The Impact of College Instructors' Educational Technology Profiles on Student Academic Performance: A Two-Stage Clustering Approach

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***Abstract*—In an era of rapid educational change, faculty members must possess the essential skills and knowledge necessary for institutional success. This study aimed to examine college instructors' educational technology profiles to identify areas needing professional development and their impact on student academic performance. Specifically, it explored the extent of instructors' technology adoption, their preferred digital tools and platforms, and how these factors influence teaching effectiveness and student outcomes. A descriptive-comparative approach was used, with surveys providing data that were analyzed through a Two-Stage Clustering Approach, which groups instructors based on similar technology usage patterns before comparing their impact on student performance. This method allows for a clearer understanding of how different instructional technology profiles influence academic outcomes. The comparative analysis focused on the impact of student profiles on academic performance, utilizing tests such as one-way analysis of variance (ANOVA) and the Mann-Whitney U test. The findings revealed patterns and gaps in faculty competencies and needs, highlighting the importance of establishing a structured and flexible professional development program. In response, the DROID Program (Development, Responsiveness, Optimization, Integration, and Data-Driven Decision-Making) was proposed. This strategic initiative addresses the gaps in faculty development, enhances institutional resilience, and fosters sustainable academic excellence. The research concludes that instructors' educational technology profiles significantly affect student academic performance. The integration of technology-driven teaching practices results in increased student engagement, improved knowledge retention, and overall academic success.**

***Keywords*—college instructor, cluster analysis, educational technology, academic performance**

I. Background

The rapid advancement of educational technology has significantly transformed the landscape of higher education [1]. College instructors now have a diverse range of digital tools and platforms that can significantly improve student learning experiences. Digital technologies play a crucial role in promoting inclusive and equitable education. This has proven to be a cost-effective approach to fostering student learning while also serving as a powerful means of delivering a high-quality educational experience for all [2]. As education systems increasingly adapt to the demands of a technology-driven world, both students and instructors are required to navigate digital tools that bridge traditional learning paradigms with modern digital trends [3]. These highlight the role of technology in creating student-centered learning environments, where students engage in higher-order thinking, collaborative problem-solving, and inquiry-based learning while developing a sense of online social presence. Instructors, however, remain critical in guiding these processes, ensuring that students remain focused on learning objectives and derive meaningful outcomes from technological integration [4, 5].

With tools such as virtual learning environments, videoconferencing, social media platforms, and mobile learning applications [6], students and instructors are now able to collaborate, share knowledge, and receive immediate feedback [7]. These technologies facilitate both synchronous and asynchronous learning, allowing students to engage with content flexibly while still maintaining instructor guidance. However, [8] caution that the adoption of educational technologies is not without challenges, including technological literacy gaps, accessibility issues, and the potential for over-reliance on digital tools, which may distract students rather than enhance their learning.

The study of Hanus and Fox [9] further contributes to this discussion by exploring how technology facilitates interactive and dynamic learning experiences. They argue that digital tools empower students to investigate complex questions, develop critical thinking skills, and synthesize information from diverse sources. Similarly, Delgado *et al*. [10] observe that technology fosters better organization, efficiency, and collaborative learning environments, enabling students to set goals and test hypotheses effectively. In this crucial period, digital technologies have proven to be the cornerstone of sustaining education, ensuring continuity and accessibility despite the difficulties [3].

The recognition of digital learning has existed for many years; however, the COVID-19 pandemic significantly accelerated its adoption and reliance on technology. During this period, schools needed to transition to digital learning platforms [11]. This shift led to the widespread realization of the need to integrate digital approaches into teaching and learning, positioning both educators and students as critical stakeholders in the evolving educational landscape [12]. Concurrently, the rapid advancement and increasing accessibility of technology across various age groups have underscored the necessity of incorporating mobile learning into education. Over the past decade, the proliferation of mobile tools has facilitated the development of online learning environments and digital resources, solidifying their role in modern education [13]. As a result, mobile learning, or

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m-learning, has emerged as a key technological innovation, increasingly embedded in educational settings [14]. Research indicates that mobile learning offers numerous advantages, not only enhancing students' academic performance but also positively influencing affective factors such as attitudes, interests, and motivation [15–17]. Additionally, the ability of mobile learning to incorporate visual and auditory stimuli has been shown to make learning more engaging and appealing, fostering greater student interest [18, 19]. However, despite its benefits, recent studies have also identified challenges related to the rapid adoption of online learning, particularly concerning students' overall learning experiences [20].

The advent of mobile learning has further expanded the accessibility and flexibility of education, as internet-enabled smartphones allow instructors to conduct formative assessments and provide real-time feedback [21]. These formative assessment tools not only improve academic performance but also help instructors gauge student competencies more effectively. However, the reliance on mobile technologies also introduces concerns about screen time, potential distractions, and the addictive nature of digital tools [2].

