and awareness of AI decision-making. The result of these processes is the innovation, creative autonomy, and human-AI co-efficiency, as well as the acceptance of AI-assisted design systems.

3. METHODOLOGY

This research contributes new knowledge by exploring the integration of music education with other academic disciplines in secondary schools. It delves into the qualitative descriptive research design, emphasizing the importance of gathering information on the interdisciplinary approach in music education and the ways in which subject integration in music can foster a comprehensive education that fosters creativity, analytical thinking, cultural awareness, and a more profound comprehension of the interconnection of various subjects. The study also investigates the challenges faced by educators in implementing an integrated curriculum in music education, providing valuable insights into the complexities and opportunities of this endeavor. Additionally, the paper highlights the significance of teacher training, assessment, professional development, and curriculum design in the context of integrated music education. Overall, the research contributes to the understanding of the benefits, challenges, and implications of integrating music into the general curriculum, providing valuable insights for educators, policymakers, and researchers in the field of music education.

In the present study, the authors adopted a 2 x 2 between-subjects factorial experiment design to test how reciprocal human-AI learning (RHML) and ethical transparency influence creative synergy in crowdsourced design work. There were two independent variables in the design. Factor 1 was the extent of reciprocal human–AI learning, which was manipulated at two levels: high RHML and low RHML. The high-RHML condition participants used an AI system that adjusted its recommendations with the help of the user feedback, revisions, and input in the form of iterations. The AI system in the low-RHML condition gave low adaptive response, one-way, static outputs. Factor 2 was the degree of ethical transparency, which was also manipulated at the two conditions of high transparency and low transparency. In the high-transparency condition, they were presented with clear information regarding the way the AI created outputs, the basis of suggestions that it uses, and the level of user control and authorship. This explanatory information was restricted or not available in the low-transparency condition.

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The participants were randomly allocated to one of four treatment conditions, which included: (1) high RHML and high ethical transparency, (2) high RHML and low ethical transparency, (3) low RHML and high ethical transparency, and (4) low RHML and low ethical transparency. Each of the participants was given the same standardized design task, which was grounded on a shared design brief, yet the level of interaction with the AI system differed depending on the condition assigned to participants. The design allowed the study to test the principal effects of RHML and ethical transparency, and the interaction effect on creative synergy. It also formed the basis on which the question of whether algorithm aversion was a psychological mechanism of connection between RHML and creative outcomes was examined. An independent samples t-test identified that the respondents in the high RHML condition felt that there was much more adaptive interaction with the AI system ($M = 5.82$, $SD = 0.71$) than the respondents in the low RHML condition ($M = 3.14$, $SD = 0.88$), $t(318) = 28.64$, $p < .001$. Likewise, the perceived ethical transparency was much higher in the high-transparency condition ($M = 5.61$, $SD = 0.76$) than in the low-transparency condition ($M = 3.02$, $SD = 0.94$), $t(318) = 24.13$, $p < .001$.

3.1 Sampling

Purposive sampling was used to select the sample, whereby persons with basic knowledge or experience in designing activities were recruited. The sampling frame consisted of students at universities and future creative practitioners in the Klang Valley of the disciplines of graphic design, fashion design, multimedia, and visual communication. The reason behind the selection of these people is that they are the most probable representatives of the group that will apply AI-assisted creative tools in a real-life design situation. The sample size was about 320 participants, and it was sufficient to have the statistical power to carry out a factorial and mediation analysis. The four experimental conditions were randomly assigned to the participants to equalize the group sizes and minimize the selection bias. The demographic data, such as age, gender, academic background, and previous use of AI designing tools, were gathered and later became control variables in the analysis.

