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Innovation with Design Thinking: Engineering Students vs. Artificial Intelligence in Solution Generation

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Abstract– The intersection of human creativity and Artificial Intelligence (AI) in innovation processes is a growing area of exploration. This study investigates the application of Design Thinking (a structured, human-centered methodology) to assess how third-semester engineering students from diverse disciplines (Industrial Engineering, Innovation and Development Engineering, Mechanical Engineering, and Mechatronics Engineering) compare to AI-generated solutions in addressing a real-world educational challenge: designing innovative tools to support children with learning difficulties.

A comparative experimental approach was employed, where 67 students, divided into 13 teams, applied the five Design Thinking phases (Empathize, Define, Ideate, Prototype, and Test). Their solutions were systematically analyzed against those generated by AI tools (ChatGPT, Gemini, and Copilot), which followed the same Design Thinking framework. Quantitative metrics, such as the number of ideas generated and prototyping time, were assessed alongside qualitative variables, including originality, feasibility, scalability, and alignment with user needs. Statistical tests (Mann-Whitney U and Student's t-test) were applied to determine significant differences between human and AI outputs.

Results indicate that AI excels in originality, user alignment, and scalability, while students demonstrate greater feasibility and contextual adaptability. AI-generated solutions were consistently limited in number (4-5 ideas), whereas student teams produced a broader range. Additionally, AI significantly reduced prototyping time. These findings suggest that a hybrid approach, integrating AI's computational power with human-centered problem-solving, could optimize innovation processes in engineering education. Future research should explore AI as a collaborative design tool rather than a competing entity.

Keywords-- Design Thinking, Artificial Intelligence, Engineering Education, Human-AI Collaboration, Innovation.

I. Introduction

In the rapidly evolving landscape of innovation, the integration of human creativity and artificial intelligence (AI) has become a pivotal area of exploration. This study investigates the application of Design Thinking, a human-centered problem-solving methodology, in generating innovative solutions to real-world challenges. Specifically, it compares the outcomes produced by third-semester engineering students from diverse disciplines (Industrial Engineering, Innovation and Development Engineering, Mechanical Engineering, and Mechatronics Engineering) against those generated by an AI system. Both groups were tasked with addressing the same challenge: designing an innovative solution to support children with learning difficulties.

Design Thinking, characterized by its five-stage process (empathize, define, ideate, prototype, and test), has been widely recognized for its ability to foster creativity and user-centric solutions [1]. However, as AI systems continue to advance, their potential to replicate or even enhance human creativity in problem-solving scenarios has sparked significant interest [2]. This research aims to contribute to this discourse by examining how engineering students, trained in structured methodologies, perform in comparison to AI when both are guided by the same Design Thinking framework.

The study involved a sample of third-semester engineering students from various programs, ensuring a diverse range of perspectives and approaches. Their solutions were systematically compared to those generated by an AI tool that was also guided through the five stages of Design Thinking. The challenge focused on creating an innovative learning support tool for children, emphasizing the originality of the innovation, alignment with user needs, feasibility, and scalability.

The findings of this comparative analysis highlight the complementary roles of human ingenuity and AI in the innovation process. The implications of these findings extend beyond academia, offering valuable insights for educators, engineers, and innovators navigating the evolving landscape of human-AI collaboration. Furthermore, the study underscores the importance of integrating Design Thinking into engineering education to prepare students for the challenges of a technology-driven future [3].

This research aims to compare and evaluate the proposed solutions to a learning problem identified in children aged 3 to 8, generated by both third-semester engineering students following the Design Thinking methodology and an Artificial Intelligence tool.

II. Literature Review

A. Introduction to Design Thinking in Engineering

Design Thinking (DT) is a user-centered, iterative methodology that fosters innovation through five structured phases: empathize, define, ideate, prototype, and test. Initially popularized by IDEO and Stanford's Hasso Plattner Institute of Design (d. school), DT has been widely adopted in engineering education and practice for its ability to solve complex, real-world problems creatively and systematically [4].

