College Students' Preference in Technology-Enhanced Learning Modalities: A Two-Stage Cluster Analysis for Enhanced Instructional Design Strategies

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***Abstract*—This research investigates student preferences in technology use, content delivery, and study time, aiming to develop an integrated instructional design approach in higher education. Employing a cluster analysis methodology, the study identified distinct clusters within each variable based on survey data from college students. The findings reveal diverse preferences among students, highlighting the need for tailored instructional strategies. Gradual technology integration, multimodal content delivery, and flexible study time structures emerge as key components of the proposed instructional design. The results underscore the importance of accommodating individual preferences to foster engagement and learning. Moving forward, future research should explore the longitudinal effects of the instructional design on student outcomes and further refine strategies to meet evolving educational needs. Ultimately, the research contributes to the ongoing discourse on effective instructional practices in higher education, emphasizing student-centered approaches for enhanced learning experiences.**

***Keywords*—preference, college students, learning modality, instructional design, cluster analysis**

I. Introduction

In the wake of unprecedented global changes, higher education has undergone a rapid transformation, necessitating a thorough exploration of students' preferences in the evolving landscape. The shift to the new normal, marked by a blend of online, hybrid, and traditional learning modalities, has prompted a critical examination of college students' attitudes and inclinations toward different learning approaches. With the lifting of lockdown measures, another transition has challenged many higher education institutions, leading to a situation where numerous students once again had to quickly adjust to this sudden shift in their learning environment [1]. The emergence of the new normal in education, catalyzed by the pandemic effect, has ushered in a transformation that transcends borders. It has propelled educational institutions worldwide to adapt to new modes of learning, making flexibility and adaptability the watchwords of modern pedagogy. Educators and institutions globally are faced with the challenge of accommodating students' diverse learning preferences within this rapidly evolving educational ecosystem. The imperative is to craft instructional design strategies that are not only effective but also aligned with the individualized needs of learners.

Recent studies on online education during the pandemic have shown a noticeable increase in research attention toward various aspects of online teaching, including instructional strategies [2], teaching facilitation [1], educational resources, practices, and policies [3], as well as the impact of lockdowns on student learning [4]. However, there is a limited body of research that has systematically examined the attributes of blended learning experiences and student preferences. Thus, the study [5] recommends conducting study on this blended learning experience and preferences of students. Considering the student preferences enables them to become actively involved and absorb the information in their preferred and most convenient manner. Similarly, educational institutions can craft efficient blended instructional designs that align with learners' preferences and expectations. The creation of suitable educational materials has been recognized as a potent strategy for addressing educational gaps in online learning, as it enhances engagement [6, 7].

This leads to the main research question of interest: What technology-enhanced learning modality attributes determine students' preferences during the new normal? The researchers set out two main objectives for this study: (1) to identify the attributes and levels of learning preferences in technology-enhanced learning modality; and (2) to perform cluster segments on similarities as basis for instructional design strategy. This study is based on Filipino undergraduate students' online learning preferences and experiences enrolled in different programs and studying different subjects in blended learning modality during the post pandemic setting. This research exclusively considered blended learning attributes that educational institutions could effectively manage, focusing on blended learning attributes. Seven key attributes of interest were defined based on the demographic characteristics of the student, prior literatures, and the current practices of Mapúa Malayan Colleges Laguna (MCL) in implementing blended learning. These attributes encompassed the student's preference on: (1) learning style, (2) teaching style, (3) learning intervention, (4) technology use, (5) content delivery, (6) study time, and (7) learning management system usage.

The urgency of this research is driven by the rapid transformation of higher education in response to technological advancements, shifting student demographics, and evolving learning environments. As educational institutions face growing pressure to adapt to these changes, the traditional one-size-fits-all approach to instruction is becoming increasingly inadequate. Students today come from diverse backgrounds and have varying levels of comfort

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with technology, different learning preferences, and distinct lifestyles that impact their study habits. As such, the need for instructional designs that are flexible, inclusive, and responsive to individual needs has never been greater. By examining student preferences in technology use, content delivery, and study time, this research seeks to provide a blueprint for creating more engaging and effective educational experiences. This effort is critical to ensure that higher education remains relevant and accessible, fostering environments where all students can succeed. By focusing on student-centered approaches, this research aims to promote better engagement, improved learning outcomes, and ultimately, a more equitable educational landscape.

The findings of this study offer a foundational reference for future researchers, illustrating the utilization of clustering techniques for the purpose of categorizing students into various segments and providing instructional design strategies suited to every segment needs. Furthermore, the outcomes of this study hold the potential to provide valuable insights for educational institutions, enabling them to gain a comprehensive understanding of their students' preferences in engaging in today's new learning environment. The findings can empower educational institutions to strategize more effective approaches to instructional design.

