Journal of Pedagogical Research
Volume 9, Issue 5, 2025
https://doi.org/10.33902/JPR.202537311

Research Article

Why students do not prefer online learning: The role of e-learning readiness and community of inquiry

Sinan Keskin[1] and Osman Tat[2]

[1]*Educational Sciences, Faculty of Education, Van Yuzuncu Yil University, Van, Türkiye (ORCID: 0000-0003-0483-3897)*
[2]*Educational Sciences, Faculty of Education, Van Yuzuncu Yil University, Van, Türkiye (ORCID: 0000-0003-2950-9647)*

This study examines at how e-learning readiness and the Community of Inquiry framework affect higher education students' preferences for various teaching delivery modes. In the study, Latent Class Analysis was used to profile the participants based on autonomous learning attributes, which is the pedagogical sub-dimension of e-learning readiness. As a result of this analysis, three classes were obtained as LC1 (high self-directed learning, low e-learning motivation), LC2 (high self-directed learning, medium-high e-learning motivation) and LC3 (medium level in all factors). When students' overall teaching mode preferences were analyzed using the Bradley-Terry model, a hierarchy of preferences was found, with blended learning, followed by face-to-face and finally online learning. Blended learning was widely preferred by LC2 and LC3, while LC1 showed an overwhelming preference for face-to-face. The inclusion of Community of Inquiry in the model made these differences in preferences even more pronounced. For LC1, face-to-face learning dominated preferences for social presence, while, remarkably, it showed an almost exclusive preference for teaching presence and cognitive presence. The findings highlight the importance of direct guidance and interaction in face-to-face settings, which may be more effective than the flexibility of online environments for certain learner profiles. Moreover, they may emphasize the necessity of varied instructional methods in higher education to meet the diverse demands of students.

Keywords Blended learning; Community of inquiry; E-learning readiness; Mode of teaching delivery; Online learning

Article History: Submitted 2 June 2025; Revised 4 August 2025; Published online 8 September 2025

1. Introduction

The growing incorporation of digital technologies in education has led to an increased focus in the literature on various modes of instructional delivery, particularly face-to-face, blended, and fully online learning (Ahuja et al., 2023; Imran et al., 2023; Paechter & Maier, 2010). The supplementation of traditional classroom-based instruction with online learning has been a widely practiced approach for nearly two decades (Cooney et al., 2000). The primary goal of the approach known as blended learning is to enhance and support in-class learning through the integration of e-learning activities. Conversely, the implementation of varied teaching methodologies is not merely a matter of preference but rather an imperative in certain circumstances. For instance, during the pandemic, educational processes at all levels were largely sustained through fully online learning worldwide (Keskin et al., 2021; Watermeyer et al., 2021). Today, these three modes-

Address of Corresponding Author

Osman Tat, PhD, Van Yuzuncı Yil University, Department of Educational Sciences, B Block No. 10, 65080 Van, Türkiye.

osmantat@yyu.edu.tr

How to cite: Keskin, S. & Tat, O. (2025). Why students do not prefer online learning: The role of e-learning readiness and community of inquiry. *Journal of Pedagogical Research, 9*(5), 1-19. https://doi.org/10.33902/JPR.202537311

face-to-face, blended, and online-collectively offer flexible and diverse learning opportunities for both educators and students. However, within this diversity, the question of which learning environment is most preferred by students remains a topic of growing interest in educational research. Through the perspectives of e-learning readiness and the Community of Inquiry [CoI] framework, this study seeks to examine the learning environment preferences of students who have encountered all three mode of teaching delivery.

Although the choice of teaching delivery method is often perceived as a necessity dictated by external circumstances, such as pandemics or natural disasters, rather than student preferences, this diversity can be a valuable asset for addressing different instructional needs. For instance, online learning environments provide learners with the opportunity to access education independently of time and location. In their study of students' preferences for face-to-face versus online learning, Paechter and Maier (2010) found that online learning is often favored because it encourages self-directed learning, provides access to information anywhere and at any time, and ensures consistent learning materials. The foremost advantage in this context is the ability of students to access higher education opportunities remotely, without the necessity of campus attendance (Tat, 2020). On the other hand, blended learning is frequently employed to combine the benefits of direct interaction with the flexibility of online platforms, allowing for easier access to learning materials and the continuation of effective instruction beyond the classroom (Ahuja et al., 2023). With its strong potential to cultivate greater student interaction, blended learning stands out as both a preferred option and a supportive element for boosting learning performance (Alducin-Ochoa & Vázquez-Martínez, 2016). Blended learning enables flexible learning in higher education, cultivates student engagement, and enhances self-regulated learning (Imran et al., 2023). Additionally, the value of face-to-face learning remains indisputable when it comes to fostering strong interpersonal relationships and co-constructing meaning (Paechter & Maier, 2010). To sum up, each mode of teaching delivery offers its own advantages, but its limitations may also influence students' attitudes and preferences towards it.

