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Article

A Hybrid AHP–Machine Learning Framework for Integrating Generative AI as a Co-Creative Partner in Interior Design Engineering Studios

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Abstract: This research focuses on the increasing but poorly specified use of Generative Artificial Intelligence in interior design engineering studios, which in the past have been focused on adopting the tool and perception-based evaluation rather than conducting engineering-level reproducible evaluation of the learning that is taking place in the co-creative processes. It evaluates a framework for assessing co-creativity using three stages (Dialogical Exploration, Critical Synthesis, and Critical Synthesis) along with an Analytic Hierarchy Process (AHP) model for weighting the co-creativity criteria, the resulting Co-Creative Performance Index (CCPI), and machine learning with explainability for predicting performance based on process behaviors. Outcome analysis from the analytic hierarchy process (AHP) indicated that the relative weights were on Creativity and Conceptual Diversity (weight w = 0.20), Critical Thinking and Justification (weight w = 0.19), and AI Literacy and Prompting Competence (weight w = 0.18), with sound expert consistency (CR = 0.06). The CCPI increased dramatically from .329 (SD = .032) prior to intervention to .599 (SD = .027), securing a mean gain of .270 (SD = .046). Predictive analysis showed that co-creative performance is a behaviorally learnable process with XGBoost achieving strong cross-validated accuracy (R^2 = 0.82, RMSE = 0.041, MAE = 0.033).

Keywords: Generative AI, Multi-criteria decision-making, Machine learning.

1. Introduction

Generative artificial intelligence (GenAI) has swiftly moved from being on the periphery of experimentation to being at the forefront of the ideation process within creative and engineering-related tasks. In this regard, within various design fields, recent research trends show that GenAI has increasingly been utilized for generating and exploring design ideas at a much faster rate and for the purpose of fostering divergent thinking and co-creation between human and computational intentionality for design creation and innovation (Alharthi, 2025; Rathod, 2024; Gupta & Kyaw, 2025; Kabir, 2024; Chen et al., 2025). With regard to design practice, research now highlights that GenAI is reshaping the design interaction between designers and clients and is transforming all aspects of design production and exploration including speed, uniqueness, and design concept exploration potential and possibilities within design practice and production design processes today. Additionally, within educational design settings and research design tenets on GenAI usage and influence within the design and innovation process and practice today, emerging evidence and research now propose GenAI as being perceived within design educational milieus as being at the forefront and at the root of design experimentation and design expression and innovation within design reasoning and explanation for GenAI design and innovation today. Given these aspects and considerations within design and innovation practice today and within emerging design and innovation milieus and processes and trends today involving GenAI and other design and innovation advancements and innovations within design practice and innovation today, interior design engineering design and innovation is now being regarded and perceived today as being at the forefront and at the root within design and innovation research studies and experimentation for examining and testing all aspects and considerations within design and innovation and design experimentation and innovation involving co-creative GenAI within design and innovation today and within design practice and innovation.

Despite this momentum, however, the current state-of-the-art research on GenAI within design education reveals variability in terms of depth and methodological rigor. A significant amount of literature on the subject focuses on attitudes and perceptions and tool-driven experimentation instead of offering engineering-grade assessment frameworks that relate the quality of human and AI co-creation with measurable design and educational learning outcomes (Fleischmann, 2024; Zhang & Li, 2024). Conceptual and practice-driven descriptions of co-creation approaches and processes tend to be abundant within the discourse on co-creation but lack transferable and legitimately correlated multi-criteria assessment frameworks to be replicated within various design learning and educational settings and processes across multiple design and educational establishments and entities (Kabir, 2024). Further, with the reality and reality-driven impact of GenAI being naturally observed on the earliest design stages within architectural and other design and engineering discourses and practices in general, the absence of engineering-grade and transferable analytical frameworks on criteria weighing for educational and design quality at this stage naturally raises debate on what might constitute the definition and contextually contextual process and practice criteria for the conceptually driven advancement and achievement milestones within definitions and processes for "effective co-creation" within educational and design and development milestones and processes for design educational and design engineering programs focused on interior design at this juncture within current research and scholarly literature and discourses on the subject and field within general and current scholarly and educational literature and discourse on design and various and applicable and widely known educational and design engineering and programming and process and methodologically driven processes and approaches within the field and subject at this particular stage and process within current and educational and design engineering.

As a response to such limitations and gaps, this research aims to create and establish the validity of a hybrid decision analytic and predictive model for GenAI to be utilized as a co-creative agent within design engineering studies for interior design. This methodology involves a three-stage studio approach and the AHP method for multi-criteria analysis and arrives at a Co-Creative Performance Index (CCPI), with an additional predictive layer for co-creative process outcomes based on machine learning models that can determine such outcomes from specific process indicators. This research aims to position this AI-related form of creativity within the methodological norms established for engineering and AI research.

In keeping with this intention, this research is formulated to investigate the following research questions: (1) what criteria should be developed to constitute effective human-AI co-creation in studio-based learning? (2) what do the resulting AHP-weights mean and represent? (3) what is the measurable effectivity of this co-creative approach on student achievement? (4) what is the predictive power of machine-learning models on co-creative process indicators? (5) what behaviors and processes best relate to optimal CCPI achievement? This set of research questions aims at developing the literature from within its current adoption and description realm and identifying and providing quantitative criteria for measurable achievement based on design principles. Unlike prior studies that rely on isolated perception analysis or standalone AI adoption models, this study proposes an integrated computational evaluation pipeline combining AHP-based multi-criteria weighting, CCPI performance indexing, explainable machine learning, and behavioral learning analytics within interior design engineering studios.

The article makes four principal contributions. First, this paper develops an elaborate AHP hierarchical framework tailored explicitly for the application of GenAI in co-creative learning dynamics and quality product creation during interior design engineering projects. Second, this paper introduces a practical CCPI that integrates criteria weights into a meaningful performance indicator.

Third, this paper shows how machine learning and interpretability approaches can transform studio process data into actionable signals for successful co-creativity. Finally, this paper illustrates a repeatable evaluation pipeline that can be employed by design-engineering programs interested in incorporating GenAI effectively while upholding human autonomy, decision-making, and accountability. The rest of the paper highlights the context and motivation for this study through related work literature, describes the methodology and data strategy, presents the AHP analysis, CCPI results, and machine learning findings, and concludes with implications for engineering-oriented design pedagogy and co-creation research.

