Exploring the Integration of Artificial Intelligence into Multidisciplinary Engineering Workflows

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Abstract

This study aimed to explore how artificial intelligence is being integrated into multidisciplinary engineering workflows and how engineers perceive its effects on collaboration, design decision-making, professional roles, and organizational readiness. A qualitative descriptive design was employed using semi-structured interviews with 24 engineering professionals working in multidisciplinary engineering organizations in Muscat, Oman. Participants included civil, mechanical, electrical, software, systems, and project engineers, as well as engineering managers with direct experience of AI-supported tools in design, simulation, project coordination, documentation, quality assurance, or decision support. Participants were recruited purposively to capture variation in engineering discipline, professional experience, and organizational role. Data collection continued until theoretical saturation was reached. Interviews were audio-recorded, transcribed verbatim, anonymized, and analyzed using thematic analysis. NVivo software was used to organize transcripts, code interview data, compare patterns across disciplinary groups, and develop final themes. Four main categories emerged from the analysis: AI as a boundary-spanning coordination mechanism, AI-enabled acceleration of design exploration and technical decision-making, human oversight and trust in AI-generated outputs, and organizational readiness for sustainable AI integration. Participants described AI as useful for connecting fragmented disciplinary knowledge, reducing repetitive documentation work, supporting early-stage design alternatives, improving simulation preparation, and facilitating cross-functional communication. However, they also emphasized concerns regarding data quality, model explainability, accountability for engineering decisions, software interoperability, and uneven AI literacy across teams. The integration of AI into multidisciplinary engineering workflows is not merely a technical transition but a socio-technical transformation that reshapes collaboration, professional judgment, and organizational learning. Sustainable AI adoption requires high-quality engineering data, transparent governance, domain-specific validation, continuous professional training, and human-centered workflow redesign.

Keywords: artificial intelligence; multidisciplinary engineering; engineering workflows; qualitative research; human–AI collaboration; Muscat; thematic analysis; digital engineering

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1. Introduction

Artificial intelligence (AI) has become an increasingly influential element of engineering practice, not only as a computational technology but also as a socio-technical force that is changing how engineers define problems, coordinate knowledge, generate alternatives, evaluate risk, and make decisions. In engineering organizations, workflows are rarely linear or discipline-specific. Contemporary infrastructure, energy, manufacturing, construction, transportation, and digital systems projects usually require multidisciplinary coordination among civil, mechanical, electrical, software, environmental, safety, procurement, and project management teams. The growing complexity of these projects has intensified the need for tools that can support integration across fragmented knowledge domains, large datasets, technical standards, simulation environments, and documentation requirements. AI is increasingly presented as a potential response to this complexity because it can automate repetitive tasks, support pattern recognition, generate design alternatives, analyze large volumes of engineering data, and assist decision-making across project stages (Berente et al., 2021; Davenport & Ronanki, 2018; Poulsen et al., 2025).

In the engineering context, AI refers to computational systems capable of performing tasks that normally require human intelligence, including classification, prediction, optimization, natural language processing, image recognition, anomaly detection, and generative reasoning. Its applications in engineering workflows vary widely. Machine learning models may be used to predict equipment failure, optimize energy performance, detect defects, or analyze sensor data. Generative design tools can produce multiple design alternatives based on constraints such as weight, cost, material, performance, sustainability, and manufacturability. Large language models can assist with requirements analysis, technical documentation, code generation, design review preparation, and knowledge retrieval. AI-supported simulation tools can accelerate finite element analysis, computational fluid dynamics preparation, model calibration, and performance forecasting. In construction and built environment workflows, AI can also support scheduling, building information modeling, safety analysis, facility management, and project risk assessment (Egwim et al., 2024; Onatayo et al., 2024; Yüksel et al., 2023).

The integration of AI into engineering workflows is especially significant because engineering work depends on both formal technical knowledge and situated professional judgment. Engineering decisions are constrained by codes, safety requirements, client specifications, material properties, environmental conditions, cost limitations, and regulatory obligations. Therefore, the use of AI in engineering cannot be understood simply as a process of replacing human work with computational automation. Rather, AI creates new forms of human–machine interdependence. Raisch and Krakowski (2021) describe this as the automation–augmentation paradox: AI may automate some tasks while simultaneously increasing the need for human interpretation, oversight, and responsibility. In multidisciplinary engineering teams, this paradox becomes more complex because AI-generated outputs must be interpreted by professionals from different knowledge traditions and validated against multiple disciplinary criteria.