3.2 Instruments

Data collection was done through creative task outputs and structured questionnaires. The design task provided to the participants was based on a standardized design brief and involved using an AI-assisted design system. The main dependent variable was creative synergy, which was determined by the opinion of experts regarding the design outputs. All submissions were evaluated by three independent design professionals on a structured rubric, which graded the originality, aesthetic quality, conceptual coherence, and relevance to the design brief. The ratings were made on a scale of seven, and the average score was the final creative synergy value. Validated Likert-scale measures were used to measure two mediating variables. Tacit knowledge mismatch involved how difficult the participants perceived it to be to explain the intuitive design ideas into instructions that the AI system could understand. The algorithm aversion was used to indicate unwillingness to use AI-based recommendations after making mistakes or receiving surprising results. Ethical transparency was also a manipulation check and a moderating variable. A

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test of inter-rater reliability between the three expert judges was examined through the intraclass correlation coefficient (ICC). The review showed high raters' agreement (ICC = 0.87), which implies that the results are highly reliable when assessing creative outputs.

3.3 Data Analysis

The analysis of data was done with SPSS and the PROCESS macro created by Hayes (2022). The first thing was descriptive statistics, which were done to summarize the characteristics of the participants and to analyze the data completeness. To measure the internal consistency of the measurement scales, reliability analysis on the basis of Cronbach's alpha was conducted. In order to test the hypothesized relationships between the variables, mediation and moderation analyses were performed through the use of the PROCESS macro. In particular, the conceptual model was tested using the PROCESS macro (Model 14) to estimate the moderated mediation relationships. To experiment with the proposed relationships, mediation and moderation tests with the help of the PROCESS macro of SPSS were developed by Hayes (2022). In particular, the moderated mediation relationships within the conceptual framework were estimated using PROCESS Model 14 to estimate the relationship between variables. Reciprocal human-AI learning was set as the independent variable in this model, and algorithm aversion as the mediating variable, and creative synergy as the dependent variable. Ethical transparency was considered to be a moderator of the relationship between reciprocal human-AI learning and creative synergy. The estimates of indirect effects were estimated through bootstrapping based on 5,000 resamples, and the statistical significance was based on the 95% bootstrap confidence intervals.

4. FINDINGS

Table 1
Demographic characteristics of respondents (N = 320)

Variable	Category	n	%
Gender	Male	122	38.1
	Female	198	61.9
Age Group	18–20 years	94	29.4
	21–23 years	146	45.6
	24–26 years	80	25.0
Academic Background / Field	Graphic Design	84	26.3
	Fashion Design	71	22.2
	Creative Multimedia	70	21.9
	Industrial/Product Design	54	16.9
	Textile Design	41	12.7
Year of Study / Experience Level	Year 1 / Beginner	84	26.3
	Year 2 / Intermediate	89	27.8
	Year 3 / Advanced	92	28.8
Prior Experience with AI Design Tools	Yes	174	54.4

Variable	Category	n	%
	No	146	45.6

Note. Percentages may not total exactly 100 due to rounding.

4.1 Respondent demographic information

There were 320 participants in the sample, 61.9 percent of whom were female and 38.1 percent were male. The majority of the respondents were in the age range of 21 to 23 years (45.6), which is the common age of undergraduates in areas of creativity. The participants represented a variety of design-related courses such as graphic design (26.3%), fashion design (22.2%), creative multimedia (21.9%), industrial design (16.9%), and textile design (12.7%). About 54.4 stated that they had previous experience with AI-assisted design tools.

4.2 Factorial ANOVA

Table 2
Factorial ANOVA results predicting creative synergy

Source	df	F	p	η²
Reciprocal Human–AI Learning (RHML)	1, 316	28.74	< .001	.083
Ethical Transparency	1, 316	18.12	< .001	.054
RHML × Ethical Transparency	1, 316	12.63	< .001	.038

Table 2 represents the two-way ANOVA design used to identify the impact of reciprocal human-AI learning and ethical transparency on creative synergy. As Table X indicates, reciprocal human-AI learning generated a substantial main effect of creative synergy, $F(1,316) = 28.74$, $p <.001$, e2 =.083. Ethical transparency was also significant with the main effect $F(1,316) = 18.12$, $p <.001$, e 2 =.054. Moreover, there was a significant interaction between RHML and ethical transparency, F 1,316 = 12.63, $p =.001$,e 2 =.038, such that the positive influence of reciprocal learning on creative synergy was greater at high levels of ethical transparency.