Student preferences play a critical role in shaping educational processes, as individual choices can directly influence the quality of learning experiences, motivation levels, and academic achievement (Dun, 1987). Zeqiri et al. (2020) found that blended learning environments have a positive impact on student motivation and academic performance compared to face-to-face learning. Similarly, Kangas et al. (2017) noted that innovative learning environments based on digital technologies capture students' interest and enhance their engagement, satisfaction, and motivation. Whether fully online or blended, technology-enhanced learning environments offer both instructors and learners opportunities to experience innovative teaching and assessment practices (Ahuja et al., 2023). Such innovations contribute to more efficient use of instructional time and support the development of individuals equipped with the competencies required by the evolving labor market. On the other hand, as mentioned earlier, when instructional goals involve fostering strong interpersonal relationships, the benefits of face-to-face instruction become indispensable. Therefore, it is crucial that educational programs are designed with sensitivity to student preferences, ensuring learning environments that enable students to reach their full potential. This study aims to provide insights into student preferences that can inform future learning design, offering valuable guidance for educators and policymakers alike.

1.1. Community of Inquiry

The CoI framework is one of the systematic approaches that provides guidance to make more effective use of online learning environments. According to this approach, students go beyond being only information receivers in an online learning environment and realize meaningful and in-depth learning through their interactions with different sources (Garrison, 2007). Therefore, it is emphasized that learning environments should be structured in a way to support these interactions, not only as a source of information. According to this model, the effectiveness of the online learning process is based on three basic presence dimensions: social presence, cognitive presence, and instructional presence (Garrison et al., 2000). Social presence encompasses students' social interactions and in-group experiences. As students achieve group cohesion and the opportunities for open-emotional communication in the environment increase, students develop a sense of being socially present. Teaching presence refers to the fact that the teaching process is structured, guided, and designed in a way that facilitates learning and that this design is perceivable by students. Finally, cognitive presence is related to students' information processing processes, exploration tendencies, problem solving strategies and meaning making skills. When these three presence dimensions are adequately provided, it is accepted that an effective learning experience is created for online learning (Garrison, 2007). In summary, students' feeling of belonging to a community, the presence of instructional interventions and the provision of meaningful learning content play a critical role in building effective online learning environments.

An ideal learning experience is expected to improve learning outcomes and students' perceptions of their experiences in a positive way. Indeed, Akyol and Garrison (2008) found that presence had positive effects on both learning and satisfaction levels. Similarly, Rockinson-Szapkiw et al. (2016) found that presence had a positive effect on course success. However, the level of this positive effect may differ depending on the type of environment in which learning takes place. According to the CoI framework, presence, defined as the perceived presence of peers or teachers as stakeholders in the learning process (Garrison et al., 2000), is directly affected by the level of active participation and interaction. Shea and Bidjerano (2013) reported that blended learning environments facilitate stronger emotional and social connections. Supporting this view, Akyol et al. (2009) emphasized that blended learning is more effective than fully online learning environments in supporting teaching presence. In summary, fully online learning environments may not be as successful as blended ones in fostering a strong sense of presence (Stenbom, 2018). In this context, the CoI framework provides a theoretical foundation for how students' instructional, social, and cognitive processes are organized in online learning communities and the effects of these structures on learning. Although it is not an all-encompassing theory of online learning, this framework can be enriched with elements emphasized in learning theories such as collaboration, social learning, and self-regulation (Shea et al., 2022). Accordingly, in this study, in the context of e-learning readiness, the scope of the CoI framework was tried to be expanded by taking students' autonomous learning competencies into consideration. In the next section, the concepts of e-learning readiness and learner autonomy, which are one of the basic building blocks of the research, will be discussed.