II. Methodology

A. Conceptual Framework and Research Design

This study seeks to identify the diverse preferences of Mapúa MLC students based on their individual characteristics and attributes, employing a conjoint analysis methodology. Additionally, it aims to delineate distinct market segments within this student population using a multi-stage clustering approach. Specifically, this research incorporates seven attributes within an orthogonal fractional factor design to gauge the range of stimuli presented in the survey. The conceptual framework, which includes the attributes and levels, is generated from the fundamental demographic traits and preferences of a student. In the initial stage of the study, the authors identified the characteristics and their variations, created the group design, and developed the survey questionnaire by incorporating materials from existing literature. To evaluate the seven characteristics, this study adapted items on learning style from [8, 9], teaching style from [10, 11], technology usage from [12, 13], content delivery from [14, 15], and study time from [16]. Additionally, for assessing preferences in learning interventions, the researchers utilized four items from the initiatives of the company's guidance counselor office, and for preferences in learning management system usage, the authors utilized materials from the company's learning environments and innovation office approaches.

As depicted in Fig. 1, the sampling stage considered the key attributes and levels identified through the institutions' learning practices and literature review. It contains the traits and preferences that were adopted from [8, 17]. There are a total of seven attributes: the college the student belongs to, year level, academic status, preferred instructional delivery, preferred learning intervention, learning preference, and teaching style preference. These attributes represent the unique combinations that students prefer when engaging in today's learning environment. When participating in a blended learning setting, these demographic and preference characteristics and their corresponding levels may affect the choices made by students. Therefore, it is essential to analyze these attributes, particularly when designing instructional strategies.

Subsequently, a clustering design was generated using SPSS version 27 to group the observations into clusters using the trait approach. Additionally, SPSS employs a method to automatically determine the optimal number of clusters.

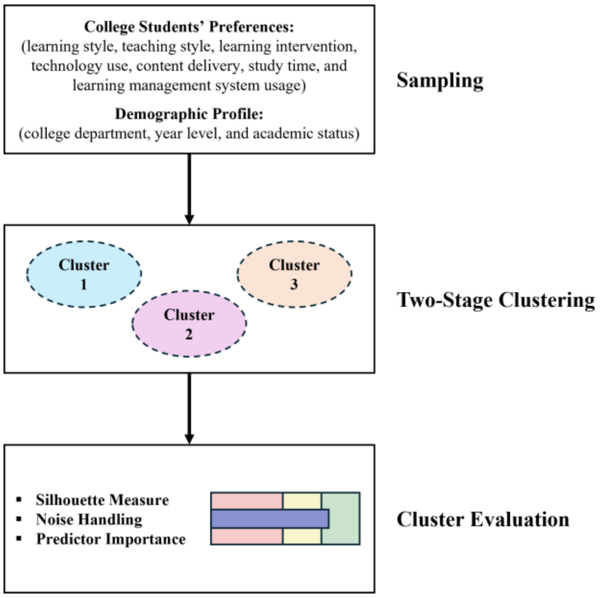

Fig. 1. Conceptual framework.

Recognizing the significance of aligning instructional design with the preferences and needs of students, this study delves into key attributes that influence the effectiveness of technology integration. By exploring aspects such as learning style preference, teaching style preference, learning intervention preference, technology use preference, content delivery preference, study time preference, and learning management system usage preference, this study aims to gain a nuanced understanding of the diverse factors that contribute to students' engagement and success in technology-enhanced learning environments. Incorporating these attributes into the research framework is not merely an exploration of preferences but a strategic endeavor to inform instructional design strategies. The insights derived from the analysis of these attributes will serve as a foundation for developing targeted approaches that resonate with the varied preferences within the student population. This, in turn, holds the promise of enhancing the overall effectiveness of technology-integrated education, ensuring that learning experiences are not only technologically advanced but also tailored to the unique learning preferences of college students. Navigating the intersections of pedagogy and technology, the findings of this study aim to guide educators, instructional designers, and institutions toward creating more engaging, adaptive, and student-centric learning environments.

B. Selection of Attributes and Levels

The first attribute pertains to the learning style preference. Learning style encompasses a broad range of modalities, preferences, and strategies, which can be assessed by individuals' inclinations towards various information and mental activities [18]. As learners become aware of their learning style and educators recognize their students' styles, learning motivation and effectiveness are enhanced [19]. In the educational interaction between teacher, student, and subject matter, the learning style approach guides professionals in maximizing students' learning [20]. This study employed the VARK model, devised by Neil Fleming in 1987, to assist students in gaining deeper in-sights into their individual learning preferences. It encompasses how students best assimilate and process information. Students exhibit varying sensory modality preferences in the acquisition of knowledge. The VARK learning style model, introduced by Fleming, offers a structured framework for understanding these preferences [21]. It comprises a questionnaire that identifies a person's sensory modality preference, classifying students into four distinct learning modes: visual (V), aural (A), read/write (R), and kinesthetic (K). By recognizing and incorporating these sensory modality preferences, educators can create tailored instructional strategies, materials, and assessments that resonate with each student's unique way of learning. This approach fosters a more engaging and effective learning experience, aligning educational content with the specific needs of each student. Understanding college students' learning style preferences is crucial for tailoring technology-enhanced learning modalities. Individuals often have distinct preferences for how they absorb and process information, such as visual, auditory, or kinesthetic learning styles. Incorporating this attribute into the study helps in identifying the most effective modes of content delivery and instructional strategies, ensuring that technology-enhanced learning aligns with the diverse learning needs of the student population. This understanding could empower facilitators to adjust teaching methodologies and instructional strategies, fostering a more impactful learning journey and improving overall outcomes [9].