Recent engineering design literature emphasizes that AI can expand the solution space available to engineers, particularly in early-stage conceptual design. Generative AI can support ideation by producing alternative concepts, visualizations, preliminary specifications, and design variants that may stimulate creativity and accelerate exploration (Choudhury et al., 2025; Fang et al., 2025). Obieke et al. (2025) argue that AI collaboration frameworks can help address the expanding knowledge demands of engineering design by enabling engineers to access, structure, and combine domain knowledge more rapidly. Similarly, research on AI in systems engineering indicates that AI has potential across requirements engineering, model-based systems engineering, verification, validation, and lifecycle decision support, although adoption is limited by barriers such as insufficient data quality, limited explainability, technical immaturity, and trust concerns (Norheim et al., 2024; Poulsen et al., 2025).

Despite these opportunities, the use of AI in engineering remains uneven and sometimes fragmented. Many organizations adopt AI tools for isolated tasks rather than redesigning the entire workflow around human–AI collaboration. For example, one team may use AI for document summarization, another for predictive maintenance, and another for simulation acceleration, without establishing shared governance, data standards, or integration protocols. This fragmentation can reduce the strategic value of AI because multidisciplinary engineering work depends on traceability, interoperability, and shared accountability. AI-generated outputs that are useful to one discipline may be difficult for another discipline to interpret or validate. A design alternative generated by an AI tool may satisfy structural constraints but conflict with maintenance requirements, cost assumptions, environmental standards, or client preferences. Therefore, the practical value of AI depends not only on algorithmic performance but also on how AI is embedded into collaborative workflows.

Trust is another central issue in AI-supported engineering. Engineers are professionally accountable for the safety, reliability, and performance of systems. As a result, they cannot rely on AI outputs merely because they are fast, persuasive, or technically sophisticated. Large language models, for instance, may generate fluent technical text while producing inaccurate, incomplete, or unverifiable claims. Bender et al. (2021) warned that language models can reproduce biases, produce misleading outputs, and obscure the limitations of their training data. In engineering workflows, such limitations can create serious risks if AI-generated recommendations are accepted without domain-specific validation. Therefore, engineers must develop new forms of AI literacy that include not only tool operation but also critical evaluation, uncertainty awareness, data provenance, and ethical accountability.

The integration of AI into engineering work also raises organizational questions. AI adoption requires data infrastructure, cybersecurity measures, software integration, training, leadership support, and governance mechanisms. Berente et al. (2021) argue that managing AI involves coordinating technological capability with organizational structures, decision rights, and evolving work practices. In engineering organizations, these requirements are amplified because workflows often depend on specialized software ecosystems such as CAD, BIM, GIS, simulation platforms, enterprise resource planning systems, project management tools, and document control repositories. If AI tools do not connect effectively with these systems, they may become additional isolated applications rather than workflow enablers. Conversely, when AI is integrated with existing digital engineering infrastructure, it may strengthen coordination, reduce duplication, improve traceability, and support more informed decisions.

The context of Muscat, Oman, provides a relevant setting for examining AI integration in engineering workflows. Oman's national development agenda emphasizes digital transformation, economic diversification, and the adoption of advanced technologies across strategic sectors. Recent national initiatives have promoted AI applications in areas such as energy, public administration, investment, tourism, healthcare, and environmental data management (Al Maashani, 2025). Muscat is a central hub for engineering consultancy, infrastructure development, energy services, technology providers, and project management organizations. These conditions make it an appropriate context for studying how engineering professionals experience AI adoption in practice, particularly in multidisciplinary teams where technical coordination and organizational transformation intersect.

Although many studies examine AI technologies from technical, algorithmic, or system-performance perspectives, fewer studies investigate how engineers themselves experience AI integration in daily multidisciplinary workflows. This gap is important because the success of AI adoption depends on professional interpretation, work practices, organizational routines, and trust relations. Engineers are not passive users of AI; they actively adapt, resist, validate, reinterpret, and reshape AI tools according to disciplinary norms and project demands. Qualitative research is therefore well suited to exploring the meanings, tensions, and practical adaptations associated with AI-supported engineering work.