1.2. E-Learning Readiness

The term "e-learning readiness" describes students' capacity to make efficient use of the tools and resources available during the online learning (Kaur & Abas, 2004; Lopez, 2007). The primary purpose of this competence is to enable students to achieve the most efficient learning experience in their digital learning environments (Yurdugül & Demir, 2017). Consequently, ensuring readiness necessitates that students possess a certain level of knowledge, skills, and motivation (Hung et al., 2010; Parkes et al., 2015; Zine et al., 2023). A prominent model in the literature, proposed by Hung et al. (2010), posits that e-learning readiness is composed of two key dimensions: technical skills and pedagogy. The technical skills dimension specifically includes aspects such as computer usage proficiency, internet access availability, and self-efficacy in utilizing online communication technologies. For students to effectively navigate and benefit from online learning environments, a requisite level of self-efficacy with these technologies is essential. The pedagogical dimension, considered within the framework of autonomous learning, encompasses components that directly influence the quality of the learning process (Horzum et al., 2015). These components can be categorized as self-directed learning skills, perceived learning control, and intrinsic motivation towards e-learning. Notably, self-directed learning emerges as the foundational element that underpins the active engagement of the learner in the process (Prihastiwi et al., 2020). From a holistic standpoint, e-learning readiness emerges as a significant determinant that positively influences students' engagement with online learning processes, their motivation levels, and their overall learning experience (Çebi, 2023). Consequently, this construct plays a critical role in predicting the degree to which learners can benefit from the provided instructional environment.

The purpose of this study is to examine students' preferences for online, face-to-face, and blended modes of teaching delivery in the context of CoI framework and e-learning readiness. While the CoI theoretical framework argues that effective learning is based on the interaction between social, cognitive, and instructional presence dimensions, e-learning readiness focuses on assessing individuals' technical competence and autonomous learning levels that affect their participation in online learning processes. In this context, understanding students' learning environment preferences and the cognitive and affective factors affecting these preferences will contribute to both the development of instructional designs and the adaptation of learning processes according to individual needs. The findings of the study are expected to guide educators and policy makers in planning future instructional modalities.

2. Method

2.1. Research Design

This study employed a correlational research design (Frankel et al., 2012) and used two types of instruments: a Likert-type scale and a tool developed within the Community of Inquiry framework that included items based on pairwise comparisons. The purpose was to investigate relationships between the variables under study without manupulating or controlling them. This approach one of the most appropriate methods for examining relationships that may be occur naturally in educational environments.

2.2. Participants

The study group comprised undergraduate students studying at the faculty of education of a public university. A total of 273 students took part in the study, of whom 111 were male (40%) and 162 were female (60%). Participation was voluntary, and students accessed the data collection tool via a link in an online invitation. Of these participants, 22% (n=60) were in their second year, 69% (n=188) in their third year and 9% (n=25) in their fourth year. All participants had prior experience of face-to-face, online, and blended learning through various courses, ensuring familiarity with each mode of teaching delivery.

2.3. Data Collection

The data of this study were collected using a data collection tool consisting of three sections. The first part includes a personal information form that includes items to demographically diagnose the participants. The data collection tools used in the other sections are described in detail in the following sections.

2.3.1. Learners' mode of teaching delivery preference pairwise comparison form

The second data collection tool was developed by the researchers to explore students' preferences regarding modes of teaching delivery (see Appendix 1). This form was structured based on the CoI framework. According to this framework, an effective online learning community is established through the combined presence of three core elements: social, cognitive, and teaching presence (Garrison et al., 2000). The form consists of 10 items, with 1 item measuring general teaching mode preference and 9 items assessing preferences based on the Community of Inquiry framework. Each item presents three teaching mode options, requiring learners to compare and choose between them. In total, the form includes 30 paired comparisons (10 items × 3 pairwise combinations per item), systematically capturing learners' preferences across different teaching delivery modes.

The subscale for social presence included items comparing participation in discussions, peer communication, and collaboration. The cognitive presence dimension addressed aspects such as the effectiveness of learning activities, interest in the subject, and curiosity. The teaching presence subscale focused on the instructor's ability to communicate effectively, encourage participation, and stimulate intellectual exploration. For each item, students were asked to choose their preference among online, blended, or face-to-face learning environments. Through this method, the study aimed to determine students' priority preferences in relation to the three dimensions of presence as defined within the CoI framework.

2.3.2. E-learning readiness scale

The final section of the data collection tool comprised the autonomous learning subscale of the E-learning Readiness Scale, which was developed by Yurdugül and Demir (2017). This subscale is designed to assess learners' degree of readiness for autonomous learning in e-learning environments. The instrument uses a seven-point Likert-type rating scale. The subscale consists of 19 items in total, covering three sub-dimensions: self-directed learning [SL] (items 1–8), learner control [LC] (items 9–12) and e-learning motivation [LM] (items 13–19). The developers of the scale presented evidence regarding the validity and reliability of this measurement tool in detail in the related study (Yurdugül & Demir, 2017). Following analysis of the data obtained within the scope of this study, the Cronbach α internal consistency coefficient of the scale was calculated as .93. The fit indices (χ^2/df = 394.573/149=2.648, CFI=0.890, TLI =0.874, GFI=0.996, RMSEA= 0.078, SRMR=0.058) obtained from the confirmatory factor analysis conducted to assess the construct validity of the scale indicate that the hypothesized model supports construct validity.

