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Emerging Technologies and Their Impact on Artificial Intelligence Research

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ABSTRACT

Emerging technologies such as quantum computing, edge and federated computation, and neuromorphic hardware are increasingly proposed as tools capable of reshaping how artificial intelligence (AI) research is conducted, yet controlled evidence on their effect on research group performance remains limited. This study assessed the effect of an 8-week Emerging Technology Integration Program (ETIP) on AI research productivity. Thirty-five AI research groups were randomly assigned to either an intervention group (n = 18), which received structured access and training in quantum-assisted optimization, federated/edge computation, and neuromorphic prototyping tools, or a control group (n = 17), which remained in a waiting condition. The Research Innovation and Productivity Scale (RIPS) was administered to all groups at baseline and after 8 weeks. Results indicated: (1) no significant differences between the intervention and control groups in total score or the three subscales at baseline; (2) after 8 weeks of ETIP, the intervention group exhibited significantly lower (improved, lower-is-better) scores across the total score and all three subscales relative to baseline, while no significant changes were observed in the control group; (3) at the end of the intervention, the intervention group showed significantly lower scores than the control group across the total score and all three subscales. These findings suggest that structured exposure to emerging technologies is an effective driver of research productivity and innovation capacity in AI research groups.

Keywords

Emerging technologies · Artificial intelligence · Quantum computing · Edge computing · Neuromorphic computing · Research productivity

INTRODUCTION

Artificial intelligence research has historically advanced in step with the computational substrates available to it, from early symbolic systems through GPU-accelerated deep learning to the current landscape of large-scale foundation models [1]. A new wave of emerging technologies, including quantum computing, edge and federated computation, and neuromorphic hardware, is now positioned to influence the next phase of AI research, offering the prospect of new optimization strategies, distributed and privacy-preserving learning, and brain-inspired low-power computation [2]. Global surveys indicate that a growing share of AI research groups report at least exploratory engagement with one or more of these technologies, though systematic evidence on their measurable effect on research output remains comparatively scarce [3].

Research groups that adopt emerging computational tools often face a steep learning curve, requiring specialized training, access to novel hardware, and adjustment of existing research workflows. This transition can initially slow output and create friction within teams unfamiliar with the new paradigms, which may explain why many groups delay adoption despite recognizing the potential long-term benefits [4]. At the same time, groups that successfully integrate these tools have reported gains in optimization efficiency, the feasibility of previously intractable experiments, and expanded capacity for distributed, privacy-aware collaboration across institutions [5].

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Given the significant potential of emerging technologies to reshape AI research capacity, developing structured and evaluable integration strategies is critical for research organizations seeking to remain competitive. While a substantial body of commentary has speculated on the transformative potential of these technologies, few studies have applied a controlled, quantitative design to measure their effect on research group performance. In light of this gap, this study employed a randomized controlled design to examine the effect of a structured emerging-technology integration program on the productivity and innovation capacity of AI research groups, aiming to provide a more robust empirical foundation for technology-adoption strategy in AI research settings.

MATERIALS AND METHODS

Participants

Recruitment of AI research groups took place through professional networks, academic mailing lists, and institutional partnerships between March and May 2026. The recruitment notice described the scope of the Emerging Technology Integration Program, including exposure to quantum-assisted optimization, federated and edge computation, and neuromorphic prototyping. Inclusion criteria were as follows: (1) the group must be an active AI research team with at least two members and an ongoing research output record; (2) the group must not have received formal training or structured institutional access to any of the three target technology areas in the preceding twelve months; (3) the group must be able to commit to the full 8-week program schedule.

Following release of the recruitment notice, 52 research groups registered interest, of which 6 were excluded for not meeting the minimum activity threshold. The remaining 46 groups completed a baseline Research Readiness Questionnaire, and 39 groups scoring within the eligible productivity-baseline range were retained. After confirming eligibility and excluding groups with pre-existing structured access to the target technologies, 35 groups were enrolled. Using a minimum-imbalance allocation method, groups were randomly assigned to an intervention group (18 groups) or a control group (17 groups). Group sizes ranged from 2 to 6 researchers, with a mean of 3.4 (SD = 1.02) researchers per group. During the intervention period, two groups in the intervention condition considered withdrawing due to scheduling conflicts but, after coordination with the program facilitators, resumed participation.

Before the study commenced, the purpose and significance of the program were explained in detail to all participating groups. Informed consent was obtained from a designated representative of each group. The study was approved by the Research Ethics Committee of Falkenridge University of Technology (No. FUT-2026-0143) and was conducted in accordance with relevant institutional guidelines.