2. Related Work

Recent literature shows how generative AI has become more than an exploratory layer in visualization, becoming a structural part of various steps in architectural and interior-design-related processes. Research focusing on GenAI usage in the context of concept formation, shape exploration, and representation discusses increased interest in text-to-image and multimodal workflows shaping the beginning of ideation and further improvement while still focusing mostly on technical characteristics of the tools without validating any specific learning process and its outcomes (Li et al., 2024; Onatayo et al., 2024; Wan et al., 2024). At the same time, reviews addressing the role of GenAI in the educational field more broadly note how its effectiveness depends on appropriate implementation and assessment, otherwise, it can produce only superficial learning and skills acquisition (Mittal et al., 2024). This problem aligns with the debate taking place among the creative industry professionals who regard GenAI as a valuable aid to creativity while recognizing its impact on authorship standards and metrics (Epstein et al., 2023; Amro & Ammar, 2018; Arabasy & Ghoneim, 2025). From the policy front, similar frameworks again and again underpin the critical role that responsible adoption principles play within educational initiatives for the creative industry—especially with regard to transparency and bias considerations that play a critical role within design studies involving innovation and cultural context as trenchant educational goals within themselves (Alnusairat & Abu Qadourah, 2025).

In this dynamic context, the literature on human-AI co-creation is now trending from a characterization of AI as a supportive tool and increasingly towards treating AI as a conversationally interactive partner for idea generation and discourse. Research on co-creative processes and testing platforms highlights the critical necessity for a human-centered approach and feedback for designers to harness while retaining agency and for AI's potential for rapid exploration and unexpected notions for concept generation (Lorenz et al., 2023). Also, systematic syntheses for human-AI co-creativity research confirm the conditioning for collaboration quality to be contingent on interaction protocols and approaches for output curation and evaluation practices that extend and allow for more than simple preference tests for collaborations and co-creations (Banh & Strobel, 2023). Current design thinking and techniques for integration tend to justify that GenAI can and can be used advantageously as a methodically directed catalyst for sustained and exploratory idea generation processes with complementary approaches for human ethical judgment and reason and instead for augmentative approaches and aims that promote and switch from substituting human judgment with methodologically directed approaches for GenAI system design and application integration and development platforms and research processes and threads for educational innovation and project solutions based on interior design engineering and objectives for design innovation processes and applications for GenAI research and assessment approaches within design-inspired and design-driven research approaches and methods.

Multi-criteria decision-making literature offers a methodological link and can be used to overcome these evaluation constraints. Specifically, AHP has been used across various fields for establishment and quantification for complex judments with significant values and qualifications that might be qualitative in nature and can therefore be applicable for evaluation within the studio for creativity and professionalism with ethical and intellectual advancements incorporated for multiple considerations at the same time (Talib et al., 2025). In built environment literature and research, AHP and AI content integration for evaluation for renovation for historical backgrounds has already gained attention and can therefore benefit AHP for decision-logic establishment even for design ecosystems with AI content for evaluation and quantification within the industry (Liu et al., 2024). It is therefore likely that AHP can be applicable and feasible for establishing and quantification for advanced human and AI integration within the studio with minimum ambiguity associated with GenAI content within policies and educational forums at this time (Alnusairat & Abu Qadourah, 2025; Amro & Ammar, 2018). At the same time, the emerging body of literature on learning analytics research bears out the potential for ML to transform educational assessment from description towards predictive and diagnostic model-building. Research on GenAI support for non-experts on learning analytics shows that ML can facilitate more structural approaches to educational decision-making with well-crafted indicator and data structure design (Ochoa & Huang, 2025). In general, educational uses of explainable ML methods prove the viability of capturing complex notions of readiness, competence, and success factors while retaining the necessary interpretability features for high-pressure educational scenarios wherein predictive capacity alone is insufficient and must be complemented with diagnostic and prescriptive capabilities for curriculum and educational support design and decision-making (Zine et al., 2025). The existence of well-established toolkits for ML model interpretability, such as SHAP-based analysis, further supports the argument for including explanatory components for educational ML model deployments to ensure predictive results can be mapped back to educational interventions as opposed to strictly being evaluative indicators (Ponce-Bobadilla et al., 2024). It is found from the literature that there is a significant gap with respect to methodological and conceptual considerations. Although GenAI adoption for architecture and design education is gaining momentum and increasingly complex theories on human-AI co-creativity emerge, the literature is dominated by adoption impact descriptions with a bias towards perception studies and tool-based isolated experiments indexed neither by standardized measurements for co-creative processes nor by their measurable performances (Li et al., 2024; Mittal et al., 2024; Banh & Strobel, 2023). Conversely, AHP-based structural integration is still pending with regard to its combination with ML-based learning analysis to structure a holistic evaluation and predictive tool specifically for interior design engineering studio activities and processes even though both methods seem equally suitable for multi-dimensional function representation and integration and process-derived indicators (Liu et al., 2024; Zine et al., 2025; Talib et al., 2025). Also, this state implies the non-existing issue on consensual criteria for comparison such as co-creative functional performances with a specific and measurable index for reference across research. This problem is solved by the concept of a comprehensive approach for GenAI co-creativity evaluation ready for state-of-the-art research on engineering and artificial intelligence.

3. Methodology

3.1. Research Design

This research articulates and validates a hybrid evaluation and prediction approach meant to operationalize Generative AI (GenAI) as a co-creative tool within interior design engineering design studios. A simple-group pre–post intervention design was adopted as the primary evaluation framework to investigate the educational and co-creative impact of integrating Generative Artificial Intelligence (GenAI) within interior design engineering studios. This research design ensured that changes in co-creation competencies, critical thinking skills, AI literacy, and design performance could be tracked during the controlled experimental period lasting for a semester while maintaining ecological validity by means of authentic studio settings. Pre-intervention baseline measures were conducted in order to compare the findings obtained before and after the implementation of the three-phased co-creative studio model. Both perception-oriented and process-oriented assessments along with portfolio-based evaluation were incorporated to avoid the potential influence of possible biases and obtain a more objective picture of co-creation performance. In line with this notion, previous literature suggests that effective human-AI co-creation performance assessment should combine evidence from both process-related and outcome-focused criteria as opposed to solely focusing on perception or isolated measures of AI utilization (Arabasy & Ghoneim, 2025; Lorenz et al., 2023; Banh & Strobel, 2023; Ponce-Bobadilla et al., 2024).