2.4. Data Analysis

In the present study, three main analytical approaches were used to analyze the collected data: descriptive statistical methods, latent class analysis [LCA], and the log-linear Bradley-Terry model. Descriptive statistics were used to identify the distributional characteristics and dominant trends of participants' responses to the autonomous learning subscale, thereby clarifying the internal structural characteristics of the dataset. Results of descriptive analyses are presented in Table 1.

Table 1
Descriptive Statistics Regarding Autonomous Learning

Factor	*Items*	*Mean*	*SD*	*Median*	*Min*	*Max*	*Range*	*Skewness*	*Kurtosis*
Self-directed Learning	8	5.33	1.14	5.62	1.00	7.00	6.00	−1.13	1.80
Learner Control	4	5.58	130	5.75	1.00	7.00	6.00	1.09	1.16
e-Learning Motivation	7	4.04	1.69	4.14	1.00	7.00	6.00	−0.03	-1.04
Autonomous Learning	19	4.91	1.11	4.95	1.00	7.00	6.00	−0.57	0.74

The descriptive statistics pertaining to students' readiness levels for autonomous learning indicate a generally positive profile. According to Table 1, students scored relatively high on the dimensions of learner control (M = 5.58) and self-directed learning (M = 5.33) and exhibited greater openness to growth in motivation (M = 4.04). In general, it can be said that the participants perceived themselves as highly competent in terms of autonomous learning (M = 4.91).

2.4.1. Latent Class Analysis

Within the scope of this study, latent tendencies among participants regarding their perceptions of e-learning readiness were examined through Latent class analysis. Following this, the extent to which membership in the identified latent classes could explain participants' preferences in the pairwise comparisons constructed within the CoI framework model was investigated. LCA is a statistical method utilized to identify underlying (latent) classes or groups within observed variables. LCA is typically applied in situations involving numerous categorical variables, such as those found in survey data. It enables the classification of individuals into groups that exhibit similarities in terms of specific characteristics or behaviors, based on their responses to survey or scale items. Through this method, the probability of each participant's assignment to a particular latent class can be estimated (Bartholomew, 1987; Bergan, 1983; Lazarsfeld & Henry, 1968).

Consequently, from larger, heterogeneous groups displaying varied attitudes towards a measured trait, more homogeneous subgroups can be derived. In social science research, the assumption that studied groups are homogeneous with respect to a measured trait can lead to numerous erroneous inferences (Marsh et al., 2009). Thus, this study employed LCA to enable in-depth exploration of latent subgroup behaviors, thereby improving our understanding of their preferences and the precision of resulting recommendations.

In LCA, determining the number of latent classes inherent in a sample is an exploratory process. Specifically, the optimal number of classes is identified by comparing the Akaike Information Criterion [AIC] and Bayesian Information Criterion [BIC] indices of multiple models estimated under assumptions of varying class numbers (Lanza & Rhoades, 2011). Typically, the number of latent classes suggested by the model exhibiting a lower BIC value is considered to provide a better model-data fit (Nylund et al., 2007). Accordingly, in this study, the number of latent classes based on participants' perceptions of e-learning competencies was investigated by concurrently examining AIC, BIC and entropy values, utilizing the poLCA package in R (Linzer & Lewis, 2011).

2.4.2. Log-linear Bradley-Terry model (LLBT)

Scaling methods based on paired comparisons have recently regained popularity, particularly within the social sciences. Among these, Log-linear Bradley-Terry [LLBT] models (Bradley & Terry, 1952) are one of the most well-known and frequently applied (Cattelan, 2012). The paired comparison method, also known as the method of comparative judgment, is a scaling technique used to capture individuals' perceptions of the relative magnitude of two concurrently presented objects (Tanswell et al., 2023).

Data for LLBT analysis are obtained by asking judges (or participants) to indicate their preference between two paired objects presented to them. In this study, participants were presented with 10 items where they indicated their preference among three teaching delivery modes: face-to-face, blended, and distance learning. One item measured their overall teaching preference, while nine items assessed their preferences in specific contexts related to the CoI framework. This was achieved by presenting these teaching delivery modes in pairs and asking participants to select their preferred mode from each pair. Consequently, each participant responded to three distinct paired comparison items for the three modes (e.g., face-to-face vs. blended, face-to-face vs. distance and blended vs. distance).

