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RESPONSIBLE AI-READINESS IN HIGHER EDUCATION: VALIDATING A DUAL-MODEL FRAMEWORK FOR FACULTY DEVELOPMENT

Sanskriti Rawat*	Christ University, Bangalore, India	sanskriti.rawat@res.christuniversity.in
Robert Linton Tavis Ashton-Bell	Christ University, Bangalore, India	robert.linton@christuniversity.in

* Corresponding author

ABSTRACT

Aim/Purpose	This study validates a responsible artificial intelligence (AI) framework designed to strengthen AI-readiness among higher education faculty in India.
Background	With the increasing use of AI in education, faculty require structured support; however, faculty development models for responsible AI integration remain limited.
Methodology	A mixed-methods pilot study with ten humanities and performing arts faculty used a dual-model evaluation approach. Three sessions from the framework were implemented, and data were collected through knowledge-attitude-practice (KAP) surveys, cognitive-affective-psychomotor (CAP) performance rubrics, and reflective responses.
Contribution	This study validates a dual-model framework for faculty development regarding responsible AI readiness.
Findings	The adapted KAP survey demonstrated strong reliability, with higher AI knowledge associated with more positive attitudes. However, knowledge did not consistently translate into practice, highlighting the need for structured hands-on learning. CAP-based performance assessments and reflections indicated improved ethical awareness, critical engagement, and foundational AI-integration skills.
Recommendations for Practitioners	Institutions should embed structured AI-training for faculty, with authentic instructional tasks.

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Recommendations for Researchers	Future research should test this approach across larger and more diverse institutional contexts.
Impact on Society	Developing AI-ready faculty can foster ethical and future-focused learning environments.
Future Research	Future studies should expand across disciplines and examine longer-term outcomes.
Keywords	artificial intelligence, AI-readiness, dual-model validation, faculty development

INTRODUCTION

Artificial Intelligence (AI) is rapidly reshaping teaching, learning, and academic work in higher education (Bhatia et al., 2024; George & Wooden, 2023). As universities adopt AI-enabled systems and generative AI (genAI) tools, opportunities emerge for automation, personalisation, and new forms of knowledge production (Balushi, 2024; Singh, 2023). At the same time, higher-education institutions face urgent concerns regarding ethics, academic integrity, equity, and responsible use (Malik et al., 2024; Módné Takács et al., 2023). This shift has prompted universities to rethink digital pedagogy, develop guidelines for AI use, and explore structured support for educators integrating AI in teaching (Pratschke, 2024). In India, the National Education Policy (NEP) 2020 calls for the integration of emerging technologies, including AI, to strengthen access and quality in higher education (Das & Barman, 2024). Yet, despite the policy emphasis, challenges such as infrastructural limitations, uneven digital literacy, and insufficient faculty training continue to impede meaningful AI adoption (Patwardhan, 2023). Reskilling and upskilling faculty with attention to ethical and contextual considerations remains a national priority (Venugopal & Mamatha, 2023).

Faculty perspectives in higher education consistently highlight the growing role of AI in teaching and learning. As AI becomes embedded in learning environments, Chakraborty (2024) suggests that faculty focus on going beyond mere understanding of AI tools and also gain familiarity in using them to model ethical decision-making, transparency, and critical engagement for students. Módné Takács et al. (2023) similarly highlight the need for AI training, yet also touch upon the need for trust-building and structured capacity development for higher education faculty. Acosta-Enriquez et al. (2025) agree, stating that while AI supports teacher leadership development, faculty raise concerns regarding privacy, academic integrity, and the evolving nature of pedagogical roles.

Likewise, Ibrahim et al. (2024) identified a strong link, where faculty perspectives raise concerns about assessment integrity and academic honesty, highlighting potential causes to trust AI. On the other side of the pedagogical coin, student expectations and anxieties regard the quality of delivery, especially when considering Okulich-Kazarin et al. (2023), who found that "... students in Eastern European countries are confident that AI will replace university teachers in five years" (p. 14), may also be a factor in Indian contexts. Such insights underscore the importance of preparing faculty not only to use AI but also to employ it in an ethical and pedagogical manner.

University professors further report multiple challenges in integrating ethical and pedagogical AI, including algorithmic bias, infrastructural constraints, and concerns about dehumanising academic work or rendering educators redundant (Abdelaal & Al Sawy, 2024). Although faculty recognise the potential of AI to enhance curriculum planning, instruction, personalised learning, and assessment design, concerns persist around copyright, intellectual property, reliability, bias, plagiarism, and "boilerplate" AI-generated content (Malik et al., 2024). Educators also emphasise the need to re-evaluate learning objectives, curriculum, pedagogy, and assessment design to align with AI-enabled environments (Kallunki et al., 2024). Despite this urgency, most faculty-development efforts emphasise technical training or general digital literacy. Few offer structured, pedagogy-aligned, and ethically

grounded preparation for AI integration, and even fewer are empirically validated; particularly in the Global South, where contextual needs and resource constraints differ significantly.

This creates a critical need: faculty are expected to guide responsible AI use. This being said, there are established models and competency frameworks that guide meaningful integration of technology and AI in education, offering structured approaches to support pedagogical innovation, digital capability building, and ethical practice among educators. For instance, the Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006) emphasises the intersection of technology, pedagogy, and subject content, highlighting the knowledge that educators require to integrate technology into discipline-specific teaching in a meaningful way. Next, the Substitution-Augmentation-Modification-Redefinition (SAMR) model (Puentedura, 2014) provides a continuum for evaluating technology integration, moving from enhancing existing instructional processes to transforming learning experiences through innovative digital practices.

In addition to this, the European Digital Competence (DigCompEdu) framework (Redecker, 2017) outlines six key areas, from professional engagement to empowering learners, that define the digital competencies required for effective teaching, assessment, collaboration, and learner support in the digital age. Furthermore, UNESCO's AI Competency Framework for Teachers (Attwell, 2023) guides educators in developing AI literacy and ethical awareness, ensuring teachers can understand, critically evaluate, and responsibly integrate AI tools in ways that uphold equity, data privacy, and human-centred values in education.

Despite the abovementioned guiding models, evidence-based, context-specific frameworks that support faculty in practically applying competencies for responsible AI integration remain limited, particularly in higher education settings within emerging economies such as India. While existing frameworks offer conceptual clarity on digital and AI readiness, they often lack structured, measurable pathways to build and evaluate educator preparedness in real-world instructional environments. There is thus a need to include human-centered learning domains that holistically represent deeper qualities of ethical judgment, responsible action, and embodied practice.