The second was teaching style preference. The exploration of college students' teaching style preferences is integral to optimizing instructional design. This explores how students respond to distinct patterns of teaching exhibited by their instructors. Grasha [17] defines teaching style as a specific pattern of needs, beliefs, and behaviors that teachers manifest in the classroom. These styles influence how teachers present information, engage with students, oversee coursework, and, in the end, influence students' overall success. Recognizing the impact of teaching styles allows educators and institutions to harmonize instructional methods with students' preferences, fostering a more effective learning environment. Students may favor different teaching approaches, such as traditional lectures, collaborative learning, or problem-based instruction. The study [11] indicated that instructors employed a variety of teaching styles, including expert, formal-authority, personal-model, and delegator. This diverse spectrum of teaching methods caters to most student learning preferences, positively impacting the learning process. By exploring teaching style preferences, the research aims to inform the development of technology-supported learning methods that resonate with students' preferences, boosting engagement and knowledge retention. This insight aids in making informed decisions about instructor assignments and professional development, ensuring better alignment between teaching styles and student preferences.

Third, pertains to the learning intervention preference. Recognizing university students as a high-risk population for mental health issues highlights the significance of addressing their wellbeing through innovative means [22]. Despite this, many students hesitate to seek professional help when facing academic and mental challenges. This study delved into the potential of online interventions to promote student wellbeing, examining factors such as help-seeking behavior, intention to utilize online resources, and content preferences for such interventions. Past studies have shown that the intentions to seek help as measured by General Help-Seeking Questionnaire are correlated with actual help-seeking behaviors [23]. By acknowledging the importance of support mechanisms, the research encapsulated various intervention methods, including remedial assessments, consultations, counseling, tutorial/mentoring sessions, collaborative activities, and notifications/reminders. Integrating this attribute into the study yielded valuable insights into the types of interventions that resonate with students, thereby facilitating the development of targeted strategies to enhance the overall learning experience through technology.

Fourth is the technology use preferences. Understanding the interaction between students' attitudes towards technology and their actual technology use is crucial within the realm of technology-enhanced learning. Assessing students' preferences for technology usage is essential, as individuals may differ in their comfort levels and inclinations towards utilizing technology tools and platforms. This attribute offers insight into students' openness to technological integration, thereby assisting educators in selecting and deploying suitable technologies that align with students' preferences and enhance the learning experience. The study [24] revealed that students possess a good understanding of how social media can be utilized in the teaching and learning process. It suggests that a thorough examination of social media platforms should precede their integration into educational practices. Considering how each student learns best is key to figuring out how much technology-driven applications (e.g., chatbots) can help in teaching. Teachers should also make sure students don't rely too heavily on this technology and can develop critical thinking and problem-solving skills [25]. This aligns with the importance of assessing students' technology use preferences to ensure the effective integration of technology-enhanced learning methods.

Fifth is the content delivery preferences. Understanding how students prefer to receive content is essential for effective instructional design. Whether through videos, interactive simulations, or written materials, content delivery preferences significantly impact engagement and comprehension. A significant oversight exists in the current research on online classes. Studies haven't yet combined the perceptions of students from different academic disciplines within a single project [26]. It appears that assessing the technological environment and gauging the comfort level with the technology employed could facilitate the delivery of curated content. In addition to having high-quality content and seamless technology, the effectiveness of E-learning implementation ultimately hinges on the design and organization of the content [27]. By exploring this attribute, the study aims to inform the design of technology-enhanced learning experiences that align with students' preferences, fostering a more effective and enjoyable educational journey.

Sixth involves the study time preferences of students. Considering the variability in students' schedules and time management habits, investigating study time preferences is crucial [28]. This attribute provides insights into when students are most receptive to learning, facilitating the scheduling of technology-enhanced learning activities at optimal times. Tailoring the delivery of content based on study time preferences contributes to increased engagement and better learning outcomes.

The last attribute was the learning management system usage preferences. Given the widespread use of Learning Management Systems (LMS) in educational settings, understanding students' preferences regarding LMS features and functionalities is pertinent. This attribute explores students' comfort levels with different aspects of LMS. This allows students to benefit from a range of online resources for information, communication, collaboration, and sharing with their peers [29]. The findings contribute to the refinement and customization of LMS platforms to better meet the needs and preferences of college students engaged in technology-enhanced learning.