Bradley and Terry (1952) demonstrated that data of this nature can be analyzed using a log-linear model, which is a special case of the generalized linear model (Agresti, 1990). The LLBT method has further evolved into a highly versatile scaling approach through the incorporation of judge-specific covariates, allowing for the modeling of their influence on preferences (Dittrich et al., 1998; 2002; 2007). In this model, the "worth" parameter represents the relative value of the objects, enabling their ranking along a latent scale, typically ranging from 0 to 1 (Dittrich et al., 1998).

For the LLBT analysis in this study, the prefmod R package (Hatzinger & Dittrich, 2012) was utilized. A total of eight models were fitted: two models for participants' general teaching delivery mode preferences (a base model and an explanatory model with a covariate), and two similar models (base and explanatory with a covariate) for each of the preferences of teaching delivery mode within the contexts of social, cognitive, and teaching presence. To compare model fit, a likelihood-ratio test was conducted, based on the goodness-of-fit comparison between the base model and the explanatory model. A significant result from this test ($p < .05$) indicates that the explanatory (extended) model provides a significantly better fit to the data compared to the base model (Berger, 1997).

3. Findings

This section presents the findings from Latent Class Analysis, which was conducted to segment students into homogeneous latent classes based on autonomous learning, a sub-dimension of e-learning readiness. Additionally, it details the results from Log-linear Bradley-Terry models that incorporated these derived latent classes to examine students' general preferences of mode of teaching delivery, as well as their preferences within the context of the CoI framework and autonomous learning.

3.1. Latent Class Analysis of Students Based on Autonomous Learning

LCA was employed to investigate how participants might be segmented into distinct, unobserved classes based on their autonomous learning. As LCA is an exploratory process where the optimal number of latent classes is determined by estimating and comparing multiple models, five different models (specifying one to five classes) were estimated, considering patterns of similar responses. Upon examination of the parameters derived from the LCA (see Table 2), it was observed that the Bayesian Information Criterion index consistently decreased for models up to the three-class solution, after which it began to rise for subsequent models.

Table 2
LCA Parameters

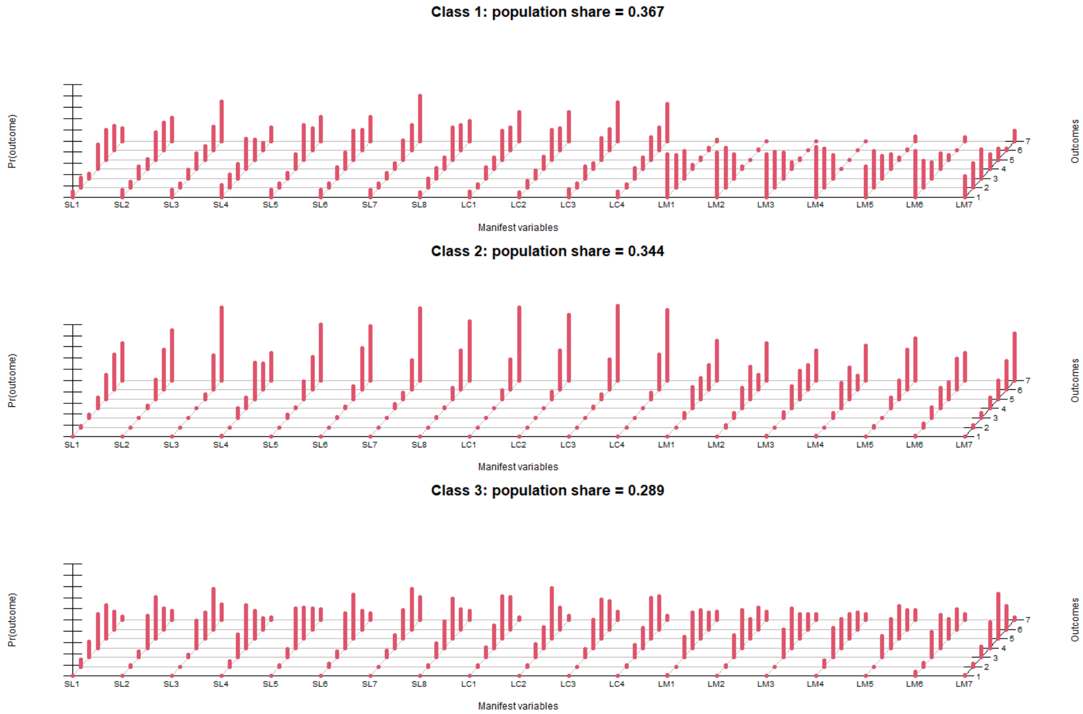
Fit Statistics	*1 Class*	*2 Class*	*3 Class*	*4 Class*	*5 Class*
Log-likelihood	−8975.28	−8209.14	−7781.43	−7481.43	−7251.471
AIC	18178.56	16876.27	16250.87	15880.86	15650.94
BIC	18590.04	17702.84	17492.53	17537.61	17722.78
G^2	14906.66	13374.37	12518.96	11918.95	11459.04
X^2	$3.19*10^{24}$	$6.55*10^{19}$	$6.96*10^{17}$	$4.73*10^{17}$	$7.52*10^{16}$
Two-class model	n = 148	n=125			
	54.4%	45.6%			
Three-class model	n = 100	n=94	n=79		
	36.7%	34.4%	28.9%		
Four-class model	n = 74	n=77	n=73	n=49	
	27.1%	28.25	26.8%	18.0%	
Five-class model	n = 41	n=47	n=77	n=78	n=30