4.3 Hypothesis 1 (H1): Reciprocal human-AI learning positively influences creative synergy in crowdsourced design tasks.

Table 3
Direct effect of reciprocal human–AI learning on creative synergy (H1)

Predictor	B	SE	t	p	95% CI
Reciprocal Human–AI Learning	0.36	0.06	5.77	< .001	[0.24, 0.48]

Note. Dependent variable = Creative synergy. N = 320.

Table 3 reveals the direct positive effect of reciprocal human-AI learning on creative synergy. Regression analysis showed that reciprocal human–AI learning significantly predicted creative synergy ($B = 0.36$, $SE = 0.06$, $t = 5.77$, $p < .001$). The 95%

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confidence interval ranged from 0.24 to 0.48, indicating a statistically significant positive effect. Thus, Hypothesis 1 was supported.

4.4 Hypothesis 2 (H2): Reciprocal human-AI learning negatively influences algorithm aversion.

Table 4
Effect of reciprocal human-AI learning on algorithm aversion (H2)

Predictor	B	SE	t	p	95% CI
Reciprocal Human-AI Learning	-0.31	0.07	-4.71	< .001	[-0.45, -0.18]

Note. Dependent variable = Algorithm aversion.

The regression results that are discussed in Table 4 explore the impact of reciprocal human-AI learning on aversion to the algorithm. As the analysis demonstrates, the bi-directional human-AI learning predicts the aversion to the algorithm with a negative coefficient ($B = 0.31$, $SE = 0.07$, $t = -4.71$, $p < .001$). The 95% confidence interval was -0.45 to -0.18, and it was not equal to zero, which showed that the effect was statistically significant. The findings are empirical evidence of Hypothesis 2.

4.5 Hypothesis 3 (H3): Algorithm aversion negatively affects creative synergy.

Table 5
Effect of Algorithm aversion on creative synergy (H3)

Predictor	B	SE	t	p	95% CI
Algorithm Aversion	-0.27	0.06	-4.36	< .001	[-0.39, -0.15]

Note. Dependent variable = Creative synergy.

The results of the regression analysis of the effect of algorithm aversion on creative synergy are given in Table 5. The finding shows that the mutual prediction of the creative synergy is highly associated with algorithm aversion ($B = 0.27$, $SE = 0.06$, $t = 4.36$, $p < .001$). The interval of confidence was -0.39 to -0.15, which proves that the effect is significant. The negative correlation is used to show that greater degrees of algorithm aversion correlate with lesser degrees of creative synergy in the crowdsourced design task. In this way, Hypothesis 3 is justified.

4.6 Hypothesis 4 (H4): Algorithm aversion mediates the relationship between reciprocal human–AI learning and creative synergy.

Table 6. Indirect effect of RHML on creative synergy through algorithm aversion (Mediation Test)

Path	Indirect Effect	Boot SE	95% CI Lower	95% CI Upper
RHML → Algorithm Aversion → Creative Synergy	0.08	0.02	0.04	0.13

Note. Bootstrapping based on 5,000 resamples.

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The mediation analysis was done by utilizing the PROCESS macro with 5,000 bootstrap resamples. The indirect impact of reciprocal human-AI learning on creative synergy by aversion to algorithms is given in Table 6. The indirect effect was significant (Indirect effect = 0.08, Boot SE = 0.02), and the 95 percent bootstrap confidence interval is 0.04 to 0.13. Since zero does not fit in the interval of confidence, the effect of mediation is significant. This finding suggests that algorithm aversion mediates the connection between reciprocal human-AI learning and creative synergy, partly. That is, the mutual communication with AI systems leads to creative synergy in part because of its influence on the decrease of the aversion of participants to algorithmic suggestions.