To enhance the research design in terms of its methodological rigor and engineering contribution, this study used an integrated computational evaluation framework, comprising AHP criterion evaluation, construction of a Co-Creative Performance Index, machine learning, and explainable AI analysis all within one computational workflow. In comparison with the usual descriptive approach used to evaluate design education facilitated by AI tools, the proposed framework allows transforming human-AI co-creation into a measurable and computable phenomenon. See Figure X below for an illustration of the computational evaluation framework used in the study.

The computational evaluation framework begins with the collection of behavioral and portfolio data produced throughout the studio course, namely, prompt histories, concept iterations, design refinement processes, justifications, and results. Next, the collected data streams are being used to engineer measurable behavioral features using feature engineering procedures. Among independent variables were included prompt iteration depth, concept branching diversity, human refinement intensity, prompt specificity, duration of studio phase exploration, and material/spatial diversity indicators. The dependent variable is the Co-Creative Performance Index (CCPI), calculated based on AHP criterion weights with rubric evaluations included.

The modeling structure for the variable was developed to create a computational link between educational behaviors, evaluative criteria, and analytics. Within this subsystem, the AHP algorithm calculated the weights of the importance of the six co-creative criteria: Creativity and Conceptual Diversity (C1), Critical Thinking and Justification (C2), AI Literacy and Prompting Competence (C3), Technical Studio Output Quality (C4), Ethical Reasoning and Authorship Awareness (C5), and Human Curatorial Mastery (C6). This was used to develop the CCPI, acting as a primary dependent variable within the framework's predictive models. By establishing such a pipeline, the system moved beyond individual assessments and created a link between human-driven evaluation and computational predictive analytics.

The framework included five main computational modules for processing data. First, behavioral and evaluation data were collected from student portfolios, AI interaction log files, and rubric-based assessments. Second, data standardization was implemented via min–max scaling to account for differences in heterogeneity among assessment criteria and behavioral indicators. Third, the features were extracted and engineered, reflecting such co-creative behaviors as iterative prompting, refinement, exploration, and phase engagement. Fourth, supervised machine learning algorithms including Linear Regression, Random Forest, XGBoost, LightGBM, and Support Vector Regression were employed and trained via k-fold cross-validation to predict CCPIs based on behavioral features. Lastly, SHAP-based explainability techniques were leveraged to analyze model behaviors and identify the role of each particular behavioral feature in predicting the CCPI.

Accordingly, the proposed research design does not treat AHP, CCPI, and machine learning as isolated analytical components, but rather as interconnected subsystems within a coherent engineering-grade evaluation architecture for human–AI co-creative learning in interior design engineering studios.

3.2. Participants and Context

Participants in this study were undergraduate students enrolled in mid-to-advanced interior design engineering studio courses. The study adopted a controlled single-studio cohort approach that was considered appropriate for paired pre–post educational assessment and supervised machine learning analysis using cross-validation strategies. Prior experience with artificial intelligence applications was assessed at the beginning of the semester to ensure that pre-existing familiarity with AI tools did not disproportionately influence the intervention outcomes.

Ethical approval for this study was obtained from the Research Ethics Committee at Gulf University, Kingdom of Bahrain, prior to data collection. The pedagogical implementation and participant involvement were additionally coordinated in accordance with the academic and research guidelines of Al-Ahliyya Amman University, Jordan. All participating students received written information outlining the study objectives, anonymization procedures, data usage policies, and participant rights. Written informed consent was obtained before the beginning of the intervention. To ensure voluntariness within the graded studio environment, participation in the research component was entirely optional and had no influence on academic grading, studio evaluation, or instructor assessment. The participants were told that they had the freedom to leave the experiment at any point in time without facing any repercussions in terms of their academic performance. In addition, all logs for AI interactions, reflection documents, and portfolios used were anonymized before undergoing the process of analysis to safeguard privacy and prevent possible power-based bias within the educational context. This practice is especially crucial within the realm of education powered by artificial intelligence, where issues related to attribution, transparency, and algorithmic discrimination become relevant (Alnusairat & Abu Qadourah, 2025; Amro & Ammar, 2018).

The model was purposefully applied to an interior design engineering studio setting to guarantee internal validity through controlled observation. However, additional validation of the model within different institutions and design fields is advised.

3.3. Pedagogical Intervention: Three-Phase Co-Creative Studio Model

The pedagogical intervention was created to be an integrated three-stage co-creative studio model focusing on process-based learning, not merely exposure to the use of AI tools. This is consistent with the existing human-AI co-creativity literature, which suggests that meaningful co-creative learning involves the development of skills such as dialogue and interaction abilities, reflective reasoning, and ethics as opposed to just using AI tools in response to prompts (Arabasy & Ghoneim, 2025; Lorenz et al., 2023; Banh & Strobel, 2023). It was incorporated into the weekly studio process to facilitate AI-assisted learning through real decision-making experiences.

Phase 1: Foundational Fluency and Ethical Grounding

The initial stage was dedicated to basics of artificial intelligence (AI) literacy, the concept of prompt engineering, and ethical considerations concerning the use of generative AI for design purposes. The students were provided with guidelines about prompt writing, capabilities and constraints of generative AI, dataset biases, and appropriate use of the technology. This pedagogical strategy presupposes that GenAI algorithms can replicate biases inherent in their training data, hence necessitating human moderation and filtering (Alnusairat & Abu Qadourah, 2025; Arabasy & Ghoneim, 2025).

Phase 2: Dialogical Exploration

Phase two shifted the mode of interaction from one-sided prompting to iterative co-creation between students and AI. Students produced several sets of concept families, tracked the evolution of their prompts, and explained their rationale for accepting, rejecting, or improving AI outputs. In this scenario, the concept of Dialogue Exploration was used as an iterative model of interaction where prompts, responses, criticism, and improvement together helped in creating concepts and reasoning in a co-creation manner. The design of this phase was based on literature highlighting the importance of iterative reframing and divergent exploration in making human-AI collaboration work (Lorenz et al., 2023; Banh & Strobel, 2023).

In this context, Human Curatorial Mastery referred to the students' ability to analyze, improve, reorganize, and contextualize the AI-generated results into viable interior designs. The students were urged to consider the AI-generated ideas as explorative designs rather than complete ones.

Phase 3: Critical Synthesis

This stage revolved around developing an approach to translate AI-supported conceptual research into design proposals that were coherent and context-aware. Students refined the ideas generated by AI using human judgment, context, and analysis. In light of these activities, AI-generated ideas were considered temporary conceptual prompts that would need to be interpreted and developed further. In today's creative industries, there is an increasing concern about the threat of superficial, AI-generated products without depth or critical human authorship (Amro & Ammar, 2018; Arabasy & Ghoneim, 2025).