Accordingly, this study examines the integration of AI into multidisciplinary engineering workflows from the perspective of engineering professionals in Muscat. The aim of the study was to explore how engineers perceive and experience the integration of AI into multidisciplinary engineering workflows, with particular attention to collaboration, technical decision-making, trust, professional accountability, and organizational readiness.

2. Methods and Materials

This study employed a qualitative descriptive design to explore engineering professionals' experiences of integrating artificial intelligence into multidisciplinary engineering workflows. A qualitative approach was considered appropriate because the study sought to understand meanings, perceptions, practices, and organizational dynamics rather than measure predetermined variables. The study focused on how engineering professionals interpret AI adoption in real workflow contexts, including design coordination, simulation, project planning, documentation, technical review, and decision support.

The participants were 24 engineering professionals working in Muscat, Oman. The sample size was determined through theoretical saturation, meaning that recruitment continued until additional interviews no longer generated substantially new categories, patterns, or interpretations relevant to the research aim. Participants were selected through purposive sampling to ensure variation in discipline, professional role, experience level, and exposure to AI-supported tools. Inclusion criteria were: being employed in an engineering-related organization in Muscat, having at least three years of professional engineering or engineering management experience, working in multidisciplinary project environments, and having direct or indirect experience with AI-supported tools or AI-enabled digital transformation initiatives. Participants who had no exposure to digital engineering workflows or AI-related tools were excluded.

The final sample included civil and structural engineers, mechanical engineers, electrical engineers, software and data engineers, systems or project engineers, and engineering managers. Participants worked in engineering consultancy, construction and infrastructure, energy services, industrial operations, digital engineering, and project management organizations. This diversity supported a broad understanding of AI integration across multiple engineering domains.

Data were collected using semi-structured interviews. Semi-structured interviews were selected because they allowed the researcher to explore predefined topics while also giving participants flexibility to describe their own experiences, concerns, and interpretations. The interview guide included questions related to participants' professional background, types of AI tools used or observed, workflow areas affected by AI, perceived benefits, challenges in multidisciplinary collaboration, changes in professional roles, trust in AI-generated outputs, organizational readiness, and future expectations.

Sample interview questions included: "How is AI currently used in your engineering workflow?" "Can you describe a situation in which AI helped or complicated collaboration between disciplines?" "How do engineers in your organization evaluate AI-generated outputs?" "What kinds of tasks do you think should remain under human control?" and "What organizational conditions are necessary for AI integration to be successful?" Follow-up probes were used to clarify examples and obtain deeper explanations.

Interviews were conducted individually, either face-to-face or through secure online communication platforms, depending on participant availability. Each interview lasted approximately 40 to 70 minutes. With participant consent, interviews were audio-recorded and transcribed verbatim. All transcripts were anonymized by removing personal names, organization names, project names, and any identifying information. Participants were assigned codes from P1 to P24.

Data were analyzed using thematic analysis, following the six-phase approach proposed by Braun and Clarke (2006): familiarization with the data, generation of initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. The analysis was primarily inductive, meaning that codes and themes were developed from participants' accounts rather than imposed through a rigid predetermined framework. However, the interpretation was also informed by literature on human–AI collaboration, engineering design, systems engineering, and digital transformation.

NVivo software was used to support data organization and coding. Interview transcripts were imported into NVivo, read repeatedly, and coded line by line. Initial codes captured recurring ideas such as "faster design alternatives," "lack of data readiness," "AI as second opinion," "cross-disciplinary translation," "fear of overreliance," "documentation automation," "validation responsibility," and "software integration barriers." Codes were then grouped into broader categories by comparing similarities and differences across participants and disciplines. Memos were written throughout the analysis to document analytic decisions and emerging interpretations.

To enhance trustworthiness, several strategies were used. First, data were reviewed repeatedly to ensure that themes were grounded in participant accounts. Second, codes were compared across professional roles to identify both shared and discipline-specific patterns. Third, illustrative quotations were selected to represent the meaning of each theme. Fourth, the study followed relevant principles from the COREQ checklist for transparent reporting of qualitative interview studies (Tong et al., 2007). Reflexive attention was also given to the possibility that participants' views of AI might be shaped by organizational culture, professional identity, and unequal access to advanced digital tools.