Engineering students applying DT learn to incorporate empathy and user needs into the innovation process, leading to solutions that are not only functional but also aligned with real-world requirements. Research suggests that DT enhances problem-solving skills, collaboration, and adaptability among engineers, making it an essential approach for fostering innovation in technology-driven industries [5].

Concurrently, Artificial Intelligence (AI) has emerged as a transformative technology with the potential to augment various stages of the design thinking process. AI can assist in generating a multitude of ideas during the ideation phase and expedite prototyping by providing rapid simulations and optimizations. A study by Ding et al. introduces DesignGPT, a multi-agent collaboration framework in design, illustrating how AI can be integrated into design processes to enhance creativity and efficiency [6].

B. The Role of Artificial Intelligence in Design Thinking

Concurrently, Artificial Intelligence (AI) has emerged as a transformative technology with the potential to augment various stages of the design thinking process.

Artificial Intelligence (AI) is revolutionizing the way innovation occurs by automating tasks, analyzing vast amounts of data, and generating novel ideas [7]. Within the context of Design Thinking, AI has the potential to enhance human creativity by providing alternative perspectives, identifying hidden patterns, and accelerating the prototyping process [8].

AI can assist in generating a multitude of ideas during the ideation phase and expedite prototyping by providing rapid simulations and optimizations.

The advent of Artificial Intelligence (AI) has introduced new possibilities for enhancing each phase of the Design Thinking (DT) process by leveraging data analysis, pattern recognition, and automation [6]. In the Empathize phase, AI can process large datasets from surveys, social media, and user feedback to uncover insights into user preferences and behaviors. During Define, machine learning models help identify patterns in user problems, refining problem statements with greater precision. In the Ideate stage, generative AI models, such as GPT-based systems, can rapidly propose multiple innovative solutions, complementing human creativity. Finally, in the Prototype and Test phases, AI-driven simulations and rapid prototyping facilitate faster iterations, reducing both time and costs in product development. These AI-powered enhancements optimize the DT methodology, making innovation processes more efficient and data-driven.

C. Comparing Engineering Students and AI in Innovation Processes

The comparison between engineering students and AI systems in applying design thinking methodologies raises questions about the strengths and limitations of each approach. While students bring contextual understanding and empathy to problem-solving, AI offers efficiency in data analysis and solution optimization. However, AI currently lacks intuitive and emotional insights inherent to human designers. De Peuter et al. discuss the potential of AI assistants in design, noting the importance of allowing designers to maintain control over creative decisions while leveraging AI capabilities [9].

Engineering students bring contextual knowledge, critical thinking, and ethical considerations to innovation, whereas AI contributes efficiency, scalability, and data-driven insights. While AI can generate a large volume of ideas quickly, students excel in applying human intuition and ethical reasoning—factors critical in decision-making processes [10].

Research indicates that AI-assisted DT processes outperform traditional human-only approaches in speed and efficiency but lack the ability to integrate human-centric nuances, such as emotional intelligence and user empathy [11].

D. Ethics & innovation, using AI.

The use of AI is increasing exponentially in all fields, including higher education. And as in everything that is present in science, technology and education, it is important to consider ethical aspects in this use of AI as well as to be sensitive to what AI provides as answers to the questions posed to it, considering the quest to take full advantage of the benefits that AI offers [12]. Regarding innovation and the use of AI, it leads to consider issues such as its proper use, fairness, and protection of people. Critical thinking and inquiry of students and professors should lead to questioning, comparing, analyzing and concluding, to ensure the proper use and reliability of what is obtained from AI [13,14]. The involvement of stakeholders is linked to innovation, policies, regulations and recommendations with the use of IA in innovation and design processes, and the challenges that arise such as privacy and intellectual property are issues to keep in mind in higher education.

III. Methodology

For the development of this study, a comparative experimental approach was conducted in which 67 engineering students, divided into 13 teams, generated innovative solutions to address learning challenges faced by children aged 3 to 8 years. Subsequently, an AI tool was employed to generate proposed solutions for the same challenges previously addressed by the student teams, following the Design Thinking methodology. The solutions produced by both the student teams and the AI were evaluated and compared in terms of quality, creativity, feasibility, and alignment with user needs.