3.4. AHP Framework Development

For a precise measurement of co-creation-based evaluation in terms of engineering standards, an Analytic Hierarchy Process (AHP) approach was adopted to determine the priorities assigned by the experts for various co-creative performance parameters in interior design engineering studios. The approach comprised creativity, reasoning skills, knowledge of AI, ethics, technical quality, and curatorial refinement considering literature related to ethical implementation of AI and human-AI collaboration (Alnusairat & Abu Qadourah, 2025; Arabasy & Ghoneim, 2025; Lorenz et al., 2023; Banh & Strobel, 2023).

The pairwise comparison matrix can be expressed as follows: $A = [a_{ij}]$,, where a_{ij} represents the importance of criterion i over criterion j. The priority weight vector w was determined using the principal eigenvector approach.

$$Aw = \lambda_{\max} w \tag{1}$$

The consistency of expert judgments was analyzed using the Consistency Index (CI) and Consistency Ratio (CR)

$$CI = \frac{\lambda_{\max} - n}{n-1}, CR = \frac{CI}{RI} \tag{2}$$

where nis the number of criteria and RIis the random index. Six major categories of co-creation dimensions were thus included in the created hierarchy: (C1) Creativity & Conceptual Diversities; (C2) Critical Thinking & Justification; (C3) AI Literacy & Prompting Ability; (C4) Technical Studio Output Quality; (C5) Ethical Reasoning & Authorship Awareness; and (C6) Human Curatorial Proficiency.

Construction of the Co-Creative Performance Index (CCPI)

The weight values obtained from the AHP approach were utilized in forming the Co-Creative Performance Index (CCPI), which became the major quantifiable dependent variable in educational measurement and forecasting applications. The rubric scores were standardized to the range s_i∈[0,1], and the CCPI value was calculated as:

$$CCPI = \sum_{i=1}^{n} w_i s_i \tag{3}$$

where w_i denotes the weight associated with criterion i from the AHP analysis. This equation filled a void in existing human-AI co-creation research methodology wherein co-creation quality is commonly theorized but not quantitatively defined to enable reproducibility and predictive analysis (Arabasy & Ghoneim, 2025; Lorenz et al., 2023; Banh & Strobel, 2023)

Machine Learning Modeling and Explainability

Machine learning layer was implemented for predicting the value of CCPI based on features such as behavioral and interaction-related features derived from the studio processes and AI interaction process. Features were generated based on theory-backed factors such as depth of prompt iterations, diversity of concept branches, strength of human refinements, and phase engagements.

For a given data $\{(x_k, y_k)\}_{k=1}^{m}$, where y_k is the value of CCPI and x_k is the feature vector, the estimation of model parameters θ was performed using mean squared error

$$\min_{\theta} \frac{1}{m}\sum_{k=1}^{m} (y_k - f_\theta(x_k))^2 \tag{4}$$

Tree-based algorithms like Random Forest, XGBoost, and LightGBM were preferred because of their capability to handle non-linear relationships among behavioral factors and their suitability for interpretable machine learning approaches (Lin, 2025; Jain et al., 2024). Furthermore, Support Vector Regression (SVR) was selected as a robust regression algorithm for smaller education datasets (Dubey et al., 2024).

For assessing the generalization capacity of the algorithms, K-fold cross-validation was adopted. The average accuracy of each fold was calculated as:

$$\bar{M} = \frac{1}{K}\sum_{k=1}^{K} M_k \tag{5}$$

where M_k denotes validation metrics such as RMSE, MAE, or R^2 estimated on fold k. Hyperparameter tuning was additionally conducted using grid-search optimization to reduce overfitting and improve predictive robustness.

Explainability analysis was performed employing SHAP, which helps in analyzing the importance of features at the output level. The additive explanation model from SHAP works as:

$$f(x) = \phi_0 + \sum_{i=1}^{d} \phi_i \tag{6}$$

where ϕ_0 is the estimated output for the model, and ϕ_i is the effect of variable i. This layer of explainability improved understanding and interpretative capability in terms of connecting predictions to co-creation behaviors and decisions in an education setting (Ponce-Bobadilla et al., 2024; Zine et al., 2025).

3.5. Reliability and Validity

Reliability and validity measures were also introduced to enhance the scientific soundness of the results obtained through the CCPI and machine learning analysis. The survey-derived variables were assessed based on Cronbach's alpha formula below:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_T^2}\right) \tag{7}$$

where k denotes the number of items, σ_i^2 represents item variance, and σ_T^2 denotes total score variance.

Portfolio assessments were independently evaluated by multiple reviewers to reduce subjectivity in creative assessment contexts. Inter-rater reliability was evaluated using the Intraclass Correlation Coefficient (ICC):

$$ICC = \frac{\sigma_b^2}{\sigma_b^2 + \sigma_w^2} \tag{8}$$

where σ_b^2 is for between-subject variance while σ_w^2 is for within-subject variance. This process helped in making the approach more reproducible, understandable, and engineering oriented (Anantrasirichai & Bull, 2020; Davis & Rafner, 2025; Singh & Hindriks, 2025).

4. Results

4.1. AHP Outputs

At the AHP phase, the foundation of the proposed assessment system was formed based on a formalized assessment process through the formation of a consistent weight system for the assessment of human–AI co-creation. Operational definitions of the selected criteria are presented in Table 1: AHP criteria + definitions where the six dimensions are defined as a balanced construct consisting of ideation, reasoning, fluency, craftsmanship, ethics, and human-driven synthesis. The calculated weights are presented in Table 2: Weights + CR, revealing that the creative dimension and the judgment dimension are significantly weighted by the experts. Creativity and Conceptual Diversity (C1) proved to have the highest weight (w1 = 0.20) followed by Critical Thinking and Justification (C2 with w2 = 0.19) and AI Literacy and Prompting Competence (C3 with w3 = 0.18). It is clear from this set of findings that the criteria unpack the conceptuality of co-creative superiority as emerging from the collaboration of creativity and critical thinking/justification processes for AI production. The other criteria—Technical Studio Output Quality (C4 with w4 = 0.16), Ethical Reasoning and Authorship (C5 with w5 = 0.14), and Human Curatorial Mastery (C6 with w6 = 0.13)—can be seen to carry significant weight as well. Overall, this serves to ensure that co-creation is perceived here as more than the aesthetic novelties and tool-based proficiency at play. Finally, the endogeneity of comparison within experts is ensured by the Consistency Ratio (CR = 0.06) listed under Table 2: Weights + CR, which is well within proper AHP parameters.