Based on the BIC values, which are recognized as one of the most reliable fit indices in LCA (Nylund et al., 2007), it was concluded that participants clustered into three homogeneous latent classes with respect to autonomous learning. The first class of the three-latent-class model encompassed 36.7% (n=100) of the participants, the second class 34.4% (n=94), and the third class 28.9% (n=79). The response patterns exhibited by these latent classes on the learner autonomy scale and its factors (self-directed learning, learner control, and e-learning motivation) are presented in Figure 1.

As illustrated in Figure 1, participants assigned to the first latent class tended to select mid-to-high response categories (e.g., 5-7) for the self-directed learning and learner control factors. In contrast, for the e-learning motivation factor, they generally gravitated towards the lowest response categories (e.g., 1-3). Consequently, this latent class can be characterized as a group exhibiting high SL and LC but low LM. The response patterns of the second latent class indicate that they represent a group with high levels of SL and LC, and moderate to high levels of LM. Finally, the third latent class appears to consist of students who exhibited moderate levels across all subscales.

Figure 1

Latent Class Response Patterns



Note. SL:self-directed learning, LC: learner control, LM: e-learning motivation, class 1: high self-directed learning & learner control (categories 5-7), but low e-learning motivation (categories 1-3), class 2: high self-directed learning & learner control (categories 5-7), with medium to high e-learning motivation (categories 4-7), class 3: moderate levels across all factors, with responses concentrated in middle categories (3-5)

3.2. Students' Overall Preferences for Mode of Teaching Delivery

Table 3 presents the results from the Bradley-Terry model applied to determine students' general preferences of mode of teaching delivery without considering any explanatory variables (covariates). In this analysis, the blended mode was treated as the reference category. According to the model, the preference levels for face-to-face ($\beta = -0.28$, $p < .05$) and distance $\beta = -1.26$, $p < .05$) modes are significantly differ from reference category, blended learning ($\beta = 0.00$). When examining the worth values, which reflect the relative probabilities of preference for the modes, the blended mode exhibits the highest value (worth=0.61), followed by face-to-face (worth=0.34) and distance (worth=0.05) teaching delivery modes.

Table 3

Base Model Parameters for General Preferences of Mode of Teaching Delivery

Mode: Coefficient	*Estimate*	*Std. Error*	*z value*	*Pr(>|z|)*	*Worth*
Face to face	−0.28	0.06	−4.90	0.00*	0.34
Distance	−1.26	0.08	−15.74	0.00*	0.05
Blended†	–	–	–		0.61

Note. †blended mode is reference; *$p < .05$

To determine how students' general teaching delivery mode preferences varied across the latent classes derived from autonomous learning, a comparison of the estimated explanatory model with the base model revealed that the explanatory model provided a statistically significantly better fit ($\chi^2 = 95.07$, $p < .05$) to the data than the base model (see Table 4).

Table 4

LLBT Model Comparison for General Preferences of Mode of Teaching Delivery

	AIC	*Resid. df*	*Resid. Dev*	*df*	*Deviance*	*Pr(>χ^2)*
Base Model	245.92	7	139.75			
Explanatory Model	158.85	3	44.69	4	95.07	0.00*

Note. *p < .05

Upon examining the explanatory model parameters presented in Table 5, it is observed that the preference for face-to-face mode significantly differs from the reference category, blended mode, across all three latent classes. However, the preference for distance teaching delivery mode significantly differs from the blended preference only for students in the first latent class (LC1) ($\beta=-1.67$, p < .05). For the other two latent classes, no significant difference was observed in preferences between blended and distance modes.