Data collection was carried out as follows: the 13 teams were assigned the task of addressing a specific learning challenge faced by children aged 3 to 8 years. Using the Design Thinking methodology, they worked through each of its stages (Empathize, Define, Ideate, Prototype, and Test) to develop their solutions. The problems selected by each team of students, after completing the empathize stage of the Design Thinking methodology, are presented in table I.

TABLE I
Learning problems identified by each team for children.

Learning problems identified by each team for children between 3 and 8 years old			
Team 1	Development of resilience and patience in the learning process	Team 8	Promote Physical activities in children
Team 2	Development of motors skills in children with autism	Team 9	Improve reading comprehension in children
Team 3	Development of mathematical skills in children	Team 10	Development of the habit of reading
Team 4	Improve concentration in children with ADHD (attention deficit hyperactivity disorder) in the learning process	Team 11	Development of cognitive processes in children with Down Syndrome
Team 5	Promote socialization and learning of blind children	Team 12	Improve concentration in children
Team 6	Development of mathematical skills in children	Team 13	Improve concentration in children with ADHD
Team 7	Improve concentration in children with ADHD in the learning process		

Once the student teams completed and presented their proposed solutions and prototypes, they were instructed to use AI tools (ChatGPT, Gemini, Copilot) to generate alternative solutions following the same Design Thinking phases, based on the same problem information provided to the students.

Data collection involved analyzing the information recorded by both the student teams and the AI across each of the five Design Thinking stages. The variables analyzed were divided into qualitative and quantitative categories. Quantitative variables included: the number of ideas generated during the ideation phase and time spent designing the prototype. Qualitative variables included: originality of the innovation, alignment with user needs, feasibility, and scalability.

For data analysis and processing, a normality test was applied to determine the distribution of the qualitative data. Figure 1 shows the results of the normality test for the number of ideas generated by the 13 student teams. For this test, the p-value is greater than 0.05, therefore there is not enough evidence to reject the null hypothesis of normality. This indicates that the data follows a normal distribution.

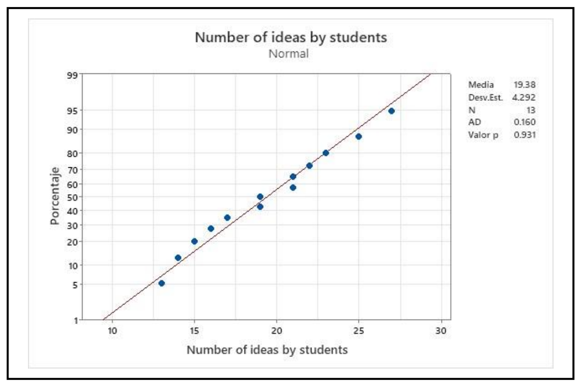

Fig. 1 Test of normality for the number of ideas generated by students.

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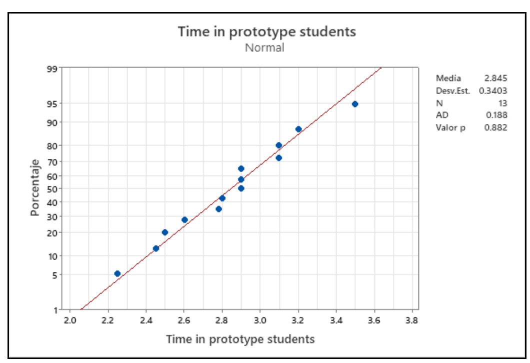

Fig. 2 Test of normality for time in prototype by students.

Figure 2 shows the results obtained for the normality test applied to the times taken by the 13 student teams to generate the prototype sketch. The p-value obtained indicates that the data follows a normal distribution.