Table 1. AHP criteria + definitions.

Criterion	Label	Operational definition
C1	Creativity & Conceptual Diversity	Ability to generate diverse, original, and contextually appropriate spatial/material concepts with AI support.
C2	Critical Thinking & Justification	Quality of evidence-based reasoning, selection rationale, and critical evaluation of AI outputs.
C3	AI Literacy & Prompting Competence	Competence in prompt formulation, iteration, tool awareness, and understanding of AI limitations.
C4	Technical Studio Output Quality	Technical accuracy and feasibility of plans, layouts, detailing, and presentation standards.
C5	Ethical Reasoning & Authorship	Demonstrated awareness of bias, IP/authorship transparency, and responsible AI use.
C6	Human Curatorial Mastery	Strength of human-led curation, refinement intensity, and coherence of final narrative/design intent.

Table 2. Weights + CR

	Criterion	Label	AHP weight w_i
0	C1	Creativity & Conceptual Diversity	0.2
1	C2	Critical Thinking & Justification	0.19
2	C3	AI Literacy & Prompting Competence	0.18
3	C4	Technical Studio Output Quality	0.16
4	C5	Ethical Reasoning & Authorship	0.14
5	C6	Human Curatorial Mastery	0.13
6		Consistency Ratio (CR)	0.06

4.2. CCPI Descriptive Results

Building on the validated weights, student-level co-creative outcomes were aggregated into the Co-Creative Performance Index using

$$CCPI = \sum_{i=1}^{n} w_i s_i, \tag{18}$$

where w_i is the AHP weighted importance for criterion i, and s_i is the rubric score for the same criterion. The results achieved through this aggregation process can be found in Table 3: CCPI statistics, which demonstrates a marked process of improvement after the educational intervention. The mean CCPI score prior to this process was 0.329 (SD = 0.032), while after the process the mean CCPI score was 0.599 (SD = 0.027); this represents a mean increase of 0.270 (SD = 0.046). It can be suggested that this represents a marked shift from partially realized co-creative processes typical at this stage and closer to fully realized co-creative processes involving collaboration between AI and human synthesis. This is supported through the mean and SD found within Figure 1: CCPI distribution, which suggests that while improvements were marked, they were more evenly distributed after the educational process than prior to the intervention.

Table 3. CCPI statistics

Metric	Mean	SD	Min	Max

Pre-CCPI	0.329	0.032	0.261	0.399
Post-CCPI	0.599	0.027	0.552	0.656
Gain (post-Pre)	0.27	0.046	0.164	0.344

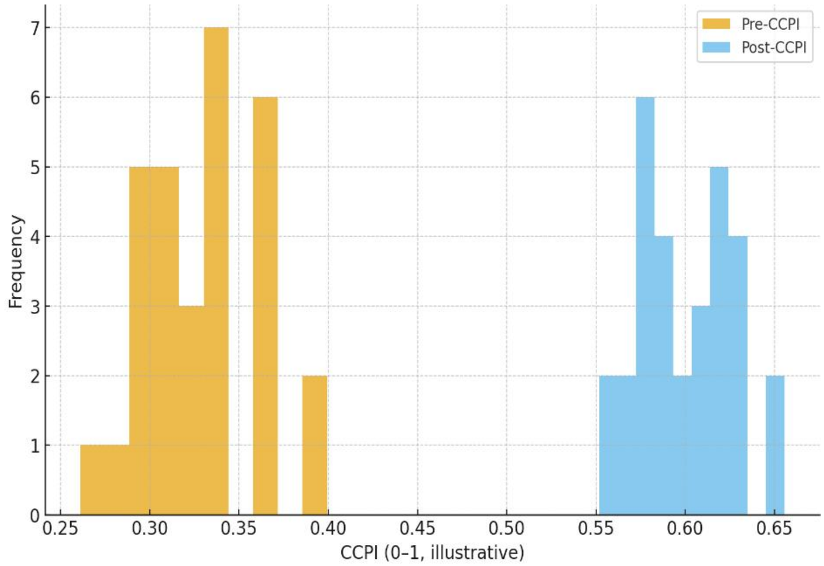

Figure 1. CCPI distribution.

4.3. Impact of the Pedagogical Intervention

Criterion-level movement provides more detailed resolution on the nature of improvement on the overall CCPI. The pre-post comparative analysis is represented in Figure 2: improvements on criteria from pre-to post represent advancements on all six AHP criteria. The greatest advancement is found on AI Literacy & Prompting Competence (C3), as expected within the three-phase model: basic fluency and ethical prompt engineering were specifically trained and practiced. Advancements on Creativity & Conceptual Diversity (C1) and Human Curatorial Mastery (C6) demonstrate that students expanded their concept ideas and honed their ability to filter and contextualize AI output as design narratives. At the same time, advancements on Technical Studio Output Quality (C4) and Ethical Reasoning & Authorship (C5) confirm that improvements were made without compromising studio quality for speed and novelty; instead, they advocated for a more disciplined form of AI-fueled exploration. The overall trend represented in Figure 2 again supports that the method was more than a simple enhancement on prompt competence practice and was instead a holistic co-creative training method.

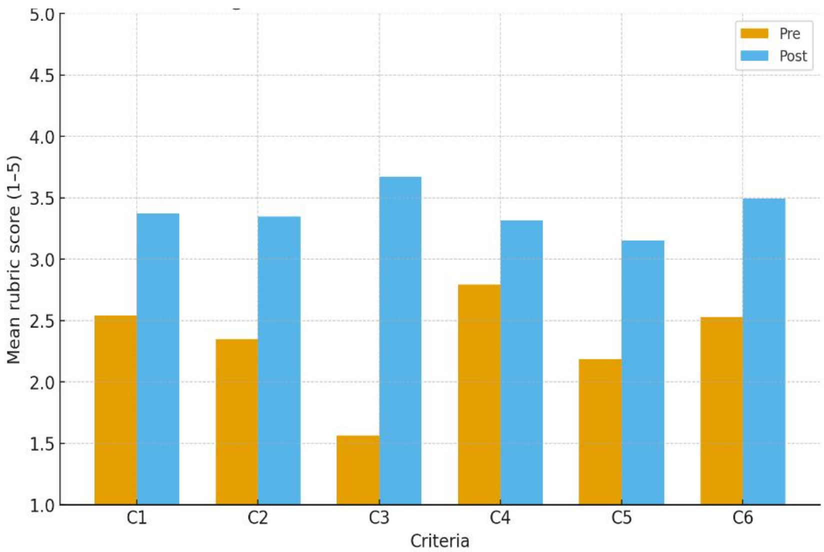

Figure 2. Pre–post gains across criteria.