Despite the evident benefits, there remains a persistent hesitation among educators to fully embrace technological change in their pedagogical practices [22]. This reluctance stems from uncertainties surrounding the efficacy of these tools, as well as concerns about their long-term impact on student engagement and knowledge retention. While the integration of technology into education offers numerous advantages, including enhanced student engagement, collaborative learning, and personalized feedback, its implementation must be carefully planned and critically evaluated. Instructors play a central role in mediating the use of these tools, ensuring that they complement pedagogical goals rather than hinder them. As Haleem *et al*. [2] suggest, striking a balance between technological innovation and traditional teaching methodologies remains essential for achieving meaningful academic outcomes.

One of the critical issues in higher education today is the varying degrees of effectiveness in implementing educational technology among college instructors. The differential use of digital tools and platforms can lead to disparities in student academic performance. As institutions of higher learning strive to keep pace with these technological innovations, it is crucial to understand the impact of instructors' educational technology profiles on student academic performance [23]. Moreover, understanding the impact of instructors' educational technology profiles on student academic performance is crucial for addressing this problem. Thus, this study aims to answer the main problem statement: how do the educational technology profiles of college instructors, identified through two-stage cluster analysis, affect the academic performance of students across different groups?

This research aims to examine the impact of different educational technology profiles of college instructors on student learning outcomes. Specifically, the study seeks to: (1) identify distinct educational technology profiles among college instructors using a two-stage clustering analysis; (2) analyze how these instructor profiles influence student academic performance and learning experiences; (3) assess the implications of these profiles for optimizing educational technology use in higher education; and (4) provide insights to inform the design of professional development programs that enhance instructors' effective integration of educational technology.

By directly aligning these objectives with the selected analytical approach, this study aims to enhance understanding of how instructors' educational technology profiles influence student learning outcomes. Additionally, it will offer practical recommendations to improve teaching strategies and optimize learning environments in higher education.

II. Methodology

A. Conceptual Framework and Research Design

This descriptive-comparative study examines college instructors' educational technology profiles by selecting key attributes from existing literature, including teaching style preference, multimedia integration, content personalization, adoption of new technologies, collaborative learning activities, and instructional design integration. A two-stage clustering method was applied, utilizing log-likelihood distance and Bayesian criterion to classify instructors into distinct groups. To validate the clustering results, silhouette measures, noise handling techniques, and predictor importance analysis were conducted. Finally, the identified clusters were compared in terms of their impact on academic performance, providing insights into how different instructional technology adoption patterns influence teaching effectiveness. A detailed framework of the study can be seen in Fig. 1.

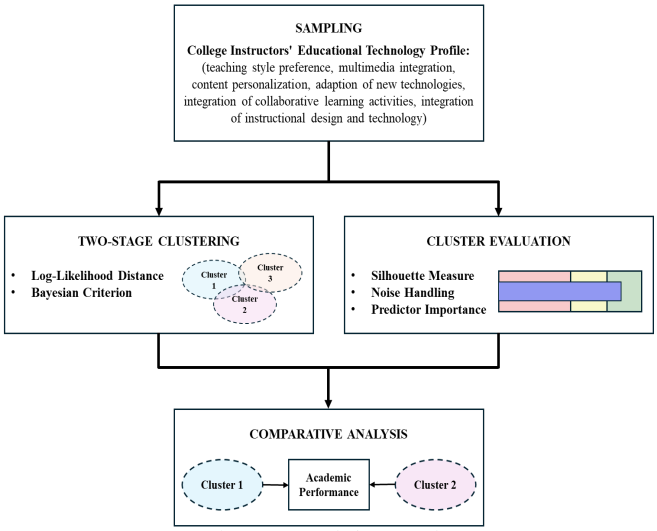

Fig. 1. Research framework.

The selection of teaching style preference, multimedia integration, content personalization, adaptation of new technologies, integration of collaborative learning activities, and integration of instructional design and technology as attributes for cluster analysis in this study is firmly rooted in existing literature. A teacher's inherent pedagogical approach, whether leaning towards teacher-centric or student-centered learning, significantly influences their adoption and implementation of technology [24]. Similarly, the integration of multimedia elements in teaching, as highlighted in [25] and [26], caters to diverse learning styles and boosts student engagement, making it a valuable attribute for analysis.

Furthermore, the ability to personalize content to individual student needs, as emphasized in [27], reveals the depth of an instructor's technology utilization. While not explicitly addressed in the provided snippets, the literature consistently underscores the importance of continuous professional development and adaptation to new technologies, making it a crucial aspect of an instructor's technology profile. Finally, the integration of collaborative learning activities, known for fostering critical thinking and communication skills, provides valuable insights into an instructor's approach to technology-mediated learning. By examining these interconnected attributes, this study can contribute to a nuanced understanding of how instructors' technology profiles impact student academic performance.