Figure 3 shows the results of the desirability test using Minitab software for the number of ideas generated by Artificial Intelligence. Clearly, the AI results yield 4 or 5 proposals using ChatGPT, Gemini, and Copilot. Based on the obtained p-value, we can conclude that it does not follow a normal distribution.

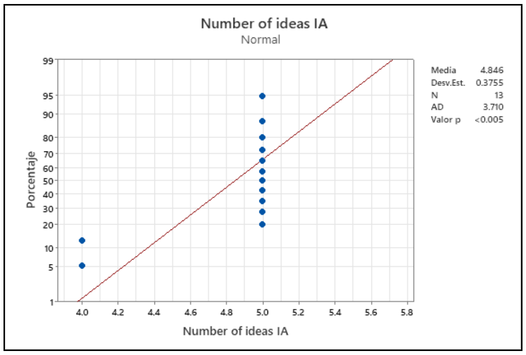

Fig. 3 Test of normality for the number of ideas generated by I

Figure 4 shows the results obtained for the normality test applied to the times taken by Artificial Intelligence to generate the prototype sketch. The p-value obtained indicates that the data follows a normal distribution.

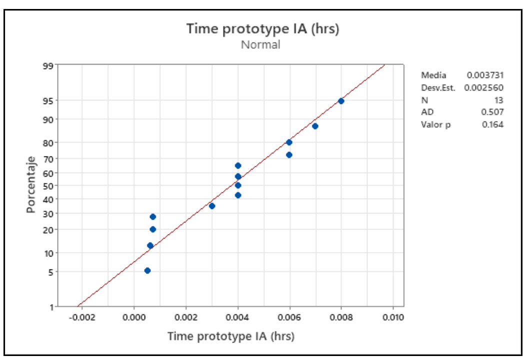

Fig. 4 Test of normality for time in prototype by IA.

To assess the difference in the number of ideas generated and time spent designing the prototype by the student teams and the AI, a t-test was used. The evaluation of technical feasibility was conducted using a 1-to-5 scale based on established technical criteria. Qualitative variables such as originality, feasibility, and scalability were evaluated using a Likert scale assigned to a panel of 5 experts. Meanwhile, alignment with user needs was assessed through a desirability test administered to potential users.

Furthermore, it is important to note that the teams employed design software, specifically Tinkercad and SketchUp, in the development of their prototypes following the selection of a viable solution for prototyping. This design process was undertaken autonomously and preceded the application of AI tools.

It is important to underscore that despite the development of a final physical prototype utilizing corrugated cardboard by each team, in accordance with their AI-independent solutions, the subsequent evaluation by a panel of five experts, focusing on originality, feasibility, and scalability, involved a comparative analysis of the teams' prototype sketches against those generated by the AI

A comprehensive listing of the prompts administered at each stage of the Design Thinking framework, enabling a direct comparison between the solutions conceived by the student participants and those autonomously generated by Artificial Intelligence, is provided hereunder (see Table II).

TABLE II
PROMPTS ADMINISTERED AT EACH STAGE OF THE DESIGN THINKING FRAMEWORK

Design Thinking stage where AI was utilized	Prompt utilized by each team based on the defined problem
Brainstorming	Generate novel ideas for assistive technologies that could help children with [specific disability] overcome [specific learning barrier]
Prototype Design	Generate a concept for a physical learning prototype designed to address [Specific Learning Problem, aged [Specific Age Range, e.g., 6-8 years old] with [Specific Learning Difference]. The prototype's structure must be composed of at least 80% cardboard and should incorporate [Number, e.g., three] distinct interactive elements that facilitate [Specific Learning Goal, Describe the prototype's form, the function of each interactive element, and how the cardboard construction supports these functionalities and considers the sensory needs of children with [Specific Learning Difference]

IV. RESULTS AND DISCUSSIONS

To compare the difference between the number of ideas generated by students and the number of ideas generated by AI, a Mann-Whitney test was used. Table III shows the number of ideas obtained by each of the 13 student teams compared to the number of ideas generated by AI to solve the identified problem.