3. Findings

The study included 24 engineering professionals working in Muscat. Fifteen participants were male (62.5%) and nine were female (37.5%). Participants' ages ranged from 26 to 54 years. Regarding educational level, 11 participants held a bachelor's degree (45.8%), 10 held a master's degree (41.7%), and three held a doctoral degree (12.5%). In terms of professional experience, four participants had 3–5 years of experience (16.7%), eight had 6–10 years (33.3%), seven had 11–15 years (29.2%), and five had more than 15 years of experience (20.8%). Participants represented multiple engineering fields: civil/structural engineering (n = 6, 25.0%), mechanical engineering (n = 5, 20.8%), electrical engineering (n = 4, 16.7%), software/data engineering (n = 3, 12.5%), systems/project engineering (n = 3, 12.5%), and engineering management (n = 3, 12.5%). Their organizational sectors included construction and infrastructure (n = 7, 29.2%), oil/gas and energy services (n = 5, 20.8%), engineering consultancy and design (n = 5, 20.8%), industrial manufacturing and operations (n = 4, 16.7%), and digital engineering/technology services (n = 3, 12.5%).

The first main category concerned the role of AI in improving coordination across disciplinary boundaries. Participants explained that multidisciplinary engineering projects often suffer from communication delays, inconsistent documentation, fragmented data, and different technical languages across disciplines. AI was described as a tool that could help translate, summarize, structure, and circulate information between teams. For example, participants noted that AI-supported document review tools helped summarize meeting minutes, identify unresolved design issues, extract requirements from client documents, and prepare discipline-specific action lists. A civil engineer stated, “Before, we spent a lot of time trying to understand what another discipline had changed. Now AI summaries help us see the main implications faster, especially when the project documentation is very heavy” (P6). Similarly, a project engineer explained, “AI is useful because it creates a common starting point. It does not solve all coordination problems, but it gives everyone a clearer picture before the coordination meeting” (P14). Participants emphasized that AI was most helpful when used as a boundary object that supported shared understanding without replacing technical discussion.

The second category reflected participants’ experiences of AI as a tool for accelerating design exploration, modeling preparation, simulation support, and early-stage decision-making. Engineers reported using AI-supported tools to generate alternative design concepts, compare preliminary options, automate calculations, support parametric modeling, predict equipment behavior, and assist in simulation workflows. A mechanical engineer noted, “AI gives us more options at the beginning. It may not give the final answer, but it helps us explore directions that we may not have considered because of time pressure” (P3). A software engineer described AI as “a fast assistant for prototyping and checking logic,” but added that “the final engineering decision still depends on domain validation” (P11). Participants generally agreed that AI improved speed and widened the design space, particularly during conceptual and preliminary design phases. However, they also warned that faster output could create pressure to make decisions before sufficient verification. As one electrical engineer explained, “The risk is that because AI gives a result quickly, managers may think the engineering work is complete. But the checking and responsibility are still with us” (P9).

The third category focused on trust, validation, and professional accountability. Participants repeatedly stated that AI outputs must be treated as suggestions rather than final engineering judgments. Trust was described as conditional and dependent on data quality, transparency, explainability, and previous experience with the tool. Engineers were more willing to trust AI outputs when they could trace the source data, understand the logic of the recommendation, and compare results with established engineering methods. A senior structural engineer stated, “I cannot sign a design because an AI tool suggested it. I need to know the assumptions, the code basis, the load combinations, and the limitations. Otherwise, it is only a draft idea” (P2). Participants also expressed concern that junior engineers might become overdependent on AI-generated answers without developing sufficient technical reasoning. An engineering manager observed, “AI can make weak engineers look confident. That is dangerous if the organization does not have a review culture” (P22). Overall, participants viewed human oversight as essential, particularly for safety-critical calculations, regulatory compliance, and final design approval.