B. Selection of Attributes and Levels

The impact of college instructors' educational technology profiles on student academic performance is multifaceted, and several key attributes have been identified for cluster analysis in this research.

Teaching style preference is a significant factor, as it influences student engagement and learning outcomes. Grasha [28] identified various teaching styles, such as expert, formal authority, personal model, facilitator, and delegator, each affecting students differently. Facilitators, for instance, encourage active participation and critical thinking, often leading to better academic performance. Similarly, Felder and Silverman [29] emphasized the importance of aligning teaching styles with student learning styles to optimize learning outcomes, noting that mismatched styles could reduce academic performance.

Multimedia integration is another crucial attribute. Mayer [30] highlighted the Cognitive Theory of Multimedia Learning, which posits that students learn more effectively from a combination of words and pictures than from words alone. Moreno and Mayer [31] found that multimedia instruction incorporating both visual and auditory elements significantly enhances understanding and retention of material, thereby improving academic performance.

Content personalization addresses individual student needs, preferences, and learning paces, leading to a more effective and engaging learning experience. Dabbagh and Kitsantas [32] emphasized the benefits of personalized learning environments in fostering student engagement and self-regulated learning, critical for academic success. Chen *et al.* [33] demonstrated that personalized learning paths significantly improve students' learning efficiency and academic performance by catering to their unique needs and preferences.

The adaptation of new technologies in educational settings offers innovative ways of delivering content, engaging students, and facilitating learning processes. Kirkwood and Price [34] discussed the transformative potential of new technologies in higher education, highlighting their ability to enhance teaching and learning practices. West *et al*. [35] underscored the importance of technological adaptability among instructors for effective technology integration, which positively impacts student learning outcomes.

The integration of collaborative learning activities is essential for fostering peer interaction, knowledge sharing, and collective problem-solving, which are crucial for deeper understanding and improved academic performance. Johnson and Johnson and Johnson [36] noted that cooperative learning strategies have been shown to enhance academic performance by creating a supportive learning environment where students can learn from each other. Slavin [37] also found that students engaged in collaborative learning perform better academically due to increased engagement, motivation, and cognitive benefits of working in groups.

Lastly, the integration of instructional design and technology is vital for creating structured, engaging, and efficient learning experiences that cater to diverse learning needs. Reiser and Dempsey [38] highlighted the importance of combining instructional design principles with technology to create effective learning environments. Gagne *et al.* [39] discussed how well-structured instructional materials and activities, aligned with learning objectives, can enhance the learning experience when integrated with appropriate technology.

These attributes—teaching style preference, multimedia integration, content personalization, adaptation of new technologies, integration of collaborative learning activities, and integration of instructional design and technology—are chosen for their significant influence on various aspects of the learning process. This research used a two-step clustering method to analyze the complex relationships involved. The goal is to provide clear insights that can help improve teaching practices and boost student success.

C. Respondents of the Study

This study gathered data from 71 faculty members who participated in an online survey distributed via Google Forms. The participants were college instructors from Mapúa Malayan Colleges Laguna (MMCL), a private higher education institution selected as the primary research setting. These instructors came from various academic departments, ensuring a broad representation of faculty perspectives on educational technology use.

A convenience sampling method was utilized, meaning participants were selected based on their availability and willingness to respond while ensuring each department was well-represented and proportional to the population of the teachers in the institution. This approach allowed for efficient data collection while capturing insights from instructors with varying levels of experience, teaching styles, and technology adoption. The responses provided a diverse range of preferences and practices, offering valuable interpretations of faculty trends in educational technology integration.

Ethical considerations were strictly observed throughout the research process. Prior to participation, respondents were informed of the study's purpose, assured of their voluntary participation, and provided with consent forms emphasizing confidentiality and anonymity. The data collection instrument, which was a structured survey, was carefully designed based on validated measures from existing literature to ensure reliability and relevance. Additionally, all responses were securely stored and used solely for research purposes, adhering to ethical guidelines for data privacy and integrity.

D. Statistical Treatment

The researchers decided to employ a statistical method instead of manually categorizing the respondents based on observed characteristics. The Two-Stage Cluster Analysis technique organizes data into clusters using both numerical and categorical variables, presenting several advantages over alternative clustering methods like k-means and hierarchical clustering. It automatically identifies the optimal number of clusters, thereby streamlining the analysis process and minimizing the risk of user bias. Additionally, two-stage clustering proves to be efficient for large datasets, as it initially condenses the data into smaller sub-clusters before undertaking a more detailed analysis. This methodology enhances the accuracy and reliability of clustering results, making it a preferred choice for complex datasets. SPSS 27 was employed to conduct cluster analysis using the trait approach, incorporating a total of 7 attributes to form the clusters. The silhouette measure of cohesion and separation was chosen to ascertain a reasonable number of predictors assessed by the participants. Additionally, a similar approach was conducted by Moreno and Torres [40], further supporting the design and methodology of the study.