Therefore, the present study adopts the Knowledge–Attitude–Practice (KAP) framework and the Cognitive-Affective-Psychomotor (CAP) taxonomies of learning as complementary lenses. KAP enables a systematic assessment of faculty understanding of AI, their beliefs and ethical orientations toward its use, and their real-world adoption behaviours, making it well-suited for examining responsible AI integration in practice. In parallel, the CAP learning-domain model strengthens pedagogical rigor by aligning AI-related competencies with cognitive (knowledge acquisition), affective (ethical and attitudinal development), and psychomotor (applied skill demonstration) domains. Together, these frameworks provide a holistic, measurable, and educator-centered foundation for designing, delivering, and evaluating a structured faculty development module on the ethical and responsible use of AI in higher education. Together, KAP and CAP form a dual model that is used to validate an intervention module focused on responsible AI use among faculty in India, particularly those teaching practice-oriented disciplines.

Identifying an institutional context where such holistic learning philosophies are embedded in academic processes is therefore critical. The participating institution in this study formally integrates the CAP framework into its programme outcomes (POs) and learning outcomes (LOs), making it a unique and suitable setting for investigating an AI-ethics intervention that foregrounds human-centered competencies. This focus also aligns with the Indian higher-education context, where national policy documents increasingly emphasise holistic, ethical, and value-based education alongside technological competency. Through a mixed-methods validation process, the module was examined for face and content validity, reliability, contextual appropriateness, transparency, and fairness within the higher-education context. The next section outlines the theoretical framework informing the conceptual foundations and methodological choices of this study.

Theoretical Framework

The present study is grounded in the three domains of learning: cognitive, affective, and psychomotor (CAP). For each domain, established taxonomies were used to align learning outcomes and assessments with domain-specific competencies. The cognitive domain draws on the revised Bloom's taxonomy (Anderson & Krathwohl, 2001); the affective domain with Krathwohl's taxonomy (Krathwohl et al., 1964); and the psychomotor domain using Simpson's (1972) taxonomy. These taxonomies serve as foundational learning frameworks across disciplines and provide a structured basis for designing and evaluating performance-based learning in this study.

Given the study's focus on the ethical and responsible integration of AI, the knowledge-attitude-practice (KAP) framework further guided this research. Originally applied in health and social sciences (Aban, 2020; Jillani et al., 2025; Zarei et al., 2024), KAP has recently been adapted for education to explore pre-service teachers' engagement with genAI (Robledo et al., 2023). In this study, the KAP framework was adapted, with the author's permission, to assess faculty members' understanding of AI in education (knowledge), their beliefs towards AI integration in higher education (attitudes), and their reported use of AI in instructional practice (practice). This framework structured the survey component of the study. To complement self-reported data, the CAP framework informed the design and assessment of the hands-on intervention tasks. This dual-framework approach, combining KAP for attitudinal and perceptual measures and CAP for performance-based assessment, ensured a holistic evaluation of faculty AI readiness. By operationalising both cognitive-attitudinal measures and performance-based competencies, this dual-framework approach provided a robust foundation for assessing faculty AI readiness. Anchored in this theoretical grounding, the study advanced the following research objectives.

Research Objectives

1. To triangulate KAP and CAP aligned assessments within an AI intervention program among HEI faculty in India.
2. To validate the AI intervention program focusing on the ethical and responsible integration using statistical analyses of scores achieved throughout three sessions of the module.
3. To validate the affective and psychomotor domains of assessment rubrics using the feedback given by performing arts faculty undertaking the module.

Materials and Methods

Research Design

The study employs a mixed-methods approach to validate a faculty development program designed to enhance the capacity of higher education teachers for the ethical and responsible use of AI in teaching and learning. A purposive sampling strategy was used to recruit ten faculty members from higher education institutions in India, representing assistant professors, associate professors, and professors. Eligibility criteria for sample selection included that the participants should (a) be currently employed as faculty members of a higher education institution in India, (b) possess at least a year of teaching experience in India, and (c) belong to humanities or performing-arts disciplines. This disciplinary focus was intentional, as these domains emphasise reflective judgment, embodied learning, and values-based practice, making them a meaningful context for examining responsible AI readiness beyond highly technical fields. While the sample size was small, it aligns with exploratory faculty-development validation studies that prioritise depth, contextual relevance, and practitioner reflection rather than broad generalisation. The research followed a systematic multi-phase process to design, adapt, implement, and evaluate the program, as outlined in Figure 1.

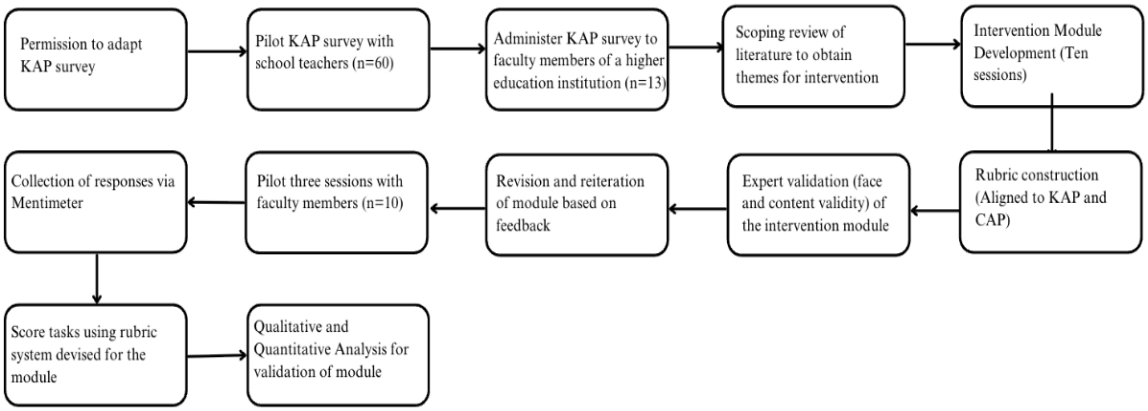

Figure 1. Methodological framework of the study

PHASES OF THE STUDY

The researchers first obtained formal permission from the original authors to adapt the KAP survey for the higher education context in India. This ensured ethical use of the instrument and preserved construct validity. The adapted survey questionnaire consisted of 20 items to be responded to on a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree" (Appendix A). To further refine and test the adapted survey, a preliminary pilot was conducted with sixty school teachers in New Delhi, India. The aim was to test clarity, item relevance, and preliminary reliability before deploying the survey to faculty. Following this, the KAP survey was administered to 13 higher education faculty members who met the basic inclusion criteria. These responses contributed to the instrument's reliability and contextual validation in the higher education setting.