C. Respondents of the Study

This study collected data from a total of 800 student participants who completed an online survey via Google Forms. The survey was administered to college students at Mapúa Malayan Colleges Laguna, a private educational institution that serves as the focal point of investigation. Purposive sampling was employed as the data collection method. Purposive sampling, as defined by Sharma [30], involves selecting a sample with the aim of generalizing the findings through a deliberate selection process. The study aimed to obtain representation from each academic level by recruiting as many respondents as possible. Following the recommendation [31], a small-scale sampling technique involving 50 respondents was considered. This approach offers insights into preferences within the larger dataset. Additionally, the sample provides diverse results and measures of preference that can be interpreted to understand population preferences.

D. Two-Stage Cluster Analysis

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, the 7 attributes utilized in the cluster analysis, 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.

III. Result and Discussion

This study gathered data from 800 individuals over a span of 60 days (Table 1). In terms of academic departments, engineering students comprised 42.6% of the respondents, business students accounted for 27.2%, arts and science students made up 18.3%, computer information science students constituted 8.0%, while maritime education and health sciences students represented 2.4% and 1.6%, respectively. Regarding year levels, the highest participation came from freshmen, comprising 45.9% of the total respondents, whereas the smallest group consisted of 5th-year students, making up only 5.6%. Additionally, the majority of respondents identified as regular students, totaling 66.6%.

This research utilized a two-stage cluster analysis method to identify students' preferences by grouping individuals with similar characteristics based on the attributes provided.

Table 1. Demographic profile of the respondents (N = 800 respondents)

Student Profile	Course/Year/Status	Percent	Count
College Department	Engineering	42.6%	341
	Business	27.2%	217
	Arts and Science	18.3%	146
	Computer Information System	8.0%	64
	Maritime Education	2.4%	19
	Health Sciences	1.6%	13
Year Level	1st Year	45.9%	367
	2nd Year	18.1%	145
	3rd Year	18.6%	149
	4th Year	11.8%	94
	5th Year	5.6%	45
Academic Status	Regular Student	66.6%	533
	Irregular Student	33.4%	267

A. Distribution of Learning Attributes Based on Preferences

Table 2 displays the findings concerning the distribution of student preferences across seven attributes examined in this study. The first attribute, learning style, encompasses four aspects. The results reveal that when students engage in new learning, memory retention, problem-solving, or explaining concepts, they predominantly favor kinesthetic methods, representing a 28.5% average response rate. Following closely is the preference for verbal interaction, accounting for 27% of responses.

Table 2. Distribution of learning attributes based on preferences

Preference	Attributes	Percent	Count
Learning Style[1]	Visual	21.5%	172
	Aural/Audio	27.0%	216
	Read/Write	23.0%	184
	Kinesthetic	28.5%	228
Teaching Style	Providing lecture with detailed information	44.2%	354
	Creating comfortable learning environment	25.5%	204
	Sharing personal experiences and actual cases	20.7%	166
	Others Combined	9.6%	76
Learning Intervention	Collaborative Activity	32.7%	262
	Tutorial/Mentoring	25.3%	202
	Notifications/Reminders	20.3%	162
	Others Combined	21.7%	174
Technology Usage[2]	Comfortable in using Technology	81.1%	648
	Online Platform/Tools Preference	59.2%	474
	Mobile Device Usage for Learning	77.6%	621
	Technology-Dependent Learners	85.9%	687
Content Delivery[2]	Preference for Video Lectures	62.6%	501
	Preference for Text-Based Materials	72.5%	580
	Preference for Interactive Multimedia	84.3%	674
Study Time[2]	Self-paced Learning	31.3%	250
	Structured Learning	12.3%	98
	Flexible Deadlines	46.7%	374
	Fixed Deadlines	6.3%	50
LMS Usage	Use of Blackboard/Canvas	92.6%	741

[1] Based on four variables: problem solving, learning new things, remembering, and explaining.
[2] Measured with three to four variables.
N = 800 respondents.

The second attribute identifies the preferred method of instruction within the classroom. A majority of students, constituting 44.2% of responses, favor detailed lectures provided by the teacher. Conversely, 25.5% of students prioritize a learning environment that encourages independent exploration and risk-taking.

Learning interventions, the third attribute, aim to enhance students' comprehension of lessons. Collaborative activities emerge as the most favored intervention method for students falling behind in lectures, garnering a 32.7% response rate. Tutorial or mentoring sessions rank second at 25.3%.

The fourth attribute concerns students' comfort and autonomy in utilizing online platform tools for learning. A significant 81.1% of students express comfort with online tools, with 59.2% preferring their integration into learning processes. Additionally, 77.6% of students use mobile devices for learning, while 85.9% depend on technology for their educational pursuits.

Attribute five pertains to students' preferences regarding lecture formats. Video lectures are favored by 62.6% of students, while text-based materials attract 72.5% interest. Interactive multimedia, such as PowerPoint presentations, are preferred by 84.3% of students.