Table 5

Explanatory Model Parameters for General Teaching Delivery Mode Preferences

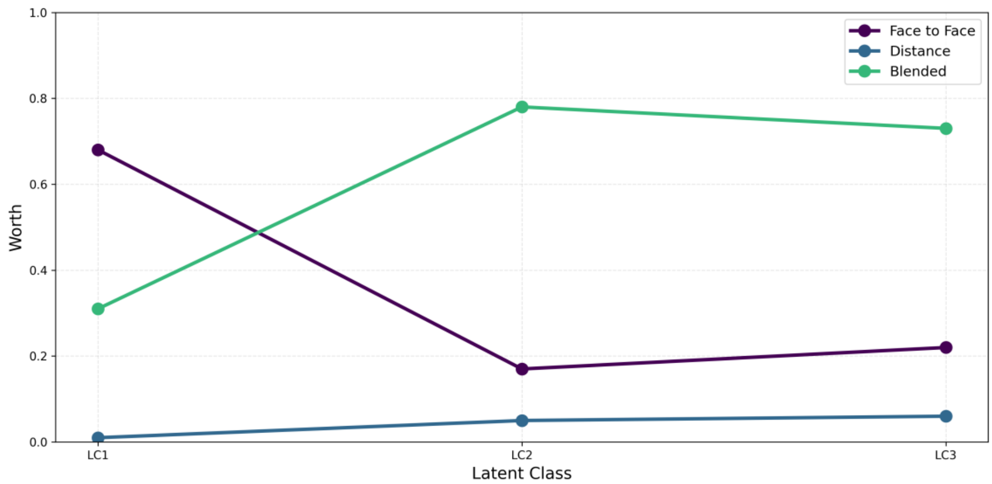
					Worth		
Mode: Coefficient	*Estimate*	*Std. Error*	*z value*	*Pr(>|z|)*	*LC1*	*LC2*	*LC3*
Face to face:LC1	0.39	0.11	3.71	0.00*	0.68	0.17	0.22
Face to face:LC2	−1.14	0.16	−7.22	0.00*			
Face to face:LC3	−0.99	0.16	−6.25	0.00*			
Distance:LC1	−1.67	0.23	−7.29	0.00*	0.01	0.05	0.06
Distance:LC2	0.31	0.27	1.15	0.25			
Distance:LC3	0.40	0.27	1.47	0.14			
Blended†:LC1	-	-	-	-	0.31	0.78	0.73
Blended†:LC2	-	-	-	-			
Blended†:LC3	-	-	-	-			

Note. * p < .05, †blended mode is reference, LC:latent class.

Figure 2, which visualizes the relative preference probabilities (worth) across latent classes, more clearly illustrates which mode has a higher probability of being preferred within each latent class. According to Figure 2, regarding general preferences of mode of teaching delivery, students in the first latent class [LC1] predominantly preferred the face-to-face mode (worth=0.68), whereas students in the second [LC2] (worth=0.78) and third [LC3] (worth=0.73) latent classes predominantly preferred the blended teaching mode. Across all latent classes, the least preferred mode of teaching delivery was the distance mode.

Figure 2

Explanatory Model worth Values for General Preferences of Mode of Teaching Delivery



3.3. Students' Preferences for Teaching Delivery Modes within the CoI Framework

3.3.1 Students' preferences for mode of teaching delivery in the context of social presence

Within the scope of this study, when comparing teaching delivery modes in terms of their capacity to foster social presence (e.g., supporting interpersonal collaboration, open and emotional communication, and similar social interactions), the explanatory model was found to provide a statistically significantly better model-data fit (χ^2 = 35.99, p < .05) compared to the base model, which did not include any covariates (see Table 6).

Table 6
LLBT Model Comparison for Teaching Delivery Mode Preferences in the Context of Social Presence

	AIC	*Resid. df*	*Resid. Dev*	*df*	*Deviance*	*Pr(>Chi)*
Base Model	163.21	7	43.58		-	
Explanatory Model	135.83	3	8.20	4	35.38	0.00*

Note. * p <.05

Upon examining the explanatory model parameters presented in Table 7, it is observed that students' preferences for face-to-face mode statistically significantly differ from their preferences for blended mode across all three latent classes. However, the preference for distance learning is significantly different from blended learning only for students in the first latent class (β =−0.76, p < .05). For the other two latent classes, no significant difference was observed between blended and distance mode preferences.