TABLE III

NUMBER OF IDEAS GENERATED BY STUDENTS AND IA

Number of ideas generated by students	Number of ideas generated by IA
22	5
15	5
25	5
21	5
19	5
27	5
14	5
16	5
17	5
13	5
21	5
23	4
19	4

The *mannwhitneyu* function from *scipy.stats* was used with a two-tailed alternative hypothesis. The test compares the distributions without assuming normality. The calculated U statistics and p-value are U: 169.0 and p-value:4.12×10^{-6}. These results suggest that the difference in the number of ideas generated by students and AI is statistically significant. The opportunity identified in this analysis is that while the number of ideas generated by students varied between 13 and 27, the results produced by AI remained constant between 4 and 5 when using applications such as Gemini, ChatGPT, or Copilot.

TABLE IV

NUMBER OF IDEAS GENERATED BY STUDENTS AND IA

Time in prototype by students (hrs)	Time in prototype by IA (hrs)
2.78	0.004
2.9	0.003
3.1	0.004
2.6	0.006
3.5	0.004
2.25	0.007
2.9	0.006
2.45	0.007
3.1	0.005
2.5	0.004
2.8	0.008
3.2	0.007
2.9	0.006

Table IV shows the time dedicated by the 13 student teams to create the sketch of their prototype compared to the time it took the AI Copilot to provide them with a prototype sketch proposal that will solve the identified problem with children.

To compare the prototype sketching time between the students and the AI, a student's t-test was performed using Minitab software. The results are presented in Table V and VI.

TABLE V

DESCRIPTIVE STATISTICS FOR TIME PROTOTYPING BY STUDENTS AND AI

Descriptive Statistics				
Sample	N	Mean	Stand. Desv.	Error
Time in prototype students	13	2.845	0.34	.094
Time in prototype IA	13	0.00373	0.00256	0.00071

TABLE VI

T-STUDENT TEST FOR PROTOTYPING TIME BY STUDENTS AND AI

Test		
Nule Hipothesis	H_0: $\mu_1 - \mu_2 = 0$	
Altern Hiiphotesis	H_1: $\mu_1 - \mu_2 \neq 0$	
Value t	Df	p-value
30.1	12	0

Since $p<0.05$, we reject the null hypothesis and conclude that there is a statistically significant difference in the time spent sketching the prototype between students and AI.

One of the requirements given to the students for the design of the prototypes—based on the problem definition developed by each team—was that at least 80% of the prototype's structure had to be made from recycled cardboard. Table VII presents the type of solution generated for each of the identified learning problems.

TABLE VII

SOLUTIONS GENERATED BY EACH TEAM FOR EACH KIND OF PROBLEM

	Learning problems identified by each team for children between 3 and 8 years old	Solutions generated by each team for each type of learning problem identified in children
Team 1	Development of resilience and patience in the learning process	Stacking game to practice patience when placing pieces and resilience if they fall
Team 2	Development of motors skills in children with autism	Board-style learning game with a duck theme that supports the development of motor, neuromotor, emotional,

		and communication skills
Team 3	Development of mathematical skills in children	Snakes and Ladders game to practice basic math operations: addition, subtraction, multiplication, and division in a fun way
Team 4	Improve concentration in children with ADHD (attention deficit hyperactivity disorder) in the learning process	Monopoly-style board game with a dinosaur theme, designed to teach multiplication to children with attention deficit
Team 5	Promote socialization and learning of blind children	A pack of inclusive board games for children with visual impairments
Team 6	Development of mathematical skills in children	Operations tower to practice math in a fun way, with a built-in timer circuit
Team 7	Improve concentration in children with ADHD in the learning process	Game focused on improving attention, coordination, and problem-solving by moving a ball through mazes with adjustable difficulty levels, allowing it to adapt to the child's progress
Team 8	Promote Physical activities in children	Game called 'Movement Bingo' that encourages healthy habits by promoting physical activity, social interaction, and physical and mental well-being
Team 9	Improve reading comprehension in children	An interactive book featuring an engaging story for children. On the last page, they'll find a special space where they can reconstruct the sequence of the story using puzzle-like image pieces
Team 10	Development of the habit of reading	Interactive educational game that promotes reading comprehension in children, using a board-map and a movement mechanism activated by rotating buttons
Team 11	Development of cognitive process in children with Down Syndrome.	Cognitive memory game to promote verbal and recognition skills
Team 12	Improve concentration in children	Cardboard maze with marbles
Team 13	Improve concentration in children with ADHD	Magic tiles made from recycled cardboard