The majority of students, representing 31.3% of responses, favor a self-paced learning environment, considering it effective. Flexible deadlines are also preferred by 46.7% of respondents, as they facilitate learning.

Finally, the utilization of Blackboard Learn Ultra and Canvas as learning management systems indicates students' heavy reliance on these platforms for accessing course materials, submitting assignments, and engaging in class activities. While Blackboard and Canvas are extensively used, students remain open to alternative methods of learning and collaboration.

B. Cluster Analysis Results

Table 3 illustrates that among the seven attributes initially identified in this study, only learning style, technology use, content delivery, and study time demonstrated fair to good predictive results. This implies that teaching style and utilization of learning management systems underwent iterations and therefore do not serve as predictors. With these four attributes exhibiting predictive capabilities, this study delves deeper into identifying the specific cluster segments associated with these attributes.

Table 3. Two-stage clustering summary

Preference	Evaluation	Results
Learning Style Preference	SMCH[1]	0.3 (Fair)
	Most Important Predictor	Problem-Solving (1.0)
	Least Important Predictor	Remembering (0.18)
Technology Use Preference	SMCH[1]	0.6 (Good)
	Most Important Predictor	Tools Preference (1.0)
	Least Important Predictor	Technology Usage (0.58)
Content Delivery Preference	SMCH[1]	0.5 (Good)
	Most Important Predictor	Video (1.0)
	Least Important Predictor	Text-Based (0.48)
Study Time Preference	SMCH[1]	0.6 (Good)
	Most Important Predictor	Deadlines (1.0)
	Least Important Predictor	Learning Approach (0.17)

[1] Silhouette Measure of Cohesion and Separation

1) Learning Style Preference Cluster

The study classified learning style preferences based on how they solved problems, remembered, learned new things, and explained what they had learned. The purpose of this was to find out the most effective way in which most students learn. After multiple iterations in the two-stage clustering, the variable 'explaining' was removed. The learning style preference cluster achieved a silhouette measure of cohesion and separation of 0.3 (Table 3), which indicates that the clusters' separation in Table 3 is fair and acceptable. To identify and disregard outliers in the clustering, 25% noise handling was used. The 'problem solving' variable obtained the highest predictor importance value of 1.0, while 'remembering' got the lowest value of 0.18. This means that the three clusters for the students' learning styles were formed based on their preferred problem-solving strategy. Fig. 2 shows the evaluation of each cluster identified.

Input (Predictor) Importance
1.0 0.8 0.6 0.4 0.2 0.0

Cluster	2	1	3
Label	Reflective Problem Solver	Aural Problem Solver	Visual Problem Solver
Size	51.2% (333)	36.7% (239)	12.1% (79)
Inputs	Problem Solving Read/Write (100%)	Problem Solving Aural (54.4%)	Problem Solving Visual (36.7%)
	Learning New Aural (36.6%)	Learning New Aural (53.6%)	Learning New Visual (100%)
	Remembering Read/Write (34.8%)	Remembering Visual (33.5%)	Remembering Visual (100%)

Fig. 2. Learning style preference cluster evaluation.

a) Reflective problem solver

This cluster represents 51.2% of the identified students after noise handling. These students use reading and writing as internal reflection and processing tools before arriving at a solution. 34.8% of them also employ the same approach while recalling lessons. Regarding learning new things, 36.6% prefer listening to oral instructions and explanations.

b) Aural problem solver

In this cluster, 54.4% of students can solve problems while communicating solutions through spoken language for collaboration or implementation. Similarly, 53.6% of students can learn new lessons by communicating through spoken language. On the other hand, 33.5% of students in the cluster find it easier to remember things when they visualize them in their minds.

c) Visual problem solver

Within this cluster, 36.7% exhibit exceptional proficiency in utilizing visual information to identify, analyze, and resolve complex problems. Interestingly, all of them learn and remember by seeing information presented visually. Visual aids such as images, diagrams, charts, graphs, videos, and demonstrations are relied on for adequate information understanding and retention. This cluster, which represents the lowest size, accounts for 12.1% of the identified students after handling noise.

2) Technology use preference cluster

The study has identified technology use preferences based on four variables: comfort in using technology, preference for online platforms/tools, mobile device usage for learning, and technology-independent learners. This aimed to find out if students would be grouped according to their usage level of technology or their preferred learning devices. After multiple iterations in the two-stage clustering process, the variables 'comfort in using technology' and 'mobile device usage for learning' were eliminated. The technology use preference cluster performed well with a silhouette measure of cohesion and separation of 0.60 (Table 3) indicating that the clusters' separation in Table 3 is acceptable. It is worth noting that outliers were not removed, or noise was not handled during clustering. The variable 'tools preference' was the most significant predictor with a value of 1.0. At the same time, the 'technology usage level' had a value of 0.58, meaning that the three clusters were created based on their preferred use of technological tools. Fig. 3 shows the evaluation of each cluster identified.