Figure 3 visually demonstrates the operational logic of the proposed human AI co-creative framework within interior design engineering studios. The illustrated examples highlight that the output produced by the AI served mainly to stimulate design concepts instead of being the final products themselves. It was through the process of feedback and contextual interpretation, followed by human-driven improvement, that students were able to turn their initial AI-derived design concepts into viable interior design projects. This is further validated quantitatively by the results presented in the CCPI and SHAP studies.

Figure 3. The Evolution of Human-AI Co-Creation in Interior Design from an AI Concept to a Human-Refined Design Solution.

Besides clarifying the methodological approach, another reason for including some examples of visual co-creation was to increase the level of transparency and interpretability of the framework. Through the illustration of the translation from AI concept to a human-refined design solution, the framework proves that human judgment and context understanding always play a crucial role throughout the co-creation process.

4.4. ML Model Performance

The predictive modeling stage tested the hypothesis that CCPI, scaled on expert-rated criteria, can be predicted from visible process parameters. A comparison of the relative validation accuracy among tested models is given by Table 4. The results demonstrate that all nonlinear models outperformed the linear model with basic rate (slope) and thus infer that co-creative process quality is conditioned upon interaction between behaviors such as iteration between prompts, exploration/branching activities, and the strength of human tweaking activities. XGBoost outperformed other models with R2 = 0.82, RMSE = 0.041, and MAE = 0.033, closely followed by Light GB and then Random Forest methods, all having satisfactory generalizability on independent validation tests. The quality of alignment between the predicted and actual CCPI outcomes is shown by Figure 4. It may be inferred from Table 4: Model performance comparison and Figure 3: Predicted vs actual CCPI that there is equal merit for applying learning analytic capabilities within design studios to support decision-making on detecting students for whom initial support is required.

Table 4. Model performance comparison

Model	R^2 (CV)	RMSE (CV)	MAE (CV)
Linear Regression	0.62	0.06	0.048
Random Forest	0.78	0.045	0.036

XGBoost	0.82	0.041	0.033
LightGBM	0.8	0.043	0.034
SVR	0.7	0.052	0.041

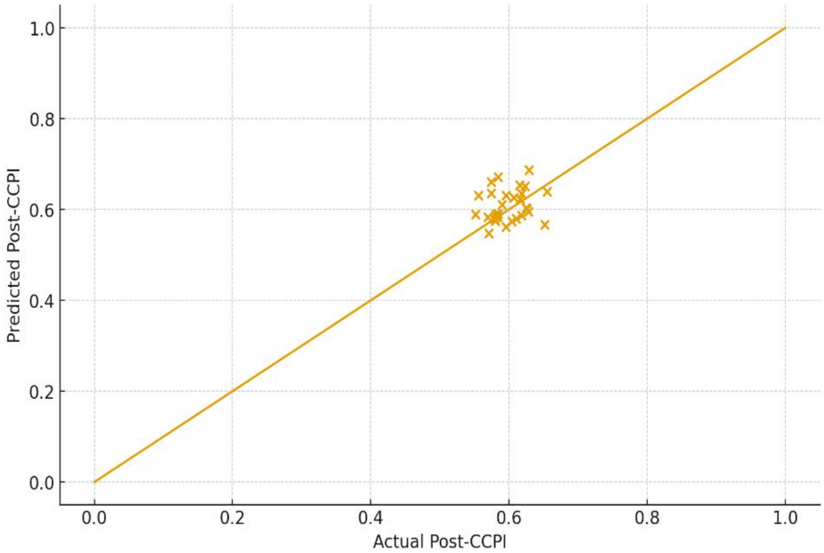

Figure 4. Predicted vs actual CCPI.

4.5. Explainability Findings

To apply predictive power for educational analysis, SHAP-based explanation was used to determine and calculate the relative impact contribution for each engineered feature. This impact ranking is depicted pictorially in Figure 5, with the human edit ratio feature standing out as having the biggest impact on promoting CCPI desirable outcomes. This supports the core educational tenet that quality co-creative production between AI and human participants is dependent on the intensity and quality of human-driven transformation and integration. The next biggest impact on desirable ends achieved through co-creative production is found to be prompt iterations and concept branches. These features support the tenet that quality co-creative production is achieved through iteratively interactive conversations and concept searches and expansions within the design process. Impact contributions from the prompt specificity score and the Phase-2 engagement feature position disciplined intent expression and dialogically driven exploration at the forefront of measurable educational indicators for co-creative competence. The appearance of material diversity and spatial variability among the impact features provides additional support for the tenet that while complexity is necessary for desirable co-creative production outcomes, this is achieved with the benefit and quality enhancement enabled through human-driven authorship and control over the resulting design process and its AI-augmented ideations.

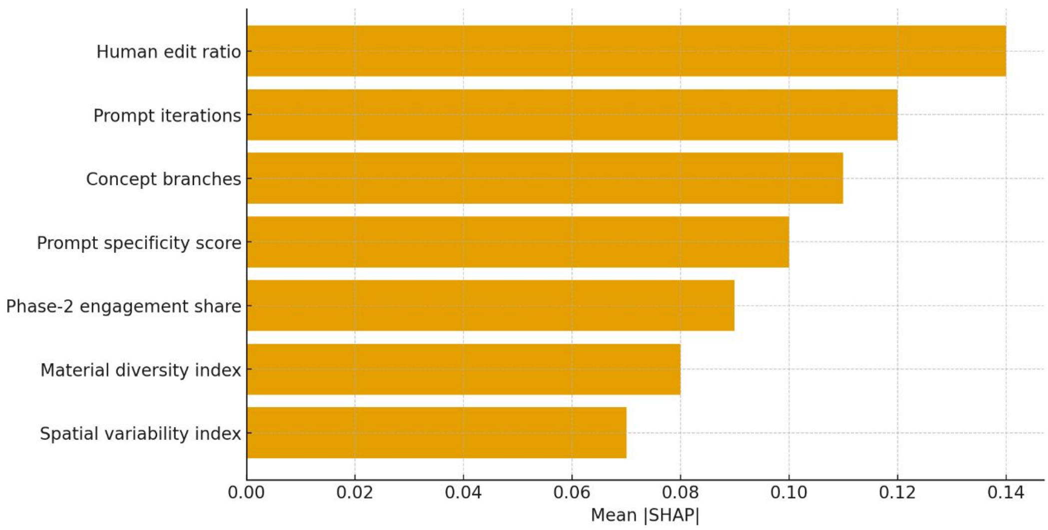

Figure 5. SHAP summary plot.