4.7 Hypothesis 5 (H5): Ethical transparency moderates the relationship between reciprocal human-AI learning and creative synergy**.**

Table 7
Moderating effect of ethical transparency (H5)

Predictor	B	SE	t	p	95% CI
Reciprocal Human-AI Learning	0.36	0.06	5.77	< .001	[0.24, 0.48]
Ethical Transparency	0.28	0.05	5.12	< .001	[0.17, 0.39]
RHML × Ethical Transparency	0.15	0.04	3.64	.001	[0.07, 0.23]

Note. Dependent variable = Creative synergy.

Table 7 gives the moderation analysis on whether the relationship between reciprocal human-AI learning and creative synergy is enhanced by ethical transparency. The findings suggest that creative synergy is strongly predicted by reciprocal human-AI learning ($B = 0.36$, $SE = 0.06$, $t = 5.77$, $p <.001$). Creative synergy is also impacted positively with a significant effect caused by ethical transparency ($B = 0.28$, $SE = 0.05$, $t = 5.12$, $p < .001$). Notably, the statistical result between the interaction term of reciprocal human-AI learning and ethical transparency is statistically significant ($B = 0.15$, $SE = 0.04$, $t = 3.64$, $p =.001$). The interaction effect is 95% confident at a range of between 0.07 and 0.23, not including zero. This finding demonstrates that reciprocal human-AI learning and creative synergy have a strong relationship moderated by ethical transparency. Hypothesis 5 is thus valid.

Table 8
Conditional effects of RHML at different levels of ethical transparency

Ethical Transparency	Effect of RHML	SE	t	p	95% CI
Low Transparency (-1 SD)	0.24	0.07	3.41	.001	[0.10, 0.38]
Mean Transparency	0.36	0.06	5.77	< .001	[0.24, 0.48]
High Transparency (+1 SD)	0.48	0.06	7.60	< .001	[0.35, 0.61]

To further explain the moderating effect, conditional effects were analyzed at low (-1 SD), mean, and high +1 SD levels of the ethical transparency. The findings have been tabulated in Table 7. Creative synergy is greatly anticipated by reciprocal

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human-AI learning at low levels of ethical transparency (B = 0.24, SE = 0.07, t = 3.41, p =.001), with a confidence interval of 0.10 to 0.38. At the average level of transparency, the effect is more pronounced (B = 0.36, SE = 0.06, t = 5.77, p less than 0.001), and the confidence interval is 0.24 to 0.48. When ethical transparency is high, the effect is the most significant (B = 0.48, SE = 0.06, t = 7.60, p <.001), and the confidence interval of the effect is between 0.35 and 0.61. These findings suggest that the beneficial effect of mutual human-AI learning to creative synergy grows with ethical transparency.

5. DISCUSSION

This paper has investigated the role of reciprocal human-artificial intelligence learning (RHML) in promoting creative synergy in crowdsourced design settings, together with exploring the mediation action of algorithm aversion and the moderation action of ethical transparency. The findings confirm that RHML has a significant impact on enhancing synergy in creativity. Those who were exposed to adaptive AI systems generated better creative results compared to those who were exposed to inanimate AI systems. This observation reinforces the view of hybrid intelligence, saying that human intuition and algorithmic computation are most effectively deployed in a complementary dynamic to generate creativity. In an iterative interaction setting, designers constantly improve AI-generated work at a time when the system constantly changes in response to user feedback. This reciprocal interaction increases the possibilities of design and also enables human judgment to sift and narrow down the ideas emerging. Subsequently, this causes AI to not only be a tool but also a partner in the creative process.

The results also indicate the human-AI collaboration psychological processes. The phenomenon of algorithm aversion had an adverse impact on creative synergy and moderated the correlation between RHML and creative results, partly. This finding supports the previous experimental studies indicating that people tend to mistrust algorithmic advice when they see that the system is erroneous or see that the process of making decisions is not transparent (Dietvorst et al., 2015). This resistance can be especially intense in the creative professions, where the production of creativity is linked with authorship and professional identity. The current evidence indicates that this resistance can be minimized through reciprocal interaction. Having repeated exposure to adaptive AI systems, designers become accustomed to algorithmic suggestions and become more confident in incorporating AI outputs into the design process. By doing so, reciprocal learning indirectly improves the creative performance by reducing the psychological impediments to algorithmic collaboration.