A scoping review of literature was carried out to identify core themes, competencies, ethical considerations, and best practices in AI-integration for faculty members. The purpose of conducting a scoping review of the literature was to align the themes of the intervention module with the gaps identified in the current literature, specifically those pertaining to AI in higher education. The chosen studies included articles published between 2020 and 2025. To deepen the interpretive understanding of educators' experiences reported in existing studies, an interpretative phenomenological analysis (IPA) lens was incorporated during the scoping review. Although IPA is traditionally applied to primary and qualitative data, in the scoping review phase, it was used as an interpretative framework to examine how educators in prior research made sense of AI, ethical dilemmas, and the shifts in professional identities that AI has brought about. This approach enabled nuanced synthesis and informed the content of the intervention module.

Themes emerging from the scoping review were systematically mapped onto the domains of the KAP framework to retain coherence with the dual-model structure (KAP-CAP) underpinning the intervention module (as shown in Figure 3 in the Results section). This ensured that the content, learning activities, and assessment criteria aligned with both the documented needs in the literature and the conceptual foundation of the study, reinforcing the integration of knowledge, beliefs, and ethical practices alongside cognitive, affective, and psychomotor competencies. Based on the scoping review and KAP-CAP mapping, a ten-session intervention module (faculty development program) was developed. Each session was designed to last around two hours, starting with a theme related to AI in education, followed by hands-on activities that allowed participants to interact with the topic, and concluding with a performance assessment and closing remarks. The module's content addressed themes such as foundational AI literacy, the ethical implications of AI for education, and responsible use strategies for teaching and assessment. The sessions included hands-on activities to be conducted with the participants. The session names, outcomes, activities, and rubric details are given in Appendix B. To evaluate participants' performance in the sessions, a performance-assessment rubric was

created, aligned with the dual model framework of KAP and CAP. For the assessment of each session, rubrics were constructed and aligned with the KAP and CAP frameworks to be evaluated on a 5-point scale for each domain: cognitive, affective, and psychomotor.

After the development of the intervention module, the validation process began. Subject-matter and pedagogical experts evaluated the module for face and content validity, clarity, sequence, contextual suitability, and ethical orientation. Their feedback ensured theoretical rigor, academic relevance, and practical applicability. Following the feedback, the module was reviewed to ensure face and content validity.

For the present study, the intervention was piloted with ten faculty members from a single Indian HEI. Although thirteen faculty members initially completed the KAP survey, only ten were selected for the pilot intervention phase as they met the full inclusion criteria. Specifically, these ten participants not only satisfied the teaching-experience and institutional requirements but also belonged to the humanities and performing arts disciplines, which are central to this study's focus on reflective, embodied, and ethically grounded pedagogical practice. The remaining three participants, while contributing to the preliminary survey reliability testing, did not meet the final disciplinary criteria and were therefore excluded from the intervention stage. This selective approach ensured alignment between the study's theoretical foundations (KAP and CAP) and participant expertise, thereby enhancing contextual validity and conceptual fit for evaluating responsible AI readiness in faculty practice.

The final sample (n = 10) consisted of six female and four male faculty members from a university in Bengaluru, India, in the field of higher education. The sample was rich and diverse based on designation, teaching experience, and disciplines. Table 1 shows the details of the participants. The study ensured adherence to research ethics by obtaining informed consent from all participants and maintaining anonymity throughout the intervention through the use of coded identifiers. The participants were coded to faculty members (FM), and the corresponding number was assigned to them randomly.

Table 1. Details of the participants

S. no	Participant	Gender	Designation	Teaching experience (years)	Discipline
1.	FM1	F	Assistant Professor	2	Theatre
2.	FM2	M	Associate Professor	9	Theatre
3.	FM3	M	Assistant Professor	11	Theatre
4.	FM4	M	Assistant Professor	4	Music
5.	FM5	F	Assistant Professor	2	Theatre
6.	FM6	F	Professor	15	Music
7.	FM7	F	Associate Professor	17	Performing Arts
8.	FM8	F	Assistant Professor	8	Dance
9.	FM9	M	Associate Professor	10	Music
10.	FM10	F	Assistant Professor	2	Music

The study participants were involved in the module transaction done by the researcher for three out of the ten designed sessions (see Appendix B). These three sessions involved themes such as AI algorithms and information, AI multimodalities, and integrating AI for lesson planning. The tasks were submitted by the participants through an online platform (Mentimeter) and analysed for the present study using thematic analysis. Simultaneously, each participant was scored based on the rubric system devised for the intervention module.

The study employed a mixed-methods analytical approach, combining quantitative (descriptive and inferential statistics) and qualitative (thematic analysis) techniques. For the quantitative component, the adapted KAP scale responses were analysed using descriptive and inferential statistics. Internal consistency of the knowledge, attitude, and practice sub-scales was assessed using Cronbach's alpha. Pearson's correlation analysis was conducted to examine relationships among the knowledge, attitude, and practice constructs. For the performance-based task scores from the three piloted CAP-aligned sessions, descriptive statistics (minimum score, maximum score, mean, and standard deviation) were calculated for each domain to understand variability and central tendencies in faculty competencies. For the qualitative component, participant reflections and task outputs were analysed using inductive thematic analysis. An iterative, multi-cycle coding process was used, beginning with open coding to identify initial meaning units, followed by focused coding to refine categories and develop final themes. This process facilitated a nuanced interpretation of faculty perspectives regarding AI integration, ethical considerations, and emerging pedagogical practices. While the intervention module comprised ten sessions, only three were piloted for this validation, which presents a limitation in terms of generalizability. However, piloting core sessions enabled an initial feasibility evaluation and structural refinement prior to future full-scale implementation.

RESULTS

The present study aimed to validate an intervention module designed for faculty members regarding the ethics surrounding the integration of AI tools within teaching and learning.