4.6. Qualitative Triangulation

These quantitative improvements can be made more interpretable with reference to the qualitative themes listed in Table 5: Themes mapped to criteria. Student feedback on increased ideation and divergent thinking is consistent with improvements seen on criteria C1 and C6, while the documented prompt learning curve is consistent with improvements seen on C3 and the general increase on C2. A consistent theme of developing curatorial skills can be seen to support the finding columns for the human edit ratio being the SHAP driver on Figure 4: SHAP summary plot, pointing again to the important recognition among students that AI should be regarded as tentative output needing human analysis and contextual understanding. Feedback on increased ethical thinking and bias recognition is consistent with improvements on criteria C5 and C3, supporting the observation that responsible use was a significant measurable outcome objective and not merely the subject of important preamble. Lastly, the theme of dedicating time to exploration can explain the simultaneous improvements on creativity and critical thinking criteria and serves to support the hypothesis that while AI reduced roadblocks and inefficiencies associated with pre-ideographic stages, they widened the thinking and evaluative horizon on the design stage.

Table 5. Themes mapped to criteria

Qualitative theme	Primary mapped criteria
Enhanced ideation & divergence	C1, C6
Prompting learning curve	C3, C2
Curatorial skill development	C6, C2
Ethical awareness & bias detection	C5, C3
Time reallocation to deeper exploration	C1, C2, C4

5. Discussion

The AHP weighting structure presented in Table 2 highlights the importance assigned by experts to Creativity and Conceptual Diversity (C1) and Critical Thinking and Justification (C2) within human–AI co-creative studio environments. In light of the increased weighting of these factors, it can be concluded that the main purpose of GenAI is seen in its use as a means of enhancing conceptual exploration, not a standalone design tool substitute. Such conclusions coincide with results obtained by other researchers who emphasize the need for the use of AI-assisted creativity to be based on human evaluation, contextual reasoning, and reflective judgment (Li et al., 2024; Mittal et al., 2024; Epstein et al., 2023). The high level of AI Literacy and Prompting Competence (C3) also corresponds to the rising prominence of prompt engineering, AI literacy, and interaction skills in design education. However, the significant weighting of Technical Studio Output Quality (C4), Ethical Reasoning and Authorship (C5), and Human Curatorial Mastery (C6) shows that professional and ethical judgment in AI-driven design practice is vital.

The positive change in pre- and post-intervention CCPI scores proves that the three-phase pedagogical intervention did not only increase the use of AI but also contributed to the development of multi-dimensional co-creative skills in students. The statistically significant increase in AI Literacy and Prompting Competence (C3) means that participants managed to develop their understanding of AI interaction techniques, such as prompt creation, adjustment, and recognition of AI limitations. At the same time, the increase in Creativity and Conceptual Diversity (C1), Critical Thinking and Justification (C2), and Human Curatorial Mastery (C6) implies that the role of human design reasoning in the context of AI assistance increased, and students started to consider GenAI outputs as initial conceptual data to be reinterpreted and modified.

These results thus indicate further that co-creative performance can indeed be considered a behavioral process with measurable performance indicators, rather than an inherently subjective educational outcome. The higher accuracy and performance of the used nonlinear models, especially XGBoost, support the idea that co-creation through human-AI interaction occurs as a result of complicated processes of behavior prompting, exploration diversity, refinement intensity, and decision-making cycles. These findings are coherent with the recent learning analytics research which emphasizes the significance of using explainable machine learning for finding interpretable causes of educational and behavioral performance (Ochoa & Huang, 2025; Zine et al., 2025).

According to the SHAP analysis, the highest positive predictors of CCPI performance were the human refinement intensity, number of iterations of human prompts, and the diversity of concept branching. These results highlight the fact that co-creation in a human-AI partnership does not rely solely on passively using AI, but requires critical reflection, iterative redefinition and curating of AI-generated outputs by humans. Specifically, the strong predictor role of the human edit rate suggests that the educational value created by AI-generated concepts relies on human engagement and iterative processes of evaluating and refining AI-generated outputs. The high SHAP values associated with iterations and branching of the prompt indicate that the interactive dialog with AI is crucial for co-creation in design development. Thus, the findings provide support for the idea discussed in recent literature about the importance of integrating AI into design processes critically and reflectively rather than treating AI as an easy way to speed up the task of design. Apart from its technical aspects, this research contributes to the discussion on human-centered use of GenAI in spatial design education.

The visual examples of the co-creations between humans and AI systems that have been shown in Figure 3 serve as additional evidence proving the results of the analysis carried out. These examples show how students developed AI-generated ideas into more sophisticated interior design solutions using the method of critique, context-specific adaptation, and curatorial intervention. Thus, they exemplify the role of human creativity within the framework under discussion, confirming the idea of GenAI serving as a co-designer rather than an alternative to it.

In comparison with existing scientific literature dedicated to using artificial intelligence systems in teaching design, the present paper adds value with the computationally integrated evaluation framework that consists of AHP-based weights, CCPI building, use of machine learning algorithms, and behavioral learning analytics. Unlike many other works dedicated to the topic, this paper proposes a scientifically justified methodology for assessing co-creative human-AI collaboration within interior design engineering studios based on objective measures.

From an engineering perspective, the proposed framework is valuable as an effective combination of such approaches to co-creative evaluation as decision analysis, performance measurement, predictive modeling, and explainable artificial intelligence. The AHP hierarchical structure can be considered a valuable tool for creating a transferable framework for evaluating the success of cooperation within design studios, while CCPI creates standardized multidimensional measures of performance. Machine learning combined with SHAP explainability allows predicting educational outcomes of co-creation. Consequently, the framework offers practical value for design-engineering programs seeking to integrate GenAI into studio education while maintaining transparency, accountability, and human-centered creative authorship.