In this study, various categories based on the frequency of student behavior concerning college department, year level, and academic status were considered to develop learning segments. However, the demographic data exhibited diverse behavior distributions, making it challenging to segment students based on their profiles for a more targeted instructional design strategy. Consequently, the authors restricted the number of clusters formed to a maximum of three and utilized evaluation fields to determine the optimal segments they could form. Furthermore, the researchers assigned unique cluster names to the segmented results and devised a comprehensive instructional design strategy that caters to all segments, with a focus on learner-centric approaches.

After determining the formed clusters, the authors performed a comparative test using Kruskal-Wallis and Mann-Whitney U tests to determine if there is a significant difference in the academic performance of students when instructors are grouped based on their educational technology profile clusters. These two statistical tests are non-parametric, rank-based methods used to compare groups with ordinal or continuous data that do not meet the assumptions of normality. In this study, the normality of each data set was evaluated using the Shapiro-Wilk test, which indicated a non-normal distribution. Consequently, the Kruskal-Wallis and Mann-Whitney U tests were employed to compare the general weighted average of students across various clusters.

III. Results and Discussions

A. Demographic Profile

The demographic profile of the respondents as seen in Table 1 reveals a balanced distribution between Non-Tenure Track (42.3%) and Tenured Employees (42.3%), with a smaller portion in Tenure-Track positions (15.5%).

Most respondents hold a Master's Degree (56.3%), followed by those with a Bachelor's Degree (29.6%) and Doctorate Degree (14.1%). Department-wise, the largest group belongs to Arts and Sciences (45.1%), while smaller groups represent Business Management (14.1%), Computer and Information Systems (12.7%), Maritime Education (11.3%), Engineering and Architecture (11.3%), and Health and Science (5.6%). This diverse profile indicates a well-rounded representation across employment status, education levels, and academic disciplines.

Table 1. Demographic profile of the respondents

	Percent	Count
Employment Status		
Non-Tenure Track (Part-time Employee)	41.3%	29
Tenure-Track (Probationary Employee)	15.5%	11
Tenured (Regular Employee)	43.7%	31
Highest Education Qualification		
Bachelor's Degree (with on-going Master's)	29.6%	21
Master's Degree	56.3%	40
Doctorate Degree	14.1%	10
College Department		
Arts and Sciences	45.1%	32
Computer and Information System	12.7%	9
Health and Science	5.6%	4
Business Management	14.1%	10
Maritime Education	11.3%	8
Engineering and Architecture	11.3%	8

N = 71 respondents.

B. Cluster Analysis Results

Table 2 illustrates that among the six attributes initially identified in this study, only teaching style preference and adoption of new technology clusters demonstrated fair to good predictive results. This implies that multimedia integration, content personalization, integration of collaborative learning activities, and integration of instructional design and technology underwent iterations and therefore do not serve as predictors. With these two attributes exhibiting predictive capabilities, this study delves deeper into identifying the specific cluster segments associated with these attributes.

Table 2. Two-stage clustering summary

Attributes	Results
Teaching Style Preference	
SMCH[1]	0.7 (Good)
Most Important Predictor	Teaching Style (1.0)
Least Important Predictor	Content Personalization (0.49)
New Technology Adapter Clusters	
SMCH[1]	0.7 (Good)
Most Important Predictor	Adoption of New Technologies (1.0)
Least Important Predictor	Instructional Design and Technology (0.01)

[1] Silhouette Measure of Cohesion and Separation

1) Teaching style preference cluster

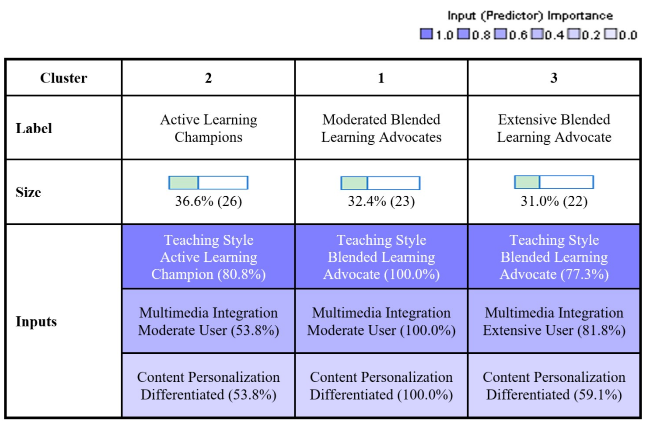

Fig. 2. Clustering teachers based on their teaching style.