Input (Predictor) Importance
1.0 0.8 0.6 0.4 0.2 0.0

Cluster	2	1	3
Label	Techno-Traditionalist	Versatile Advanced User	Versatile Active User
Size	40.8% (326)	33.1% (265)	26.1% (209)
Inputs	Tools Preference Traditional (58.0%)	Tools Preference Online/Traditional (100.0%)	Tools Preference Online/Traditional (100.0%)
	Technology Usage Active (42.9%)	Technology Usage Advanced (68.3%)	Technology Usage Active (98.1%)

Fig. 3. Technology use preference cluster evaluation.

a) Techno-traditionalist

This group, representing the largest size, comprises 40.8% of students after noise handling. These students are proficient in technology but still prefer the traditional tools for learning, such as whiteboards and textbooks. Among these students, 58% prefer using standard tools, while 42.9% are active users of online platforms and other digital resources.

b) Versatile advanced user

The students in this cluster exhibit advanced proficiency in various technologies and show a preference for both traditional and online tools when acquiring knowledge. All of this cluster's members prefer online, and traditional tools and 68.3% have advanced technology usage.

c) Versatile active user

The students in this group are active users of technology and tend to use both traditional and online tools when learning. All members of this group prefer using both online and traditional tools, and 98.1% have advanced technology skills. After removing the outliers by noise-handling, this particular cluster represents 26.1% of the identified students. This cluster represents 51.2% of the identified students after noise handling. These students use reading and writing as internal reflection and processing tools before arriving at a solution. 34.8% of them also employ the same approach while recalling lessons. Regarding learning new things, 36.6% prefer listening to oral instructions and explanations.

3) Content delivery preference cluster

Input (Predictor) Importance
1.0 0.8 0.6 0.4 0.2 0.0

Cluster	2	1	3
Label	Somewhat Dependent Multi-Modal Learner	Balanced Multi-Modal Learner	Highly Dependent Multi-Modal Learner
Size	54.9% (237)	25.7% (111)	19.4% (84)
Inputs	Video Somewhat Dependent (61.6%)	Video Somewhat Dependent (100.0%)	Video Highly Dependent (100.0%)
	Interactive Multimedia Somewhat Dependent (100.0%)	Interactive Multimedia Highly Dependent (100.0%)	Interactive Multimedia Highly Dependent (100.0%)
	Text-Based Somewhat Dependent (71.3%)	Text-Based Somewhat Dependent (63.1%)	Text-Based Highly Dependent (59.5%)

Fig. 4. Content delivery preference cluster evaluation.

The study has analyzed how students prefer to receive course content based on three variables: video lectures, text-based materials, and interactive multimedia. After running the analysis, no categories were removed. The learning style preference cluster achieved a silhouette measure of cohesion and separation of 0.5 (Table 3), which indicates that the clusters' separation in Table 3 is reasonable and satisfactory. To eliminate outliers and irrelevant data from the clustering, 25% noise handling was used. The 'video lectures' variable was the most significant predictor with an importance value of 1.0, while the 'text-based' variable had the lowest value of 0.48. This means the three clusters for students' learning styles were formed based on their usage of video lectures. Fig. 4 shows the evaluation of each cluster identified.

a) Somewhat dependent multi-modal learners

The students in this particular group have a slight dependence on any of the three options for content delivery. While the foremost factor is their preference for video lectures, it is worth noting that all group members somewhat rely on interactive multimedia to some extent. However, only 61.1% of them are slightly reliant on video lectures, whereas 71.3% of them depend on text-based materials. Therefore, most students in this cluster prefer using interactive and text-based multimedia instead of video lectures. This is the largest cluster size, with 54.9% of the total identified students after noise handling.

b) Balanced multi-modal learners

The students in this cluster can adapt to text-based materials but prefer video lectures and interactive materials. All cluster members are highly dependent on educational resources in video format or that actively engage learners in the learning process instead of simply presenting information passively. On the other hand, 63.1% can still adapt to written text to convey information and facilitate learning.

c) Highly dependent multi-modal learners

The students in this cluster have a solid potential to excel when provided with diverse learning resources and opportunities to interact with the material in various formats. All the cluster members are highly dependent on video lectures and interactive multimedia, and 59.5% highly rely on text-based materials. However, the size of this cluster only accounts for 19.4% of the respondents after removing outliers.

4) Study time preference cluster

Input (Predictor) Importance
1.0 0.8 0.6 0.4 0.2 0.0

Cluster	2	1
Label	Flexibility Seekers	Schedule Setters
Size	60.5% (332)	39.5% (217)
Inputs	Deadlines Flexible (100.0%)	Deadlines Flexible/Fixed (100.0%)
	Learning Approach Self-paced (51.2%)	Learning Approach Self-paced/Structured (75.6%)

Fig. 5. Study time preference cluster evaluation.