The fourth category concerned organizational readiness. Participants indicated that successful AI integration required more than purchasing software licenses. Organizations needed clean and accessible data, interoperable software systems, cybersecurity policies, training programs, management support, and clear rules regarding acceptable AI use. Several participants explained that their organizations had experimented with AI tools but lacked systematic implementation strategies. A project manager stated, “The problem is not only the AI tool. The problem is that our data is in different formats, different folders, and different software. AI cannot help much if the organization itself is not organized” (P17). A data engineer similarly explained, “AI depends on data discipline. If project teams do not enter information properly, the AI output becomes unreliable” (P12). Participants also highlighted the importance of training. Many engineers had learned AI tools informally through personal experimentation rather than structured organizational programs. This produced uneven skill levels and inconsistent use practices. Participants recommended that organizations develop AI governance policies, define human review responsibilities, and create multidisciplinary AI implementation teams.

4. Discussion

The findings of this study show that AI integration into multidisciplinary engineering workflows is experienced as both a technical opportunity and an organizational challenge. Participants described AI as valuable for connecting fragmented information, accelerating design exploration, supporting documentation, and improving preliminary decision-making. However, they also emphasized that AI adoption creates new responsibilities related to validation, explainability, professional judgment, data governance, and organizational readiness. These findings align with Berente et al. (2021), who argue that AI management requires organizations to coordinate technological capability with work practices, decision structures, and human expertise. The results also support Raisch and Krakowski’s (2021) automation–augmentation paradox: while AI automates certain tasks, it simultaneously increases the importance of human oversight and professional interpretation. In multidisciplinary engineering, this paradox is particularly visible because AI may accelerate outputs but cannot independently reconcile all technical, regulatory, safety, and stakeholder constraints.

The first main category, AI as a boundary-spanning coordination mechanism, suggests that participants valued AI not only for computation but also for communication and knowledge integration. Multidisciplinary engineering work often requires translation between different disciplinary languages, assumptions, and software environments. AI-supported summarization, requirements extraction, document review, and action tracking can reduce coordination friction by making information more accessible across teams. This finding aligns with recent systems engineering literature indicating that AI can support requirements management, model interpretation, and lifecycle knowledge integration (Norheim et al., 2024; Poulsen et al., 2025). It also reflects Obieke et al.'s (2025) argument that AI can help engineers navigate an expanding knowledge space by structuring information and supporting collaborative design activities. However, the participants' accounts show that AI does not automatically create collaboration. Instead, it provides a shared informational basis that must still be interpreted through professional dialogue. Therefore, AI should be understood as a coordination aid rather than a substitute for multidisciplinary engineering interaction.

The second category, AI-enabled acceleration of design exploration and technical decision-making, highlights the perceived productivity value of AI. Participants reported that AI widened the design space by generating alternatives, supporting parametric thinking, and reducing repetitive preparation work. This finding is consistent with studies suggesting that generative AI and generative design tools can enhance conceptual design by increasing the range of options available to designers and supporting early-stage ideation (Choudhury et al., 2025; Fang et al., 2025). It also aligns with broader engineering design research showing that AI can support optimization, prediction, and design intelligence across different stages of engineering work (Yüksel et al., 2023). However, participants also warned that speed may create a false sense of completion. This is an important contribution of the present study because it shows that AI-generated acceleration may shift bottlenecks from production to validation. In other words, AI may reduce the time needed to produce preliminary outputs but increase the need for careful review, assumption checking, and interdisciplinary negotiation.

The third category, human oversight, trust, and accountability, demonstrates that engineers' trust in AI is conditional rather than automatic. Participants were willing to use AI as a second opinion, drafting assistant, or exploratory tool, but they resisted transferring final responsibility to AI systems. This finding is consistent with Bender et al. (2021), who caution that language models may generate plausible outputs without reliable grounding, and with the broader literature on AI trust and explainability. In engineering, the stakes of misplaced trust can be high because design decisions may affect safety, cost, regulatory compliance, and environmental performance. The findings therefore support the argument that AI integration should be governed by human-centered validation frameworks. AI tools must provide traceable assumptions, source transparency, confidence indicators, and compatibility with established engineering standards. The study also reveals a professional identity dimension: engineers viewed judgment, accountability, and ethical responsibility as central to their role. AI was acceptable when it strengthened engineering reasoning but problematic when it encouraged overreliance or weakened technical understanding.