The study ran a two-stage cluster analysis using log-likelihood distance measure and Schwartz's Bayesian Criterion method for instructors' teaching style, multimedia integration, and content personalization preference. The purpose of this is to test if the teaching style preference of the instructors predicts their clustering when compared to how they integrate multimedia and personalize the learning of the students. As shown in Table 2, the Teaching Style Preference cluster achieved a silhouette measure of cohesion and separation of 0.7, which indicates that the clusters' separation is good and acceptable, without noise handling. The 'Teaching Style Preference' variable obtained the highest predictor importance value of 1.0, while 'Content Personalization' got the lowest value of 0.49. This confirms that the three (3) clusters were formed based on the preferred teaching styles of the instructors as seen in Fig. 2.

a) Active learning champions

This cluster represents 26 or 36.60% of the instructors who participated in the study. 80.6% of the total members of the cluster prioritize student engagement over passive lectures. They incorporate activities such as discussions, group work, simulations, case studies, and role-playing. More than half (53.8%), understand the power of multimedia but avoid overreliance. They tend to use educational videos, interactive simulations, online resources, and slides or visuals to highlight key points to complex information. Similarly, 53.8% of the instructors in the cluster recognize that students learn differently and tailor their approach to address these variations.

b) Moderate blended learning advocates

This cluster, 23 or 32.4% of instructors prefer blended learning, while moderately applying multimedia and differentiated learning methods. Interestingly, all the members in this cluster effectively blend both online and face-to-face learning opportunities. Instructors provide students with access to pre-recorded lectures, tutorials, and interactive activities outside of class to acquire foundational knowledge. While on-site, classroom time becomes more interactive, with a focus on discussions, applying concepts through activities, and providing personalized support. Alternatively, the instructors strategically utilize multimedia to enhance both online and in-person learning, with the goal of ensuring that every student excels in the blended environment. This method encourages self-guided learning, cooperation, and the skill to navigate digital and physical learning environments.

c) Extensive blended learning advocates

Within this cluster, 31% of the instructors, which is 22 out of 71, favor the extensive utilization of multimedia for blended and differentiated learning. In this cluster, most instructors, totaling 77.3%, cultivate an interactive and stimulating learning atmosphere. Students assume responsibility for their learning by engaging with online modules and subsequently applying and extending their knowledge through class projects and collaborative efforts. However, 88.1% incorporate multimedia to create an engaging learning environment, and 59.1% employ effective differentiation strategies to support students in excelling based on their unique strengths and requirements.

The distribution results exhibit only minor differences across the three clusters. This finding is consistent with the research conducted by Yoshida *et al*. [41], which analyzed the clustering of teachers based on their teaching styles through the Teaching Style Assessment Scale. This implies that teachers tend to have distinct preferences for their teaching styles, suggesting that no single teaching style prevails, even among educators of various subjects.

2) New technology adapter clusters

The study has analyzed how the instructors' preference for the adoption of new technologies in teaching and learning will influence their clustering. After multiple iterations using log-likelihood distance measure and Schwartz's Bayesian Criterion method, two clusters were produced. New technology adapter clusters achieved a silhouette measure of cohesion and separation of 0.7 as seen in Table 2, which indicates that the clusters' separation is good and acceptable. To eliminate outliers and irrelevant data from the clustering, 15% noise handling was used. The 'adoption of new technologies' variable was the most significant predictor with an importance value of 1.0, while the 'integration of instructional design and technology' variable had the lowest value of 0.01. This means the two clusters for the new technology adapter clusters were formed based on how instructors adopt new technologies as seen in Fig. 3.

Input (Predictor) Importance
1.0 0.8 0.6 0.4 0.2 0.0

Cluster	2	1
Label	Open Minded Adapter	Tech-Savvy Enthusiast
Size	51.5% (34)	48.5% (32)
Inputs	Adoption of New Tech Open Minded Adapter (100.0%)	Adoption of New Tech Tech-Savvy Enthusiast (65.6%)
	Integration of Collaborative Learning Strategic Integrator (61.8%)	Integration of Collaborative Learning Strategic Integrator (65.6%)
	Integration of Instructional Design Moderate Integrator (67.6%)	Integration of Instructional Design Moderate Integrator (62.5%)

Fig. 3. Clustering teachers based on their perspectives on new technology.

a) Open-minded adapter

This cluster represents 34 instructors, which is 51.5% of the total after noise handling. It's worth noting that all members of this cluster are enthusiastic about adopting new technologies and are constantly seeking innovative tools to engage students. Additionally, 61.8% of the members acknowledge that students have diverse learning styles, and they use technology to support a varied learning experience. As a result, 67.6% of the members prefer to moderately incorporate instructional design principles and selectively integrate technologies based on their relevance to specific learning objectives, maintaining a balanced approach.

b) Tech savvy enthusiast

In this cluster, 48.5% of instructors, following noise handling, exhibit more than just comfort with technology. They actively seek it out and become genuinely excited about its potential to revolutionize learning. Additionally, 65.6% of the members of this group frequently stay updated with the latest educational apps, platforms, and gadgets, eagerly experimenting to see how they can be applied in the classroom. Similar to the open-minded adapter cluster, 65.6% of the members thoughtfully design collaborative activities that align with learning objectives and encourage active participation from all students. Furthermore, 62.5% carefully choose technology that aligns with learning objectives and complements their teaching style.