KAP SURVEY

To validate the tools of the study, the researchers first aimed to evaluate the internal consistency of the adapted KAP questionnaire. A few survey items were reverse-coded (items 2, 3, and 5) to maintain consistency in the scoring direction. Reliability analysis was conducted using Cronbach's alpha to obtain the internal consistency of the three subscales: knowledge, attitude, and practice. The result of the Cronbach's alpha test is presented in Table 2.

Table 2. Cronbach's alpha for knowledge, attitude, and practice

S. no	Subscale	Cronbach's alpha
1	Knowledge	.719
2	Attitude	.816
3	Practice	.842

As shown in Table 2, the knowledge subscale yielded a reliability coefficient of α=.719, indicating acceptable consistency. The attitude subscale demonstrated good internal consistency with α=.816, while the practice subscale showed excellent internal consistency with α=.842. The findings from Cronbach's alpha test for the adapted KAP questionnaire support the overall reliability of the instrument in capturing faculty's perceptions regarding AI integration in HE. Next, Pearson's correlation

test was conducted to find correlations among the three subscales: knowledge, attitude, and practice. The findings of Pearson's correlation test are shown in Table 3.

Table 3. Correlation among Knowledge, Attitude, and Practice

		Knowledge	Attitude	Practice
Knowledge	Pearson correlation	1		
	Sig. (2-tailed)			
	N	10		
Attitude	Pearson correlation	.849**	1	
	Sig. (2-tailed)	.002		
	N	10	10	
Practice	Pearson correlation	.493	.646*	1
	Sig. (2-tailed)	.148	.044	
	N	10	10	10

** Correlation is significant at the 0.01 level (2-tailed)
* Correlation is significant at the 0.05 level (2-tailed)

The findings from Table 3 indicated a strong positive and statistically significant correlation between knowledge and attitude ($r = .849$, $p = .002$), indicating that faculty members with higher knowledge about AI also tended to hold more favourable attitudes towards its integration in HE. Furthermore, a moderate positive correlation was found between attitude and practice ($r = .646$, $p = .044$), suggesting that positive attitudes may facilitate the adoption of AI tools in the classroom by faculty members. However, it was found that the correlation between knowledge and practice, while positive ($r = .493$), was not statistically significant ($p = .148$). This could imply that possessing knowledge alone may not directly translate into practice due to barriers or other factors specific to the subject domain being taught. These findings necessitate hands-on intervention and assessment, extending beyond knowledge-building into the affective and psychomotor domains.

Although statistically significant relationships were found between knowledge and attitude, and between attitude and practice, the correlation between knowledge and practice was not statistically significant. This suggests that while knowledge may influence attitudes, applying AI ethically in teaching also requires experiential, reflective, and contextual engagement, aspects captured through the CAP-based performance assessment. Given the small sample size ($n = 10$), these correlations are *exploratory* in nature and should be interpreted with caution. Pearson's correlation was selected due to its suitability for examining linear associations in small, exploratory education datasets. However, statistical power is limited and effect-size trends are emphasised over significance thresholds, aligning with recommendations for early-stage intervention research. In this study, quantitative associations provide *directional insight* and are meaningfully enriched by qualitative and performance-based evidence presented below.

Intervention Module

To assess faculty performance during the intervention sessions, rubric-based scores were analysed across three domains: cognitive, affective, and psychomotor. Each session was designed to target specific aspects of AI integration through hands-on activities, and participants were scored on a 5-point rubric scale in all three domains. Three out of ten sessions were conducted with the participants for the present study. The outcome of the first session was to analyse the output generated by

different AI tools based on accuracy, ethical awareness, bias, and transparency. The outcome of the next session was to explore AI multimodalities by creating multimodal content through different AI tools. Lastly, the outcome of the third session was to equip the participants with the ethical integration of AI tools for lesson planning. The triangulated CAP results complement the KAP findings by providing evidence of faculty performance in *authentic* tasks, *beyond self-reported readiness*. Whereas KAP scores revealed variable confidence and belief in AI tools, CAP scores captured actual behavioural engagement, ethical reasoning, and applied pedagogical decisions when integrating AI tools in practice. Descriptive statistics for all three sessions, across the three domains: cognitive, affective, and psychomotor (CAP), are shown in Table 4.

Table 4. CAP performance across three sessions of intervention module

Session	Cognitive Domain	Affective Domain	Psychomotor Domain
AI Algorithm & Information	M = 3.4, SD = 0.85	M = 3.6, SD = 0.68	M = 3.8, SD = 0.74
AI Multimodalities	M = 3.6, SD = 0.82	M = 3.6, SD = 0.68	M = 4.5, SD = 0.70
AI Lesson Planning	M = 3.8, SD = 0.47	M = 4.5, SD = 0.52	M = 3.9, SD = 0.67

As per Table 4, cognitive and affective scores peaked in session three (AI Lesson Planning), whereas psychomotor scores were highest in session two (AI Multimodalities). While these trends suggest a growing comfort of faculty members with AI tools, they also highlight that psychomotor engagement can change depending on the complexity and relevance of the hands-on tasks. This is particularly important in the context of disciplines such as performing arts, wherein classroom demonstrations are central, and AI tools are less frequently used or preferred to be integrated as skills are being taught to and replicated by students. Recognising this, the researchers collected informal feedback from the participants to address these needs. The input collected from the participants helped reiterate the rubrics, especially for the psychomotor domain. Therefore, it was ensured that the hands-on tasks fulfilled the performative and expressive pedagogies. Although these findings reflect domain-specific engagement aligned with session outcomes, they cannot be generalised due to the small sample size. To gain deeper insights, open-ended questions were asked of the participants, which are reported in the next section.

Faculty Perspectives on AI Integration

To further understand participants' perspectives, six guiding questions were asked, and the responses were collected via Mentimeter. Table 5 shows the list of questions that were put to the faculty members during the intervention.

Table 5. Open-ended questions asked during the intervention

S. no.	Question
1.	What skills do you teach in your courses?
2.	How can AI hinder teaching-learning in your courses?
3.	How can AI benefit teaching and learning in your courses?
4.	Have you used AI tools for any part of your work?
5.	In which areas is AI use appropriate?
6.	I use AI tools because they help with ….