The evaluation of qualitative variables was conducted using a Likert scale, where 1 represents "strongly disagree" and 5 represents "strongly agree." The definition of the assessed qualitative variables is presented below:

a) *Originality of the innovation:* refers to the degree to which an innovation is perceived as novel, unique, or distinct from existing solutions, products, or processes [15].
b) *Alignment with user needs:* refers to the degree to which a product, service, or system is designed and developed to meet the specific requirements, preferences, and expectations of its intended users. It emphasizes understanding user behaviors, pain points, and goals to ensure that the solution effectively addresses their needs and provides a satisfactory user experience [16].
c) *Feasibility*: refers to the state or condition of being possible to do easily or conveniently. It assesses the practicality and viability of a proposed plan, project, or idea, considering various factors such as technical, economic, legal, operational, and social aspects [17].
d) *Scalability*: refers to the capacity to grow and adapt to changing demands without compromising quality or functionality. In the context of technology, scalability often refers to the ability of a system to handle a growing number of users, transactions, or data volume [18].

The data collected for the qualitative variables, such as originality of the innovation, alignment with user needs, feasibility, and scalability, are presented in Tables VIII and VIII. These data represent the evaluation results provided by a five-member evaluation committee for the innovative solutions proposed by each of the 13 teams for the selected problem, as well as the assessment of the solution provided by AI for the same issue.

TABLE VIII
EVALUATION OF QUALITATIVE VARIABLES TO STUDENTS

	Originality of the innovation	Alignment with user needs	Feasibility	Scalability
Team 1	3.9	3.5	4.2	4.4
Team 2	4.1	4.2	4.5	4.3
Team 3	4.4	4.5	4.3	4
Team 4	3.95	4.1	4.2	3.8
Team 5	4.3	3.9	4.15	4.1
Team 6	4.2	4.1	4.7	4.5
Team 7	4.5	4.2	5	4.8
Team 8	3.7	4.1	4.6	4.2
Team 9	4.15	4.3	4.7	4.15
Team 10	4.3	4.1	4.5	4.1
Team 11	4.7	4.5	4.8	4.3
Team 12	4.2	4.1	4.6	4.7
Team 13	4.15	4.2	4.8	4.4

Reviewing the results shown in Tables VIII and IX, we can conclude regarding the originality of the innovation that the evaluation given to the students has an average of 4.2, compared to 4.6 for the evaluation of AI. Additionally, reviewing the variable alignment with user needs, an average score of 4.1 was obtained for the evaluation of the 13 student teams, compared to 4.5 for AI.

For the variable feasibility, an average score of 4.5 was observed for the solution provided by the student teams, compared to an average of 4.1 for the evaluation of AI. Finally, for the variable scalability, the solution provided by the students achieved an average score of 4.3, compared to an average of 4.7 for the evaluation of the solution provided by AI.

TABLE IX

EVALUATION OF QUALITATIVE VARIABLES TO IA

	Originality of the innovation	Alignment with user needs	Feasibility	Scalability
Team 1	4.4	4.5	3.9	4.9
Team 2	4.6	4.7	4	4.7
Team 3	4.8	4.4	3.8	4.6
Team 4	4.5	4.2	4.15	4.7
Team 5	4.7	4.6	4.2	4.6
Team 6	4.5	4.5	4.5	4.7
Team 7	4.7	4.6	4.3	4.5
Team 8	4.5	4.8	4.2	4.8
Team 9	4.5	4.7	4.1	4.4
Team 10	4.7	4.9	3.8	4.7
Team 11	4.7	4.3	4	4.9
Team 12	4.6	4.5	3.9	4.5
Team 13	4.4	4.4	4.2	4.6

Analyzing the quantitative data and according to the analyses performed, it can be concluded that teamwork is more enriching in terms of idea generation. The AI only provides 4 to 5 options as ideas to the problem posed, varying between 4 and 5 depending on the AI used. Regarding the time spent sketching the prototype for the solution to the identified problem, there is a large difference between the time spent by the student teams to give shape and characteristics compared to the time it takes the AI to propose a sketch for that prototype.