The findings regarding teachers' openness to adopting new technologies align with similar studies examining the perspectives of educators in different areas. In the research conducted by Wijnen *et al.* [42], the authors investigated the clustering of primary school teachers based on their attitudes toward integrating new technology and promoting higher-order thinking among students. The results indicated that a substantial proportion of teachers are eager to embrace new technologies, while a smaller yet significant group remains hesitant or favors traditional teaching methods.

C. Academic Performance Impact

The academic performance of the students was assessed based on the educational technology profile of their instructors' using tests of mean difference. The students were grouped based on their common instructors per cluster, and their academic performance was measured using their general weighted average (GWA) for a specific term.

1) Academic performance of students under the teaching style preference clusters

The one-way analysis of variance was considered to test the differences among the general weighted average of the students under the teaching style preference cluster. However, the Shapiro-Wilk test of normality revealed that the distribution of GWA per cluster was not normal ($W_{ALC} = 0.96$, $p_{ALC} < 0.01$; $W_{MBLA} = 0.95$, $p_{MBLA} < 0.01$; and $W_{EBLA} = 0.95$, $p_{EBLA} < 0.01$), so the Kruskal-Wallis test was used instead.

Table 3. Kruskal-Wallis test summary

Cluster	n	Mean[1]	p-value
Active Learning Champions	115	2.11	0.004 $\varepsilon^2 = 0.0349$
Moderate Blended Learning Advocates	104	2.25	
Extensive Blended Learning Advocates	100	2.33	

[1] Based on the GWA of students (1 being the highest and 5 as the lowest)
Note: $\chi^2 = 11.1$; Degrees of Freedom (*df*) = 2, $\alpha = 0.0$

Table 3 shows that students whose instructors are active learning champions obtained the highest GWA compared with students under moderate blended learning advocates and extensive blended learning advocates clusters. The Kruskal-Wallis H test showed at least one difference among the general weighted average of the students on the three teaching style preference clusters, $\chi^2(2) = 11.1$, $p = 0.004$. The epsilon-squared value of 0.0349 indicates that approximately 3.49% of the variance in the data is explained by the teaching style preference of the teachers.

Table 4. Dwass-Steel-Critchlow-Flinger pairwise comparisons results

Cluster Pairing	W	p-value
Active Learning Champions Moderate Blended Learning Advocates	2.84	0.111
Active Learning Champions Extensive Blended Learning Advocates	4.46	0.005
Moderate Blended Learning Advocates Extensive Blended Learning Advocates	2.29	0.236

Table 4 shows the post hoc analysis using the Dwass-Steel-Critchlow-Flinger test, which was done to identify cluster pairings with significant mean differences. From the three pairings, ALC and EBLA showed highly significant difference ($W = 4.46$, $p = 0.005$). This means that the students whose instructors promote and advocate for using active learning strategies in classrooms or training programs performed better compared to students whose instructors are extensive blended learning advocates.

2) Academic performance of students under the new technology adapter clusters

The initial plan was to utilize the independent t-test to assess the difference in the General Weighted Average (GWA) of students under the new technology adapter cluster. However, upon conducting the Shapiro-Wilk test of normality, it was revealed that the distribution of GWA per cluster was not normal ($W_{OMA} = 0.95$, $p_{OMA} < 0.01$; and $W_{TSE} = 0.95$, $p_{TSE} < 0.01$). Consequently, due to the non-normal distribution, the decision was made to employ the Mann-Whitney U test as an alternative method for comparison. Table 5 shows that students whose instructors are tech-savvy enthusiasts obtained the highest GWA (Mdn = 1.97) compared with students under open-minded adapters (Mdn = 2.06). A Mann-Whitney U test indicated that this difference was statistically significant, $U(N_{OMA}=177, N_{TSE} = 143) = 10{,}447$, $p = 0.007$). This means that students achieved higher grades under instructors who utilized various tech tools and platforms to present information in engaging ways, such as coding simulations, interactive presentations, or virtual reality experiences. The rank biserial correlation value of −0.248 indicates a medium inverse relationship between the groups' ranks. Meaning that the ranks of one group are consistently lower than those of the other group, which, in this case, are the Open-minded Adapters.

Table 5. Mann-Whitney U test summary

Cluster	n	Median[1]	Mann-Whitney U	p-value
Open-minded Adapters	117	2.06	10,441	0.007
Tech-Savvy Enthusiast	143	1.97		$r = -0.248$

[1] Based on the GWA of students (1 being the highest and 5 as the lowest)
Note: Degrees of Freedom (*df*) = 318, $\alpha = 0.01$.