The responses to the questions (Table 5) revealed a nuanced picture of faculty members' perceptions, especially from those in performing arts and humanities backgrounds. Three key themes emerged, each grounded in multiple data points:

Teaching through action and expression

When asked, "What skills do you teach in your courses?" the responses ranged from skills from all three learning domains. From the cognitive domain, skills like writing, critical skills, analytical skills, creative problem solving, and interpretation skills were taught by the participants. Others mentioned skills that constitute the affective domain: communication, positive attitude, and empathy. Lastly, others responded with performing arts-related skills: performing, theatre, acting, performance skills, stage combat, and directing. These skills require physical or expressive presence, bypassing any form of AI intervention. Furthermore, they are learned by doing, not by mere observation, recollection, or analysis. Apart from this, these skills require real-time interaction and feedback. The responses confirmed that for many participants, teaching is physical and socially dynamic: a factor that AI tools cannot truly replicate. Some responses, like 'collaboration' and 'critical thinking,' suggest that participants value processes over product, further pointing to the gap in AI adoption.

Concerns regarding AI affecting student thinking

For the question "How can AI hinder teaching-learning in your courses?", the responses of the participants clustered around four sub-themes: (a) cognitive dullness, (b) over-standardization, (c) ethical dilemma, and (d) reduced empathy. Under cognitive dulling, the responses received were "reduced thinking," "critical thinking," "removes rigour," and "rewards incomplete thought." Responses that indicated over-standardization included "standardization," "soulless," and "echo chamber limitation". Next, many participants' responses hinted towards ethical dilemmas such as "honesty reduced," "procrastination," and "reading reduced." Lastly, there were responses that pointed out empathy reduction, such as "empathy decrease" and "unilinear opinions." These findings indicate that faculty fear that AI may discourage deep, original thinking of the student by promoting shortcuts and reducing student ownership. Terms like "soulless" and "thought" underscore that participants worry about the affective and intellectual engagement parameters of the learning process.

Use of AI as a supportive tool

For the question, "How can AI benefit teaching and learning in your courses?", it was found that the majority of participants use AI to make administrative framing tasks more efficient. Faculty members mentioned using AI for assessment and scaffolding: "creating MCQs" and "presents ideas in a coherent manner." Next, AI is used for editing and rephrasing: "helps with editing" and "summarizes the content." Many participants mentioned that they use AI for "visual aids," "infographics," "visual representation," and "PPTs." Last, participant responses pointed towards AI for administrative tasks: "Could save time completing non-creative tasks." When asked, "Have you used AI tools for any part of your work?" participants mentioned specific tools like ChatGPT and Google AI (Gemini). Others highlighted specific tasks like generating Google Meet summaries, abstracts, and modeled curricular units. A participant also mentioned how AI tools can "have errors." Furthermore, for the question, "In which areas is AI use appropriate?" interesting insights were found. Figure 2 is a perceptual map showing the level of agreement of the participants for various types of preferences and motivations for using AI tools.

In the perceptual map (Figure 2), each number represents a specific teaching-related task. The position of the number along the x-axis indicates the extent to which faculty reported using AI tools for that task, while the y-axis represents the degree of human interaction perceived as necessary for performing that task. For example, task 5 (Administrative tasks) appears at the extreme right of the x-axis, showing that faculty rely on AI most heavily for administrative work. In contrast, tasks 2 (Classroom activities) and 3 (Homework) appear higher on the y-axis and closer to the left, indicating that these tasks are viewed as requiring greater human involvement and are less frequently delegated to

AI. Assessment-related tasks (task 1) and grading (task 4) fall near the middle, suggesting cautious openness toward AI support, but with continued preference for human judgment.

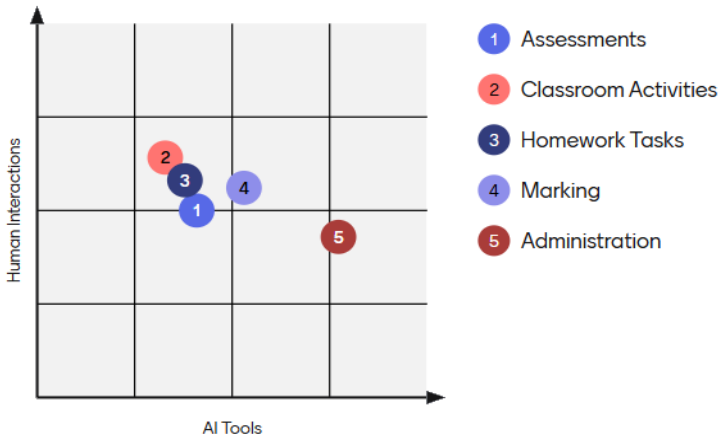

Figure 2. Perceptual map showing agreement levels of using AI tools by the participants

Overall, the distribution demonstrates that faculty perceive AI primarily as an efficiency tool for administrative and routine academic functions, rather than a substitute for interactive, practice-based teaching. Thus, it is clear that the majority of the participants deemed it useful to use AI for administrative tasks, followed by marking and assessment. The least importance was given to using AI for classroom activities and homework tasks, pointing to the fact that participants are inclined towards the non-creative use of AI more than using it to intervene with any practice-based pedagogical methods.

Motivations behind AI adoption

For the question, "I use AI tools because they help with …", participants rated their agreement with specific motivations. The highest agreement was recorded for the statement "Pressure to complete syllabus and administrative workload," with a mean score of 4, indicating that faculty members primarily view AI as a means to improve efficiency and reduce non-teaching burden. The statement "Institutional barriers like infrastructure and accessibility" received an agreement with a mean score of 3.4, suggesting that while AI may help address gaps in accessibility, confidence in its capacity to do so is not clear. Interestingly, the lowest agreement was observed for "Teaching all subjects to large class sizes" (M = 2.7). This highlights a general reluctance to rely on AI for interactive teaching scenarios, especially those involving large student groups within their specific subject areas. These findings reaffirm the insights that AI is seen as a supportive or assistive tool, with little importance given to using it for direct pedagogical purposes.

Overall, the qualitative insights reinforce the quantitative findings by showing that faculty largely value AI as a supportive and administrative tool rather than as a primary facilitator of learning. Faculty expressed ethical caution and pedagogical selectivity, reflecting neutral-to-positive KAP scores, and the CAP data suggest that hands-on support influences their ability to translate attitude into ethical practice. These converging results validate the use of a dual-framework (KAP-CAP) model, demonstrating that awareness and attitude alone are insufficient without applied practice and structured competency-building.

Triangulating KAP and CAP assessments

To ensure conceptual coherence, the KAP and CAP frameworks were explicitly aligned through a theme-based mapping process. Thematic analysis of the KAP and CAP frameworks from a scoping review of studies between 2020 and 2025 yielded Figure 3.