The study classified study time preference based on deadlines and learning approaches. Table 3 displays the results of multiple iterations in the two-stage clustering. The clustering achieved a silhouette measure of cohesion and separation of 0.6, which is 'good' and acceptable level of separation between clusters. To identify and disregard outliers in the clustering, 25% noise handling was used. The variable 'deadlines' obtained the highest predictor importance value of 1.0, while the 'learning approach' got the lowest value of 0.17. This indicates that the two clusters for the study time preference were formed based on their preferred deadlines. Fig. 5 shows the evaluation of each cluster identified.

a) Flexibility seekers

After removing the outliers, this cluster has the largest size, with 60.5% of the identified students. The students in this cluster are independent, self-directed, and value managing their workload. They prioritize completion over rigid activity schedules, which enables them to be masters of time-management. They are skilled at navigating deadlines while prioritizing in-depth learning and exploration at their own pace. All the members of this cluster prefer flexible deadlines, and 51.2% of them prefer self-paced learning.

b) Schedule setters

The students in this group tend to excel in learning environments that are well-structured with clearly defined deadlines. Alternatively, some students prefer a more flexible approach to their learning, with adaptable deadlines. However, 75.6% of the students in this cluster prefer a learning environment that offers a high degree of control over their learning experience, or one that is well-defined with clear expectations, timelines, and a logical flow of information.

C. Summary of Cluster Profile

Fig. 6 illustrates the various clusters derived from the analysis and iterations involving the seven attributes. Among these attributes, four demonstrated significant predictors.

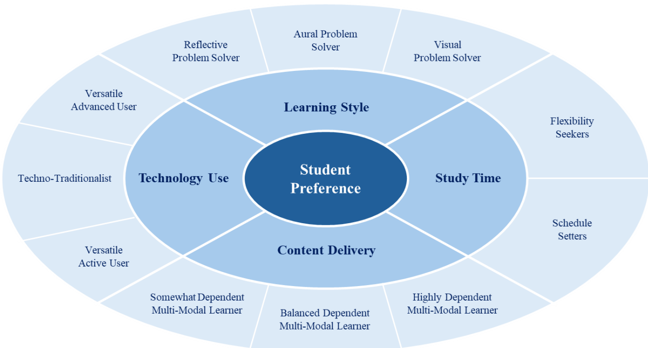

Fig. 6. Student preferences based on cluster segment.

Students' preferences regarding learning styles are grouped into three segments. Reflective problem solvers prefer writing down problem-solving steps and excel in learning through oral instructions or explanations. Aural problem solvers recall lessons through visualization but prefer problem-solving through verbal communication. Visual problem solvers can resolve problems, recall information, and learn new concepts effectively through the use of pictures and diagrams.

Students' technology use preferences are categorized into three segments. Techno-traditionalists represent traditional learners who actively use technology. Versatile advanced users denote hybrid learners proficient in technology usage. Conversely, Versatile active users are hybrid learners who actively engage with technology. The distinction between advanced and active users lies in their proficiency level and level of engagement with technology. While advanced users possess advanced technological skills, active users are characterized by their active utilization of technology in their learning processes.

Students' content delivery preferences are grouped into three segments. Somewhat dependent multi-modal learners exhibit minimal reliance on any specific content delivery option. Balanced multi-modal learners heavily depend on interactive multimedia while showing lesser reliance on other options. Highly dependent multi-modal learners rely extensively on various content delivery options. The distinctions between these segments lie in their varying degrees of reliance on different content delivery methods. Somewhat dependent learners exhibit low reliance overall, balanced learners heavily favor interactive multimedia, and highly dependent learners heavily rely on a variety of content delivery options.

Study time preferences are divided into two segments. Flexibility seekers are individuals who prefer adaptive deadlines and a self-paced learning environment. They prioritize autonomy in managing their study schedules and are comfortable with flexible timelines. On the other hand, schedule setters are students who perform effectively regardless of deadlines and learning approaches. They excel in structured environments with clear expectations and deadlines, demonstrating the ability to thrive under pressure and adhere to set schedules. The key distinction between the two segments lies in their preferred approach to time management and learning structure. Flexibility seekers prioritize autonomy and adaptability, while schedule setters thrive in structured and well-defined learning environments.

D. *Proposed Instructional Design Strategy*

In addressing the varied preferences of students in learning style, technology use, content delivery, study time, and supporting strategies, Fig. 7 embodies a spectrum of considerations tailored to student individual needs.

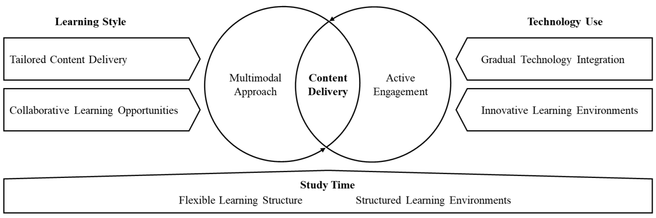

Fig. 7. Proposed instructional design strategy.