The fourth category, organizational readiness, indicates that AI integration is constrained by data quality, interoperability, training, governance, and leadership. Participants emphasized that AI cannot function effectively when project data are incomplete, unstructured, inaccessible, or stored across disconnected systems. This finding aligns with

Poulsen et al. (2025), who identify data availability, trust, explainability, and technical limitations as major barriers to AI adoption in systems engineering. It also supports findings from AEC literature showing that AI adoption requires upskilling, workflow redesign, and organizational capability development rather than isolated tool acquisition (Egwim et al., 2024; Onatayo et al., 2024). In the Muscat context, where digital transformation is increasingly linked to national development priorities, organizations may face pressure to adopt AI quickly. However, the findings suggest that sustainable adoption requires a staged and governed approach. Without clear implementation structures, AI tools may remain experimental, unevenly used, or disconnected from core engineering processes.

Overall, the study contributes to the literature by showing that AI integration into multidisciplinary engineering workflows is best understood as a socio-technical transformation. AI changes how information is produced, how decisions are prepared, how disciplines coordinate, and how responsibility is distributed. The findings challenge purely technology-centered narratives of AI adoption by showing that the practical value of AI depends on human interpretation, organizational maturity, and workflow alignment. The results also suggest that multidisciplinary engineering teams may benefit from developing explicit human–AI collaboration protocols. Such protocols should define which tasks AI may support, which outputs require human verification, how uncertainty should be documented, and who remains accountable for final decisions. In this sense, AI integration should be treated as a governance and learning process, not only as a software implementation process.

This study has several limitations. First, the research was limited to engineering professionals working in Muscat, which may restrict the transferability of findings to other regions, countries, or organizational contexts. Second, the study relied on self-reported interview data, meaning that participants' accounts may reflect perceptions, expectations, or organizational narratives rather than direct observation of workflow practices. Third, the sample included professionals from multiple engineering disciplines, which strengthened breadth but limited deeper analysis within each specific discipline. Fourth, because AI adoption is rapidly evolving, participants' experiences may change as tools become more advanced, regulated, or embedded in engineering software platforms. Finally, the study did not compare organizations with different levels of AI maturity, which could have provided more detailed insight into adoption stages.

Future studies should examine AI integration in engineering workflows using comparative and longitudinal designs. Comparative studies could investigate differences between engineering sectors such as construction, energy, manufacturing, transportation, and digital systems. Longitudinal research could explore how engineers' trust, skill development, and workflow adaptation change over time as AI tools become more embedded in organizational routines. Future research may also use ethnographic observation to examine actual human–AI interaction during design meetings, simulation reviews, model coordination, or project decision-making. Quantitative studies could test relationships among AI readiness, data quality, trust, perceived usefulness, and workflow performance. Additionally, future research should investigate how junior and senior engineers differ in AI reliance, critical evaluation, and professional learning.

Engineering organizations should approach AI integration as a structured transformation process rather than a simple technology purchase. Before implementing AI tools, organizations should assess data quality, workflow gaps, software interoperability, cybersecurity risks, and staff training needs. AI use policies should define acceptable applications, prohibited uses, documentation requirements, and human review responsibilities. Multidisciplinary AI governance teams should include engineers, data specialists, project managers, legal advisors, and quality assurance personnel. Training should focus not only on how to use AI tools but also on how to evaluate AI outputs critically. Finally, organizations should preserve human engineering accountability by ensuring that AI supports professional judgment rather than replacing technical reasoning, ethical responsibility, or final approval processes.

5. Conclusion

This qualitative study explored how engineering professionals in Muscat perceive and experience the integration of artificial intelligence into multidisciplinary engineering workflows. The findings indicate that AI is increasingly used to support coordination, documentation, design exploration, simulation preparation, and decision support. Participants viewed AI as valuable when it reduced repetitive work, expanded design alternatives, and improved access to cross-disciplinary information. However, they also emphasized that AI integration introduces challenges related to trust, explainability, data quality, accountability, interoperability, and uneven organizational readiness.

The study demonstrates that AI integration in engineering is not merely a technological development but a transformation of professional work. Its success depends on the ability of organizations to align AI tools with engineering judgment, multidisciplinary collaboration, and governance structures. AI should be treated as an augmenting partner that supports engineers while remaining subject to human validation and ethical responsibility. For multidisciplinary engineering organizations, the most sustainable path forward is not full automation but carefully governed human–AI collaboration supported by reliable data, transparent processes, continuous training, and clear accountability.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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