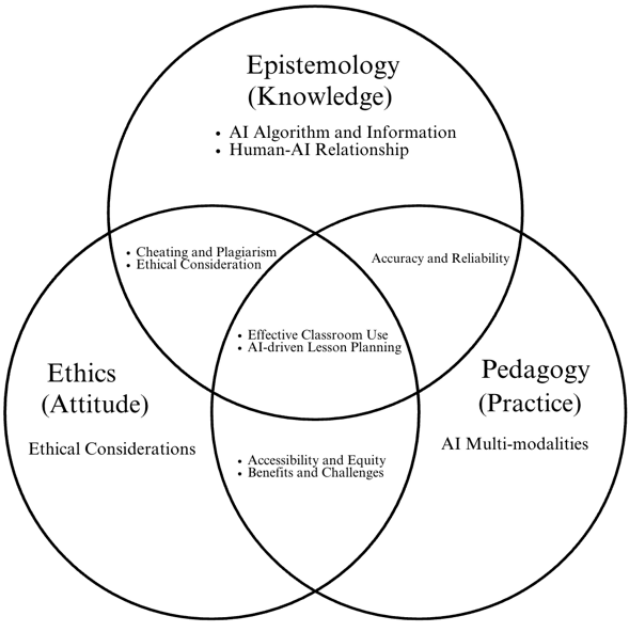

Figure 3. Conceptual mapping of KAP and CAP

Through the Venn diagram (Figure 3), epistemology, ethics, and pedagogy were aligned with the KAP framework to conceptually ground the dual-model validation. Epistemology reflects the domain of knowledge, as it concerns how individuals understand the nature, sources, limits, and reliability of information. Within the context of AI in education, epistemology relates to faculty members' understanding of AI concepts, algorithmic functioning, accuracy, transparency, and the boundaries between human and machine intelligence. Thus, epistemology corresponds to the knowledge dimension of KAP. Ethics aligns with attitude, as attitudes represent value-based positions, dispositions, and evaluative judgements. When integrating AI into teaching, ethical orientation shapes how educators perceive fairness, bias, academic integrity, equity, and responsible use. Attitudes, therefore, reflect the ethical stance an educator holds toward AI, linking ethics with the attitude component of KAP. Finally, pedagogy maps onto practice, since pedagogy concerns instructional action, how teaching strategies, decisions, and tools are enacted in real learning environments. Responsible AI use in classrooms requires not only awareness and ethical orientation, but also the ability to apply AI meaningfully through lesson planning, instructional design, multimodal content creation, and student engagement. Therefore, pedagogy corresponds to the practice domain, focusing on observable behaviours and demonstrated competence. Together, these mappings clarify how epistemic understanding, ethical judgement, and pedagogical execution form an integrated foundation for responsible AI implementation, reinforcing the necessity of triangulating knowledge (epistemology), attitude (ethics), and practice (pedagogy) when evaluating faculty readiness.

Having established the conceptual alignment between epistemology-ethics-pedagogy and the KAP-CAP frameworks, the next step involved examining whether this theoretical convergence was reflected in participants' actual scores. To do so, the KAP results were compared with the CAP rubric performance across the three piloted sessions. The study categorised KAP scores into three levels: positive (76-100), neutral (60-75), and negative (below 60), based on total scores of 100. Findings revealed that one participant demonstrated a positive KAP orientation, six participants exhibited a neutral orientation, and three of them showed a negative orientation.

Further, based on the session-wise CAP scoring done through the rubric system, participants were classified into three categories: positive, neutral, and negative CAP performance. This was done to see patterns with self-reported KAP scores. Participants with an average domain score of greater than or equal to 4 across sessions were classified as positive; those scoring in the range of 3.0-3.9

were categorised as having neutral CAP; and lastly, those with scores less than 3 were categorised as negative. The comparison of KAP and CAP assessments revealed notable misalignments: some with neutral KAP achieved positive CAP, and the participants with positive KAP had neutral CAP. These findings highlight that *self-reported perceptions may not reflect actual performance,* reaffirming the value of triangulating both KAP and CAP frameworks when validating the AI intervention.

DISCUSSION

The present study aimed to validate an AI intervention module for faculty members in HEI in India using a triangulated approach that incorporated both self-reported perceptions (knowledge, attitude, and practice: KAP) and observed performance (cognitive, affective, and psychomotor: CAP). The findings offer multi-layered insights into how participants engage with AI tools in ethically grounded and pedagogically sound ways.

THE "KNOWING-DOING" GAP

Addressing the first research objective, the study triangulated KAP and CAP assessments by thematically mapping both frameworks through a conceptual alignment process (Figure 3). While KAP scores revealed high internal consistency (Table 2), particularly in attitude and practice, a strong positive correlation emerged between knowledge and attitude (Table 3), indicating that awareness fosters openness to AI adoption. However, a weaker, non-significant correlation between knowledge and practice highlights a "knowing-doing gap," emphasizing that positive perception does not translate to classroom implementation. This phenomenon has been observed in prior technology-integration research, where conceptual understanding alone was insufficient to prompt pedagogical change without structured, supported opportunities for practice (Zawacki-Richter et al., 2023). In the context of AI in higher education, this gap is amplified by concerns around academic integrity, data ethics, and disciplinary identity, particularly in domains that prioritise embodied presence, improvisation, and artistic agency, such as performing arts. Thus, while faculty may intellectually recognise the value of AI, they may hesitate to translate this into practice without confidence that AI use will align with disciplinary values, learner development, and ethical expectations.

Interestingly, the present study also identified cases where faculty with neutral KAP scores demonstrated strong CAP performance in hands-on tasks. This suggests that even when faculty do not self-identify as confident or knowledgeable about AI, guided experiential learning can build capability and comfort. Conversely, instances where a positive KAP disposition did not translate into strong CAP performance reinforce the argument that awareness and attitude do not automatically produce pedagogical proficiency. Together, these patterns highlight the importance of performance-based faculty development that extends beyond awareness-raising to active modelling, scaffolded application, and reflective practice.