The researchers advocate for a gradual integration of technology, particularly targeting the techno-traditionalists, offering support and tutorials to ensure a seamless transition to online tools. For versatile advanced users and active users, the authors suggest for the design of innovative learning environments, fostering experimentation with emerging technologies and promoting collaboration on digital platforms. Research supports that adaptive learning systems enhance personalized learning experiences [32].

In terms of content delivery, the proposed strategy hinges on a multimodal approach encompassing video lectures, interactive multimedia, and text-based materials. This approach caters to the diverse preferences of somewhat dependent multi-modal learners, balanced multi-modal learners, and highly dependent multi-modal learners. This proposal emphasizes active engagement by embedding interactive elements within video lectures and multimedia resources, thereby enhancing comprehension, and fostering deeper engagement among balanced multi-modal learners and highly dependent multi-modal learners. Studies show that multi-modal content enhances learning by addressing diverse preferences [33]. Interactive elements like simulations and gamified content are particularly effective for kinesthetic learners [34]. Self-paced learning modules accommodate both quick learners and those needing more time [35].

Furthermore, the strategy for study time preferences promotes flexible learning structures, accommodating flexibility seekers by offering open deadlines and providing self-directed learning resources. Simultaneously, this strategy promotes structured learning environments that establish clear expectations, deadlines, and structured materials for schedule setters, while allowing for adaptable deadlines where appropriate.

Moreover, the proposed instructional design is underpinned by supporting strategies such as inclusive assessments, which allow students to demonstrate their understanding through various formats, accommodating diverse learning styles and preferences. Additionally, continuous feedback mechanisms are implemented to enable students to track their progress and make necessary adjustments to the learning strategies [36].

In summary, integrating learning styles, content delivery, technology use, and study time into the institution's instructional design framework requires coordinated efforts. Faculty should form teams handling similar courses and use various digital media to create personalized learning paths tailored to different preferences. Courses should include multiple material formats such as infographics, videos, podcasts, and narrated content, ensuring students can engage in ways that suit their learning styles [37]. Quality assurance in blended learning standards can guide this process, emphasizing clear instructions, learner support, and measurable outcomes. Adaptive learning technologies, such as but not limited to Knewton or Smart Sparrow, should be used to adjust content in real-time based on student performance, ensuring appropriate challenges and support. Fully utilizing the LMS of the institution can facilitate seamless access to diverse materials, track engagement and performance, and provide data for continuous improvement. Faculty and staff need training to effectively use these technologies and strategies. Professional development programs can help educators create multi-modal content, use adaptive technologies, and manage flexible study schedules [38]. Regular student feedback should be incorporated to refine these strategies, ensuring their effectiveness and responsiveness to student needs. By integrating these elements, the institution can create an inclusive, engaging, and responsive learning environment, enhancing educational outcomes and student satisfaction.

E. Limitations

While this study offers significant and practical insights, several limitations affect the generalization of its findings. First, the research focused solely on the preferences for seven attributes related to technology-enhanced learning among undergraduate students in general. To address varying learning needs, it's suggested to cluster students based on these needs, which could lead to different preference outcomes. Second, the study examined only student preferences, without assessing performance. Future research might integrate preference and performance using Structural Equation Modeling to provide a more comprehensive analysis. Third, the study was limited to undergraduate students at Mapua Malayan Colleges Laguna, suggesting that comparative studies with other institutions using similar learning settings could help improve the understanding of online learning delivery. Finally, the study only considered undergraduate student preferences, even though the participants experienced technology-enhanced learning. It is recommended to also study instructor preferences within the same setting for a more complete perspective.

IV. Conclusion

This study provides valuable insights into the diverse preferences of students regarding technology use, content delivery, and study time, highlighting the need for a significant shift in educational approaches. The findings underscore the importance of adopting a student-centric approach to instructional design, recognizing that a one-size-fits-all model is no longer effective in today's diverse learning landscape.

One of the key takeaways is the need for flexibility and adaptability in how technology is integrated into education. While technology can be a powerful tool for enhancing learning, it's crucial to acknowledge that students have varying levels of comfort and familiarity with digital platforms. Therefore, providing adequate support and guidance to those who need it is essential to ensure equitable access and opportunities for success.

Furthermore, embracing a multimodal approach to content delivery is paramount. By offering a diverse range of learning materials, including video lectures, interactive multimedia, and text-based resources, educators can cater to the unique preferences and learning styles of individual students. This approach not only enhances engagement and comprehension but also creates a richer and more inclusive learning experience for all.

Finally, this study emphasizes the importance of promoting autonomy and self-directed learning by striking a balance between structured frameworks and adaptable deadlines. Empowering students to take ownership of their learning journey fosters independence, accountability, and a love for lifelong learning. By embracing the insights gleaned from this research and adapting their practices accordingly, educational institutions can create dynamic learning environments that cater to the needs of all learners and pave the way for a brighter future of education.

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. All authors had approved the final version.

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