It is essential to recognize that the small sample size utilized in this analysis may have a considerable impact on the generalizability of the research findings. A limited sample can lead to biased results, making it challenging to apply these findings to a broader population. Therefore, the conclusions drawn from the tests of difference may not hold true in broader contexts or among diverse groups. It is crucial for future research to incorporate larger, more representative samples to validate these findings across various settings and populations.

D. Proposed Professional Development Program

1) Program formulation

This study developed the DROID program—an acronym for Development, Responsiveness, Optimization, Integration, and Data-Driven Decision-Making. The proposed professional development program is a comprehensive initiative designed to address the critical findings of this study. Rooted in evidence, the program responds to identified gaps in faculty preparedness, technological integration, and institutional alignment, offering a balanced approach to professional growth within academic institutions.

At the heart of the DROID Program lies Development, focusing on enhancing faculty competencies through targeted training sessions, workshops, and mentoring opportunities. This addresses the study's finding that 42.3% of respondents are non-tenure and part-time faculty members, highlighting the need for tailored professional development programs that cater to their flexible yet impactful roles in institutions. Additionally, the high percentage of educators with Master's degrees (56.3%) emphasizes the importance of continuing education programs that build on existing expertise and create pathways for advanced academic and professional growth.

The second component, Responsiveness, emphasizes the importance of agility in professional development. The study revealed gaps in faculty adaptability to rapidly changing digital tools and pedagogical approaches. By anticipating and addressing these challenges, the program ensures that faculty members are well-equipped to handle technological shifts, align with institutional goals, and cater to evolving student needs.

Optimization serves as the third pillar, aiming to maximize the use of available institutional resources. The findings showed a diverse distribution of faculty across departments, with 45.1% in Arts and Sciences, followed by smaller yet equally important groups in Business Management (14.1%) and Computer and Information Systems (12.7%). Optimization focuses on tailoring resource allocation and training content to fit these departmental needs, ensuring that professional development activities align with both general and discipline-specific requirements.

The Integration component bridges the gap between training outcomes and practical application. A significant insight from the study was the varying levels of technology integration across departments. The program emphasizes aligning professional development initiatives with institutional technology roadmaps, encouraging faculty members to seamlessly incorporate new tools and methodologies into their teaching and administrative responsibilities.

Lastly, Data-Driven Decision-Making ensures that the program remains dynamic and evidence-based. The study highlighted the importance of using empirical data to design, assess, and refine training initiatives. By incorporating feedback mechanisms, regular evaluations, and performance assessments, the DROID Program creates a continuous improvement cycle that remains aligned with faculty and institutional goals.

2) *Program implementation and evaluation*

One of the key strengths of the DROID Program is its scalable and adaptable structure, allowing it to remain effective across institutions with diverse faculty compositions and departmental clusters. While this study highlights specific trends, such as the concentration of faculty in Arts and Sciences or the prevalence of part-time faculty, the program is intentionally designed for flexibility. Institutions with varying faculty distributions, educational qualifications, or departmental structures can recalibrate the Development, Responsiveness, and Optimization components to align with their unique organizational profiles.

To enhance its practical utility and provide clearer guidance on adaptation, institutions can follow these structured recommendations:

1) For institutions with a high concentration of faculty in Business Management or Engineering, training modules should emphasize industry-relevant certifications, case-based teaching strategies, and experiential learning integration.
2) For institutions with a predominantly tenured workforce, professional development efforts may prioritize research capability enhancement, leadership training, and mentorship programs instead of foundational competency-building.
3) For institutions with a large proportion of part-time or adjunct faculty, the program can focus on flexible learning opportunities, digital teaching tools, and skill-based micro-credentialing to ensure inclusivity and accessibility.

The data-drive decision making component ensures that each institution can systematically collect and analyze internal data to refine program implementation, making it highly context-specific and effective regardless of structural differences. Embedding continuous feedback mechanisms, institutions can track progress and adjust strategies to address emerging faculty development needs.

Ultimately, the DROID Program is not a rigid, one-size-fits-all framework but a customizable blueprint for professional development. It serves as both a theoretical contribution and a practical guide for academic institutions seeking to foster faculty excellence, integrate technological advancements, and build institutional resilience in an evolving educational landscape. Whether applied to small colleges, large universities, or multidisciplinary institutions, the DROID Program offers a structured pathway for achieving sustainable growth and academic innovation.

IV. Conclusion and Recommendations

This study has provided valuable insights into the demographic profile, educational qualifications, and departmental distributions of faculty members within the institution, shedding light on areas requiring targeted intervention and strategic development. The findings revealed significant patterns, such as the prevalence of non-tenure and part-time faculty members, the dominance of Master's degree holders, and the concentration of faculty in disciplines like Arts and Sciences. These insights underscore the pressing need for professional development programs that not only address individual skill gaps but also align with institutional priorities and emerging trends in education and technology.