These findings have meaningful implications for AI capacity-building in higher education. Institutions cannot assume that conceptual training alone will adequately prepare educators for the ethical and effective adoption of AI. Instead, faculty development initiatives should integrate experiential learning cycles, including demonstration, guided experimentation, feedback, and reflective evaluation. Beyond institutional practice, these results contribute to global discussions on AI in education by foregrounding the role of values, identity, and pedagogical philosophy in shaping adoption. Faculty in this study consistently expressed that AI is most appropriate for administrative, planning, and structural support; however, they remained cautious about delegating core instructional or creative functions to AI tools. This aligns with international findings that educators value AI for efficiency but remain hesitant to replace human judgement, creativity, and emotional labour in learning environments (Kiryakova & Angelova, 2023). As AI tools evolve, faculty-development programs must not only strengthen technical fluency and ethical reasoning but also cultivate discernment about when not to use AI. This emerging competency is essential for safeguarding human-centered pedagogy.

Effectiveness of the Dual KAP-CAP Model

A key contribution of this study lies in demonstrating the value of a dual-model approach to evaluating faculty readiness for ethical AI integration. While KAP measures revealed participants' conceptual understanding, ethical stance, and perceived use of AI, these self-reported indicators alone would not have captured how these beliefs translated into real instructional behaviour. Likewise, CAP scores alone would have provided insight into demonstrated competencies but would not have revealed the epistemic and ethical orientations underlying those behaviours. By integrating perception-based (KAP) and performance-based (CAP) assessments, the study generated a more holistic profile of AI-readiness, highlighting cases where faculty expressed confidence yet hesitated to implement AI in practice, as well as instances where moderate self-perception was accompanied by strong hands-on performance. These findings validate the dual-framework design and reinforce the importance of triangulated evaluation in AI-focused faculty development, particularly as higher education systems transition from awareness-building toward competency-based and ethics-informed implementation models.

In validating the AI intervention (research objective 2), three sessions of the module were assessed through rubric-based CAP scores, which revealed moderate to high performance across all domains. cognitive, affective, and psychomotor (Table 4). These performance trends, supported by statistical analysis of mean scores and standard deviations, contribute to establishing the intervention's validity for ethical and responsible AI integration. The findings align with the current research gap: the need for continuous professional development for higher education teachers regarding AI while shifting from product-based assessments to human-AI interactions (Awadallah Alkouk & Khlaif, 2024). Moreover, the findings align with the prior studies suggesting that institutional, technical, or pedagogical constraints may prevent actual adoption of AI despite positive inclination (Ivchyk, 2024).

Ethical and Pedagogical Dimension of Responsible AI Use

For the third research objective, the feedback from faculty members, especially those from performing arts, was instrumental in validating affective and psychomotor domains of the rubric assessment. Participants highlighted the embodied and performative nature of learning, which posed challenges when engaging with AI tools. The responses from participants stressed difficulty in translating expressive, physical, and real-time teaching processes into AI-driven environments. This insight was pivotal in revising rubric parameters to better reflect discipline-sensitive and action-oriented outcomes, especially for educators whose pedagogical approaches rely on demonstrations, interaction, and spontaneity. Finally, open-ended responses enriched the findings by revealing that most faculty used AI for administrative efficacy, such as summarization, editing, and assessment, rather than direct teaching. Simultaneously, concerns about AI's influence on student learning, such as diminished critical thinking and academic dishonesty, mirrored trends in global literature.

These findings align with prior studies where university teachers express concerns like cheating, plagiarism, biased content, and data privacy issues (Kiryakova & Angelova, 2023). The findings reaffirm the importance of designing AI interventions that are ethically grounded, contextually sensitive, and validated not just by knowledge acquisition but also by meaningful application across all domains of learning. Furthermore, AI adoption in HEI is context-dependent, and interventions regarding AI use must be discipline-sensitive and ethically grounded. Furthermore, self-reported assessments must be triangulated with actual implementation-based assessments to better evaluate the training outcomes.

Limitations of the Study

Despite its contribution, the study has certain limitations. First, the participant group comprised only ten faculty members from an underrepresented domain of HE in India, selected through purposive sampling based on the practical nature of their subject domains. While the sample was diverse in terms of disciplines and roles, the limited sample size restricts the generalisability of findings to broader populations and wider subject areas. This being mentioned, the triangulation of methods has

attempted to address this shortcoming by providing thick data points for discussion. Next, the scope of the intervention is limited. Although the full intervention contained ten sessions, three sessions were piloted and analysed in this study. Thus, the findings may not capture the full developmental impact of the module. Furthermore, the KAP questionnaire was administered once, without a pre-post comparison. This only provides a snapshot and may limit the ability to assess the patterns or shifts resulting from the intervention. In addition to this, the qualitative data, while insightful, was collected via Mentimeter word clouds and short-text inputs. Deeper interviews could allow richer narratives or more nuanced reflections in future studies.

Next, while the CAP rubric was reviewed by experts and applied consistently, the scoring was conducted by the researcher alone, without multiple raters or inter-rater reliability testing, which could add subjectivity to the assessment of the tasks. Lastly, the findings are situated within the Indian higher education context. Thus, the transferability of insights to other contexts should be done cautiously. Future research can be implemented with a larger and more diverse sample, comprising a pre- and post-design. Furthermore, inter-rater reliability could strengthen the credibility and objectivity of the rubric-based assessments of the module. Lastly, the psychomotor domain could be reiterated to better suit disciplines more focused on developing demonstrative or experience-based skills, such as the performing arts. Although the small sample size reduces inferential power, such sample sizes are common in pilot faculty-development intervention studies, where the goal is depth of insight and feasibility assessment rather than broad generalisation.

CONCLUSION

This study validated a dual-framework AI intervention module for faculty in higher education, integrating self-reported perceptions (KAP) with performance-based competencies (CAP). The findings demonstrate that while faculty members showed positive attitudes and conceptual awareness of AI, this did not always translate into applied practice, signaling a notable gap between knowing and doing in ethical AI implementation. The dual-model approach thus offers a theoretically robust and empirically grounded method for assessing AI readiness in higher education, contributing to emerging literature that emphasises the need for moving beyond digital literacy toward ethical, experiential, and pedagogically aligned AI competence. Practically, the study introduces a structured, context-sensitive professional development model that foregrounds ethical judgment, discipline-specific needs, and experiential learning cycles. Insights from performing-arts faculty underscore the importance of embodied learning and human presence in teaching practices, calling for AI strategies that complement, rather than replace, relational and creative pedagogies. These findings reinforce the need for faculty AI training to be multidimensional, combining conceptual understanding, ethical reasoning, and domain-appropriate application.