6. Practical Educational Guidelines, Limitations, and Future Work

This section synthesizes the implemented implications of the AHP-CCPI-ML framework and provides a clear and understandable description of research limitations and the best possible guides for future research. The key implication for practice is that generative AI may be incorporated within interior design engineering studio practices as more than a unstructured productivity tool and instead as a carefully planned co-creative partner wherein the educational potential is contingent on process transparency, the quality of human judgment, and the accountability for outcomes. Educators can implement this guideline by carefully outlining the specific role that AI is intended to play within each process stage within studio practice and finding methods for students to evaluate prompts, AI responses, and human revisions as learning evidence. In doing so, AI-facilitated idea generation may be understood as a dialogic process wherein critical evaluation and curatorial authorship within the CCPI may be achieved among students.

A minimal viable adoption cycle can be achieved within a semester by embedding start-of-course foundational training for prompt logic and model and ethical use and then formalizing the concept branching needs within design development and finally measuring the depth of human refinement through controlled comparison portfolio works. In this model, the CCPI dimensions can inherently be maintained at six within the framework by requiring specific evidence for each: diversity for creativity concept sets, concept justification memo for critical thinking ability, prompt log evidence for artificial intelligence literacy competence, studio quality evidence for technical conformance assessment, ethical authorship declaration for ethical conduct ability, and annotated before and after refinement for curation mastery. Without actual class-based analysis software available, educators can instead use CCPI logic to grade successes based on reward for iterative prompting needs and breadth exploration requirements prior to achievement and the grade for human maturity for AI outputs to reaffirm the CCPI tenet for co-creative superiority as sense-making from human capacity for AI-based possibilities.

On the other hand, the results must be understood within the context of bounded limitations. The AHP pairwise comparison might be context-dependent to the university environment within which the study was carried out and may therefore influence the actual effect on CCPI improvement. Although the sample size is typical for studio-based educational research, future multi-institutional studies with larger cohorts are recommended to further validate the generalizability and robustness of the proposed framework across diverse educational and cultural contexts. Further, while the hierarchy is generic and transferable across similar scenarios, the exact ordering may vary depending on other programs' relatives and absolute emphasis on design details, critique literature analysis, and ethical considerations. Further, the impact is conditioned on the quality and quality trends of GenAI resources available to the participants at any given time; thus, model improvements and interface and access policies may influence student behavior and actual CCPI distribution and feature importances on ML tasks. Further, the sample size would be typical within studio research and may therefore be conditioned by the gross categorizations necessary within predictive modeling tasks, such that relative predictive stability might be contingent upon and conditioned by such categorizations. Finally, reliability analysis may be indicative across multiple raters and influence relative variability consistent with closed-form estimation and highly reduced dimensions. However, rubric review within the context retains a necessary and inherent subjectivity and may specifically be prima facie for criteria within prima facie judgments on innovation and semantic narratives. The CCPI provides necessary transparency and removes arbitrariness from relative design interpretations such that while necessary and substantial subjectivity might still attend relative interpretations consistent with design intention and authorship. Future studies should be concentrated on multi-university replications to confirm the generalizability of the AHP hierarchy and investigate whether CCPI might be implemented as a tool for benchmarking on various interior design engineering educational curricula. Also required would be longitudinal research to investigate the sustained application and transfer of co-creative skills outside the educational context and their application within the real-world constraints, client interactions, and legal conditions under which AI-powered ideation and visualization solutions are implemented. One concept application would be the integration of criteria hierarchies for sustainability and human-factors considerations to complement current priorities and pressing needs for interior design engineering to be assessed on criteria involving not merely creativity and engineering acuity, but upon sustainability considerations and human-factors considerations alike. Interdisciplinary validation research would be important for architecture and other design courses such as industrial design would further verify whether this model represents a generic paradigm for human-AI co-creative evaluation applicable across various aspects and tasks and whether a specific structural adaptation and configuration might be necessary for design-engineering tasks and aspects at stake. Also, applicable would-be application research upon larger datasets and multi-task predictive models aiming at concomitant estimation and prediction for CCPI and criterion levels alike to allow for more timely and specific educational feedback on co-creative skills requiring scaffolding support during the educational semester.

7. Conclusion

In this research endeavor, there was a strong emphasis on developing and validating an engineering-grade framework for integrating GenAI as a co-creative partner within interior design engineering studio learning, thus upgrading the state-of-the-art from descriptive adoption studies to concrete educational evidence with recognizable trends and patterns. With a strategic three-phase co-creative approach complemented by an analytic hierarchy process (AHP) decision model and framework design, this research was able to index and quantify the favored parameters within GenAI-integrated studio learning from within the design community at large. More specifically, creativity and conceptual diversity, critical thinking and explanation, and GenAI literacy were found to be the core and paramount parameters within this AHP structure under consistent expert judgments (CR = 0.06). The well-validated parameters were then utilized to create and construct a Co-Creative Performance Index (CCPI), thus creating a central and consistent educational metric aligned with CCPI values and indicative of a remarkable and significant pre-post increase (average CCPI increase from 0.329 to 0.599 with mean increase at 0.270). This specific finding is enthusiastically suggestive and supportive of students having achieved significant and greater proficiency with regard to GenAI interactions and functions and thereby advancing and developing judgments and curating power within AI outcomes and products with central and deeper design narratives and contextures aligned with contextual and need-sensitive design parameters and narratives. Further bolstering this specific research endeavor and investigation was a reliable and consistent predictive framework for CCPI within GenAI process parameters with XG Boost analysis and evaluation with an impressive and significant R^2 metric at (0.82). Additionally, and finally assessed were SHAP estimation intensity for core process parameters and drivers leading to co-creative and GenAI-based learning with leading parameters including human-refined intensity and exploration range and depth leading to predictive trends and needs within GenAI dynamic parameters and drivers.

Author Contributions

Conceptualization, Aseel Abdulsalam Al-Ayash and Mazin Arabasy; methodology, Aseel Abdulsalam Al-Ayash and Mazin Arabasy; software, Mariam Emad Edwar; validation, Yasser Ali Farghaly, Mazin Arabasy, and Aseel Abdulsalam Al-Ayash; formal analysis, Mariam Emad Edwar; investigation, Mayyadah F. Hussein; resources, Mayyadah F. Hussein; data curation, Mariam Emad Edwar; writing original draft preparation, Mazin Arabasy; writing review and editing, Aseel Abdulsalam Al-Ayash, Mazin Arabasy, and Mariam Emad Edwar; visualization, Mazin Arabasy; supervision, Aseel Abdulsalam Al-Ayash and Yasser Ali Farghaly; project administration, Mazin Arabasy. All authors have read and agreed to the published version of the manuscript.

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