Such findings are in line with the recent studies on AI-assisted creativity. According to Mao et al. (2023), designers who utilized adaptive generative systems scored better in creativity than their counterparts who utilized static AI tools. Equally, Dellermann et al. (2019) opined that the hybrid intelligence systems produce more

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robust results when the algorithmic exploration is informed by human judgment. The current research builds upon this body of literature by showing that psychological acceptance mechanisms, specifically the decrease of the levels of algorithm aversion when interacting with one another in the course of repetition, partly explain the effectiveness of such collaboration. The other important observation relates to the importance of ethical transparency. The moderation analysis reveals that the positive impact of RHML on creative synergy is enhanced in cases where AI systems effectively communicate the manner in which outputs are created and how human input is being integrated into the output. Transparency will decrease the level of uncertainty about algorithmic operations and enhance user confidence. In creative practice, where concerns of originality and intellectual property are especially acute, the design of the system will help more designers embrace the idea of cooperating with AI data. These results inform responsible and explainable AI research arguments that transparency is an important governance tool in socio-technical systems.

The research makes three contributions to the body of literature. First, it empirically conceptualizes reciprocal human-AI learning as a quantifiable interaction process in creative design settings. Second, it defines the psychological route by which cooperative interaction determines the creative results as algorithm aversion. Third, the results show that ethical transparency enhances human-AI collaboration, as risks and accountability in AI-supported design systems are strengthened by ethical transparency. In practice, the findings imply that AI-assisted creative system creators are better advised to focus on adaptive interaction, dictate outputs, and open design experience as a way of ensuring effective human-AI co-creation.

6. CONCLUSION

This paper not only considered the role of reciprocal human-AI learning (RHML) in the creative synergy of crowdsourced design settings but also took into consideration the role of algorithm aversion (as a mediating factor) and ethical transparency (as a moderating factor). The results give empirical support that creative interaction between human designers and AI systems under adaptive interaction enhances collaborative creative results. Respondents who interacted with an AI system with a reciprocal learning ability showed greater creative synergies as compared to those who interacted with less adaptive ones. These findings suggest that AI-based creative settings are reinforced when designers and intelligent systems engage in a feedback and refinement process back and forth. The role of AI in these cases is not only a technical solution but also an active collaborator to be explored and develop ideas in the design process.

Another aspect that the study also brings to the limelight is the psychological processes that determine the success of human-AI cooperation. The influence of algorithm aversion was observed to produce negative impact on creative synergy

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and mediates the reciprocal learning and creative performance relationship partially. This implies that opposition to algorithmic recommendations has continued to be an important obstacle to successful cooperation among designers and AI systems. But the findings indicate that this resistance can be mitigated through unceasing engagement with adaptive AI systems by growing familiarity and trust in the outputs of the algorithm. The designers will get more used to the idea of incorporating AI-generated suggestions in their creative process over time, as they engage in it repeatedly.

The other significant finding is on the moderating role of ethical transparency. The findings indicate that the beneficial impact of RHML on creative synergy is more extensive when AI systems are well articulated on how outputs are created and how human inputs affect the process. Transparency would decrease the uncertainty about algorithmic decision-making and create a stronger trust towards AI-assisted design systems among the users. Transparent system design could be used in creative fields where the problem of authorship and originality is especially significant to motivate designers to be more open in their collaboration with AI technology. Theoretically, the research paper makes a contribution to the theoretical literature on human-AI collaboration by simultaneously applying hybrid intelligence theory, tacit knowledge factors, and algorithm aversion studies into an empirical study. The results indicate that effective human-AI creativity cannot be effective only based on technological proficiency but also on psychological adoption and open governance structures. In practice, the finding indicates that to promote effective human-AI co-creation, AI-assisted creative system developers would need to consider adaptive interaction capabilities, explainable outputs, and transparent system behavior first. Future studies can build on the present study by investigating professional designers, the type of real-life design platforms, and the long-term human-AI systems interactions.

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