The study identified teaching style preference and new technology adoption as the only two attributes with fair to good predictive results among the six initially examined. Both teaching style preference and new technology adoption clusters demonstrated good separation. Further analysis revealed three clusters for teaching style preference: Active Learning Champions, Moderate Blended Learning Advocates, and Extensive Blended Learning Advocates. Additionally, two clusters were identified for new technology adoption: Open-minded Adapters and Tech-savvy Enthusiasts. These findings emphasize the significance of teaching style and technology adoption in predicting clustering outcomes, while attributes such as multimedia integration and content personalization were found to be less predictive.

The academic performance of students was assessed based on the educational technology profiles of their instructors, using tests to measure mean differences. The Kruskal-Wallis test, applied to teaching style preference clusters, revealed significant disparities in the students' General Weighted Average (GWA). Remarkably, students taught by active learning champions attained the highest GWA. A post hoc analysis further indicated a significant difference between the GWA of active learning champions' students and those of extensive blended learning advocates. In the context of new technology adapter clusters, the Mann-Whitney U test demonstrated that students categorized as tech-savvy enthusiasts achieved a significantly higher GWA compared to their peers identified as open-minded adapters.

One of the key revelations of this study is the critical role of continuous professional development in enhancing faculty competencies, particularly in adapting to technological advancements and evolving pedagogical approaches. The data indicated that while faculty members demonstrate a strong academic foundation, challenges remain in responsiveness to institutional goals, integration of technology, and the optimization of resources across departments. The diverse distribution of faculty across academic clusters further emphasizes the need for tailored interventions that address both shared and discipline-specific challenges. In response to these findings, the DROID Program was conceptualized as a comprehensive professional development initiative designed to address the identified gaps and promote sustainable faculty growth. The program's core components collectively create a holistic framework that not only empowers educators but also strengthens institutional resilience.

Despite its contributions, this study has several limitations that should be acknowledged. First, the sample size was limited to faculty members from a single institution, which may affect the generalizability of the findings to other academic settings with different faculty compositions, institutional policies, or technological infrastructures. Future research could expand the scope by including multiple institutions across different regions to gain broader insights into faculty technology adoption and professional development needs. Consequently, additional stability and cross-validation measures should be incorporated to enhance the generalizability of the clusters.

Second, the data collection method relied on self-reported survey responses, which may introduce potential biases such as social desirability bias or subjective interpretations of competency levels. While surveys provide valuable insights, future studies could incorporate additional qualitative methods, such as in-depth interviews or focus group discussions, to gain a deeper understanding of faculty perspectives and challenges.

Third, while the study identified key faculty trends and development gaps, it did not explore longitudinal changes in faculty competencies over time. Future research should consider a long-term assessment of faculty professional development initiatives to evaluate the sustained impact of programs like the DROID Program on teaching effectiveness, student engagement, and institutional outcomes.

From a practical standpoint, academic institutions must prioritize structured, data-driven professional development programs that evolve alongside technological advancements and educational demands. Institutions should regularly assess faculty competencies, identify emerging skill gaps, and implement responsive training programs tailored to both institutional objectives and individual needs. Furthermore, fostering a culture of innovation and adaptability among faculty members is essential to ensure the successful integration of technology into the teaching and learning process.

This study makes a significant contribution to the literature on educational technology by demonstrating how faculty members' technology integration directly influences student engagement, knowledge retention, and overall academic performance. Unlike previous studies that focus broadly on faculty competencies, this research delves deeper into specific educational technology profiles of instructors, identifying gaps and opportunities for professional development that align with institutional goals.

A key theoretical contribution of this study is the introduction of the DROID Program, a structured framework designed to enhance faculty digital competencies, optimize technology-driven teaching strategies, and ultimately improve student learning outcomes. This model bridges the gap between faculty development and student success by ensuring that professional training is not only institutionally relevant but also pedagogically effective in today's technology-driven learning environment.

From a practical standpoint, this study provides empirical evidence supporting the need for continuous, data-driven faculty development initiatives. By aligning professional development programs with institutional priorities and emerging technological trends, academic institutions can create a sustainable model for enhancing teaching effectiveness, fostering student success, and strengthening overall educational resilience.

Moving forward, professional development should not be seen as a one-time initiative but as a continuous, evolving process that adapts to changing educational landscapes. Through these efforts, institutions can build a strong foundation for academic excellence, innovation, and long-term growth, ensuring that both educators and students thrive in a dynamic learning ecosystem.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Donn Enrique Moreno conceptualized, designed, and wrote the original draft preparation. Ramachandra Torres curated the data, conducted the formal analysis, and reviewed the final manuscript. Both authors have read and agreed to the published version of the manuscript.

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