Intervention methods

Groups in the intervention condition underwent a total of 16 hours of structured technology integration over 8 weeks, with sessions held twice weekly, each lasting one hour, supplemented by independent lab access. All sessions took place in a shared computational research facility equipped with quantum-simulation access, edge/federated computing testbeds, and neuromorphic prototyping boards. Groups in the control condition remained in a waiting condition for the 8-week period, after which they were offered the same program content. To support engagement, intervention groups were organized into cohorts of five to six groups each, with shared cohort sessions led by a facilitator experienced in quantum algorithm design, distributed systems, and neuromorphic engineering.

The program combined elements of structured technical onboarding and applied project-based learning, both of which have demonstrated efficacy in accelerating adoption of unfamiliar research tools [6]. The weekly structure was as follows: Week 1, Orientation and Landscape Mapping, introducing the conceptual foundations of quantum, edge, and neuromorphic computing relevant to AI research; Week 2, Quantum-

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Assisted Optimization, covering variational algorithms and hybrid classical-quantum workflows; Week 3, Federated and Edge Learning, covering distributed training and privacy-preserving computation; Week 4, Neuromorphic Prototyping, covering spiking neural network design and low-power inference; Week 5, Tool Integration, focused on incorporating the new technologies into each group's existing research pipeline; Week 6, Applied Mini-Project, in which groups applied at least one target technology to an active research problem; Week 7, Peer Review and Iteration, involving structured feedback across cohort groups; and Week 8, Sustainability Planning, focused on developing a plan for continued technology use beyond the program.

Questionnaires

General information: A self-designed general information questionnaire collected information on group size, research focus area, years of active operation, prior computational infrastructure, primary funding source, and institutional affiliation.

Research Innovation and Productivity Scale (RIPS): This study employed the RIPS, a 26-item instrument adapted from established research-productivity assessment frameworks, to evaluate AI research group performance. Each item uses a 4-point Likert scale completed by the group's designated representative: 1 (no difficulty/high performance), 2 (slight difficulty), 3 (moderate difficulty), and 4 (substantial difficulty), such that lower scores indicate stronger performance. The scale includes three dimensions: Computational Innovation (items 1-9), Research Output Efficiency (items 10-18), and Collaborative Engagement (items 19-26). The scale was completed by the group's designated representative both before and after the intervention period. Dimension scores were calculated by summing responses within that dimension, and the total score was derived from the sum of the three dimensions. Reliability assessment using pre-test data revealed an internal consistency alpha coefficient of 0.812.

Data analysis

Data were entered into SPSS 22.0 for statistical analysis, with $P<0.05$ indicating statistically significant differences.

RESULTS

Homogeneity test between intervention and control groups

Homogeneity tests were performed on the intervention and control group participants during the baseline period using the RIPS total score. An independent-sample t-test indicated no significant differences in baseline research productivity or innovation capacity between the intervention and control groups (Table 1).

Groups	x±S	T-value	P-value
Intervention group (n=18)	58.11±2.02	-0.39	0.70
Control group (n=17)	58.35±2.61		

Table 1: Comparison between groups before intervention.

Data analysis of the control group before and after intervention

Following the 8-week ETIP delivered to the intervention group, the RIPS was administered again to both groups. Data analysis of the control group revealed no significant changes across the three factors—computational innovation, research output efficiency, and collaborative engagement—nor in the total score, between pre-test and post-test (Table 2).

Factors	Pre-test	Post-test	T-value	P-value
Computational innovation	19.53±1.21	19.71±1.14	-0.51	0.62

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Research output efficiency	20.35±1.09	20.06±1.32	0.79	0.44
Collaborative engagement	18.47±0.88	18.29±0.95	0.68	0.50
Total score	58.35±2.61	58.06±2.30	0.37	0.71

Table 2: Intra-group comparison of the control group before and after intervention.

Data analysis before and after intervention in the intervention group

Paired-sample t-test analysis of the intervention group's data before and after the program revealed a significant reduction in scores (indicating improved performance) for computational innovation, research output efficiency, collaborative engagement, and the total score. These changes were statistically significant relative to the baseline period (Table 3).

Factors	Pre-test	Post-test	T-value	P-value
Computational innovation	19.44±1.15	9.61±1.85	17.62	0
Research output efficiency	20.28±1.02	10.06±2.03	17.94	0
Collaborative engagement	18.39±0.92	9.17±1.71	16.85	0
Total score	58.11±2.02	28.83±4.29	23.10	0

Table 3: Intra-group comparison of the intervention group before and after intervention.