While the study was conducted with a small, purposively selected sample and piloted only three sessions of the full intervention, the triangulated design, expert validation, and CAP-based assessment strengthen its internal validity. Future research should involve longitudinal, multi-institutional studies, pre-post comparisons, inter-rater reliability for rubric scoring, and adaptations for diverse disciplinary clusters such as STEM, humanities, and professional studies. Further research is also needed to explore policy mechanisms, institutional support structures, and scalable faculty-development pathways aligned with NEP-2020, UNESCO AI competency frameworks, and global responsible-AI agendas. The study contributes a theoretically grounded and practice-ready model for ethical AI faculty development, offering a foundation for scaling, contextual adaptation, and international application. By demonstrating the value of combining perception-based and performance-based evaluation, it advances global discourse on responsible AI in higher education and provides actionable guidance for institutions seeking to foster human-centered, ethical, and pedagogically sound AI adoption.

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APPENDICES

APPENDIX A: ADAPTED QUESTIONNAIRE (KAP)

The KAP questionnaire comprised 20 items on a 5-point Likert scale. The following are the details of the point scale: 5: Strongly Agree; 4: Agree; 3: Neutral; 2: Disagree, and 1: Strongly Disagree.

1. I think AI tools use artificial intelligence to generate human-like responses.
2. In my opinion, AI tools can provide answers only in English.
3. I believe the responses given by generative AI tools are 100% accurate.
4. I think AI tools can cater to the needs of all learners.
5. AI tools can only provide text-based responses.
6. I believe AI tools can check and grade student assignments.
7. In my view, AI tools can help teachers plan lessons, considering diverse learning needs.
8. I find AI tools helpful in answering questions.
9. I trust the responses provided by AI tools.
10. I believe AI tools have the potential to revolutionise education.
11. I am concerned about the ethical implications of using AI tools.
12. I think the responses provided by AI tools are biased.
13. I am encouraged to use AI tools for my learners.
14. AI tools can create learning resources for learners with special needs.
15. AI tools can help differently abled learners understand concepts.
16. I use AI tools in the teaching-learning process.
17. I encounter challenges in using AI tools in education.
18. I find AI tools helpful in creating inclusive classrooms.
19. I like to explore multiple AI tools to cater to the needs of all my learners.
20. I feel the need for training in using AI tools to foster inclusive education.

APPENDIX B: RUBRICS SYSTEM

The following is a rubric for one of the conducted sessions (AI Algorithm and Information). The session's assessment outcome was to use different genAI tools and ask any questions about them. The output was to be analysed using questions based on content accuracy, bias awareness, ethical considerations, and source verification (Centre for Faculty Development and Teaching Innovation, 2023).

Criteria	Excellent (5)	Exceeds expectation (4)	Meets expectations (3)	Needs improvement (2)	Did not meet expectations (1)
Knowledge (cognitive domain)	Synthesizes knowledge of the AI algorithm and outputs to develop original instructional strategies. Designs tasks that reflect a deep understanding of the AI algorithm and information.	Critically examines AI tools to identify AI algorithms and issues like accuracy and reliability. Justifies the use of AI with clear reasoning and evaluates implications for the classroom.	Accurately explains the AI algorithm and bias. Uses this knowledge to relate to the classroom.	Demonstrates basic understanding of an AI algorithm and output. Can explain concepts like accuracy, reliability and bias but with limited depth.	Can recall terms like accuracy, reliability, and bias, but shows limited comprehension of their function or implications for education.
Attitude (affective domain)	Takes initiative to integrate ethical algorithm understanding into teaching. Advocates for fairness, transparency; explains how to remove potential biases. The excitement of discovery can be heard within delivery.	Compares AI tools and ethical frameworks and outlines a personal approach to AI integration. Confidence in personal beliefs can be heard as the delivery is given.	Participates in discussions and recognizes the importance of fairness and transparency in AI. Demonstrates a positive attitude towards responsible AI use.	Responds when prompted but does not actively contribute to deeper analysis. The attitude to learn is neutral throughout the presentation. A monotonous tone of voice is used as the presentation is given.	Receives information passively. Shows limited concern or curiosity about the topic. No excitement to learn is visible throughout the presentation. Boredom can be heard whilst presenting.
Practice (psychomotor domain)	Fluently integrates the concept into a hands-on classroom scenario. Body language shows confidence, preparedness and complete involvement. Movements show a grasp of the concept. Collaboration with team members is visible throughout the presentation.	Expressive and structured physical action. Shows coordination between concept and expression. Body language shows a willingness to express and learn from others. Body language is open, facing the audience and welcoming to dialogue.	Performs a clear, task-based demonstration. Movement is controlled and is aligned with the concept (hand movements and natural conversational gestures show). Body language displays interest throughout the completion of the task.	Attempts to demonstrate AI processes through movement, but lacks clarity. Needs cues or corrections. Stiff body language accompanied by physical dependence on AI tools throughout the presentation (gripping phone tightly, looking only at phone, etc.).	Mimics movements or demonstrations shown by others. Shows limited understanding of the concept being embodied. Body language is closed and shows a disconnect from the presentation or disinterest during fellow group members' presentations and throughout the completion of the task.

AUTHORS

Sanskriti Rawat is a Research Scholar at the School of Education, CHRIST University, where her doctoral research focuses on the integration of artificial intelligence in teacher education. Her PhD work examines the knowledge, attitudes, and ethical practices surrounding AI adoption among pre-service teachers, with an emphasis on designing and validating intervention modules for the meaningful and responsible use of AI in educational settings.

She has published and presented research on AI in education across diverse stakeholder groups, including in-service teachers, faculty members, and students from various disciplines. Her scholarly contributions span AI-integrated pedagogy, ethical AI frameworks, curriculum innovation, and the evolving landscape of teacher professional development.

Associate Professor Dr R. L. Tavis Ashton-Bell has been the Head of the Department of Music at CHRIST University since 2019. He received his doctorate in Higher Education Music Teacher Education at Monash University, Australia. His PhD was an autoethnographic case study that focused on learner-centred approaches to music using mathematical modelling to scaffold the development of individual artistry in visual capacities.

He holds membership to the Australian and New Zealand Association of Research in Music Education (ANZARME), the International Society for Music Education (ISME), and the International Society of Assessment in Music Education (ISAME). He is a member of CHRIST University's core strategic planning committee and is a master trainer for the Teaching and Learning Enhancement Cell.