The analysis of the evaluation results for the different qualitative variables reveals key insights into the comparative performance of student-generated solutions versus AI-generated solutions in the context of innovation.

Originality: AI-generated solutions received a slightly higher average score (4.6) compared to student-generated solutions (4.2). This suggests that AI was perceived as producing more novel or unique ideas. This may be attributed to AI’s ability to rapidly analyze vast amounts of data and generate diverse ideas that might not be immediately considered by human designers. However, while AI excels in generating innovative solutions, human creativity (especially when combined with contextual understanding) remains an essential factor in innovation.

Alignment with User Needs: The AI-generated solutions also scored higher (4.5) than the student-generated solutions (4.1) in terms of meeting user needs. This could be a reflection of AI’s capacity to synthesize user preferences from large datasets, leading to highly tailored solutions. However, human-driven processes often incorporate empathy and nuanced user insights, which are crucial for long-term user satisfaction. The slightly lower score for students might indicate that their solutions, while thoughtful, may not have been as data-driven as AI’s approach.

Feasibility: In contrast, student-generated solutions outperformed AI in feasibility, with an average score of 4.5 compared to 4.1 for AI-generated solutions. This suggests that while AI may generate creative and user-aligned solutions, the practicality of implementation remains a challenge. Engineering students, drawing from their knowledge of real-world constraints, were better able to propose solutions that could be realistically executed with available resources, technologies, and current industry limitations.

Scalability: AI-generated solutions received the highest score (4.7) in scalability compared to student-generated solutions (4.3). These finding highlights AI's strength in optimizing large-scale implementation. AI's ability to analyze trends and predict long-term impacts likely contributed to its advantage in scalability. Meanwhile, student-generated solutions, though feasible, may have been more context-specific and not as broadly adaptable.

IV. CONCLUSIONS

This study highlights the distinct contributions of both human creativity and artificial intelligence (AI) within the Design Thinking framework for problem-solving in engineering education. By comparing the solutions generated by third-semester engineering students and AI tools for addressing learning challenges in children, key differences and complementary strengths were identified.

The findings demonstrate that AI exhibits strengths in generating original, user-aligned, and scalable solutions, likely due to its capacity for rapid data processing and pattern recognition. However, AI-generated solutions often lack feasibility, indicating challenges in practical implementation. In contrast, engineering students, leveraging their contextual knowledge and critical thinking, produced solutions that were more feasible but slightly less scalable and user-aligned when compared to AI.

Quantitative analysis revealed that students generated a significantly higher number of ideas during the ideation phase, reinforcing the value of collaborative human creativity. Additionally, while AI significantly reduced prototype development time, students engaged in a more iterative and thoughtful refinement process, emphasizing real-world constraints and user needs. These findings underscore the importance of integrating AI as an augmentation tool rather than a replacement for human-driven problem-solving in innovation processes.

A hybrid approach, where AI serves as a co-creative partner to human designers, could offer a balanced methodology that leverages AI’s efficiency while preserving human intuition, empathy, and ethical considerations. Future research should explore structured frameworks that guide students in effectively incorporating AI tools to enhance creativity while maintaining feasibility and ethical responsibility. Furthermore, refining AI models to better address feasibility constraints could enhance their practical applications in engineering design and innovation.

Overall, this research reaffirms the value of integrating Design Thinking into engineering education while advocating for a symbiotic relationship between AI and human problem-solving capabilities to drive innovation in educational and technological contexts.

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