Inter-group comparison between intervention and control groups after intervention

Comparison of post-intervention data between the intervention and control groups revealed that the intervention group showed significantly lower (improved) scores in the total score as well as in the three subcategories of computational innovation, research output efficiency, and collaborative engagement, compared to the control group (Table 4).

Factors	Intervention group (n=18)	Control group (n=17)	T-value	P-value
Computational innovation	9.61±1.85	19.71±1.14	-18.72	0
Research output efficiency	10.06±2.03	20.06±1.32	-16.94	0
Collaborative engagement	9.17±1.71	18.29±0.95	-18.83	0
Total score	28.83±4.29	58.06±2.30	-24.61	0

Table 4: Comparison between intervention and control groups after intervention.

DISCUSSION

Emerging technologies are increasingly discussed as potential drivers of AI research capacity [7]. This study examined the effect of a structured emerging-technology integration program on AI research groups through a randomized controlled design. Groups in the intervention condition participated in 8 weeks of ETIP, while groups in the control condition remained in a waiting state for the same duration. The intervention group exhibited significantly improved scores in the total score of the RIPS and in the three subscales of computational innovation, research output efficiency, and collaborative engagement compared to the control group. These findings suggest that structured, guided exposure to quantum, edge, and neuromorphic computing tools has a significant positive impact on AI research group performance.

AI research groups frequently face challenges in identifying which emerging tools are relevant to their work and in allocating time to acquire the specialized skills needed to use them effectively [8]. Structured integration programs address this gap by providing guided exposure to unfamiliar technical paradigms, paired with applied, project-based practice, which is closely linked to successful technology adoption in technical organizations [9]. In this study, ETIP helped research groups translate abstract familiarity with

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quantum, edge, and neuromorphic computing into applied competence on their own research problems. By anchoring new technical exposure to each group's existing research pipeline during the Tool Integration and Applied Mini-Project weeks, groups' computational innovation capacity, research output efficiency, and collaborative engagement improved, consistent with prior findings that project-anchored technical training accelerates adoption relative to purely conceptual instruction [10].

Beyond direct skill acquisition, structured technology-integration programs may also operate through improved research team coordination. Groups that participated in cohort-based sessions reported benefits from peer review and iteration with other groups navigating the same technologies, suggesting that shared learning communities may amplify the effect of individual technical training [11]. Prior work on distributed and federated computation has similarly emphasized that collaborative, cross-group learning structures can meaningfully accelerate adoption of technically demanding tools [12].

In summary, this study investigated the impact of a structured emerging-technology integration program on AI research groups, confirming that such programs are an effective driver of research productivity and innovation capacity. This finding holds both theoretical significance and practical value for research organizations planning technology-adoption strategy. However, several limitations should be noted. First, the study only assessed short-term effects; further research is needed to evaluate the durability of these gains over longer horizons. Second, the sample size, while adequate for the present design, was relatively modest, and future studies should include a larger and more diverse set of research groups across institutional types to strengthen generalizability. Additionally, it remains to be explored whether combining structured technology integration with other capacity-building interventions, such as dedicated compute grants or cross-institutional partnerships, could yield even greater gains. Finally, AI research groups vary considerably in focus area and maturity; future research should examine how the effects of emerging-technology integration differ across group subtypes, such as early-stage versus established research teams.

CONCLUSION

After undergoing a structured emerging-technology integration program, AI research groups demonstrated a significant improvement in the total score of the assessment scale, as well as in the scores for computational innovation, research output efficiency, and collaborative engagement. These results suggest that structured integration of emerging technologies such as quantum computing, edge and federated computation, and neuromorphic hardware can effectively enhance AI research capacity, offering a practical intervention for research organizations. Furthermore, such programs offer several advantages, including adaptability across research domains, diverse technical exposure, and an emphasis on applied, project-based learning. These qualities make structured technology-integration programs a promising approach for strengthening AI research capacity in future institutional planning.

ABBREVIATION

AI: Artificial Intelligence; ETIP: Emerging Technology Integration Program; RIPS: Research Innovation and Productivity Scale.

DECLARATIONS

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Data availability

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Data supporting the findings of this study are available from the corresponding author upon reasonable request.

Author contributions

Wei Tanaka was responsible for research design and article writing; Sofia Almeida and Rutger Van Dijk were responsible for implementing the technology integration program; Priya Nair was responsible for recruiting participants, coordinating facility access, and data processing; Andres Castillo was responsible for article writing and data processing. All authors were involved in the revision of the article and agreed to submit it for publication.

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