Table 7
Explanatory Model Parameters for Teaching Delivery Mode Preferences in the Context of Social Presence

					Worth		
Mode: Coefficient	*Estimate*	*Std. Error*	*z value*	*Pr(>|z|)*	*LC1*	*LC2*	*LC3*
Face to face:LC1 vs blended	0.70	0.11	6.17	0.00*	0.77	0.47	0.49
Face to face:LC2	−0.60	0.14	−4.16	0.00*			
Face to face:LC3	−0.60	0.15	−3.99	0.00*			
Distance:LC1	−0.76	0.12	−6.54	0.00*	0.04	0.14	0.10
Distance:LC2	0.26	0.15	1.75	0.08			
Distance:LC3	0.06	0.16	0.39	0.70			
Blended†:LC1	-	-	-	-	0.19	0.39	0.41
Blended†:LC2	-	-	-	-			
Blended†:LC3	-	-	-	-			

Note. * p < .05, †blended mode is reference, LC:latent class.

Interpreting the model findings through worth values rather than regression coefficients will facilitate a clearer understanding of the LLBT model results. In light of the information summarized in Figure 3, which illustrates the relative preferences within each latent class, the most preferred mode in the context of social presence across all latent classes is face-to-face, followed by blended, and finally distance learning. Face-to-face instruction was most preferred by students in the first latent class (worth = 0.77), whereas blended (worth = 0.19) and distance instruction (worth = 0.04) were least preferred by this class. While there was a notable difference between the preference for face-to-face and other teaching delivery modes in LC1, preferences for face-to-face and blended modes were quite similar for LC2 and LC3.

3.3.2 Students' preferences for mode of teaching delivery in the context of teaching presence

To ascertain which teaching delivery mode students exhibited a stronger preference for in supporting their teaching presence, and to examine the effect of latent classes in explaining these preferences, the explanatory model was found to provide a statistically significantly better model-data fit (χ^2 = 60.13, p < .05) compared to the base model, which did not include any covariates (see Table 8).

Figure 3
Explanatory Model worth Values for Teaching Delivery Mode Preferences in the Context of Social Presence

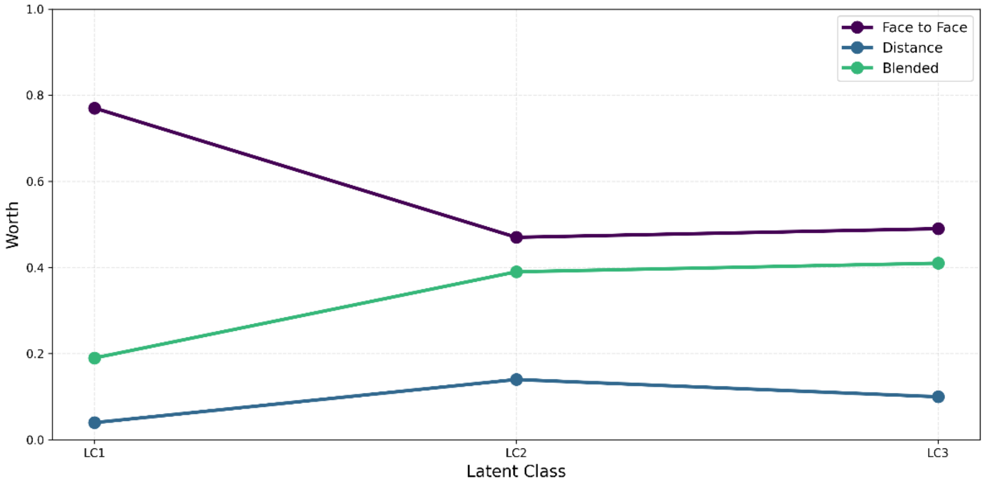


Table 8
LLBT Model Comparison for Teaching Mode Preferences in the Context of Teaching Presence

	AIC	*Resid. df*	*Resid. Dev*	*df*	*Deviance*	*Pr(>Chi)*
Base Model	168.97	7	55.37			
Explanatory Model	220.17	3	5.24	4	50.13	0.00*

Note. *p < .05

Upon examining the explanatory model parameters presented in Table 9, it is observed that students' preferences for face-to-face mode statistically differ from their preferences for blended mode across all three latent classes (LC1, LC2, LC3). However, the preference for distance learning significantly differs from the preferences for blended mode only for classes LC1 ($\beta = -1.32$, $p < .05$) and LC2 ($\beta = 0.69$, $p < .05$); for class LC3, no significant difference is observed ($\beta = 0.44$, $p = .07$).

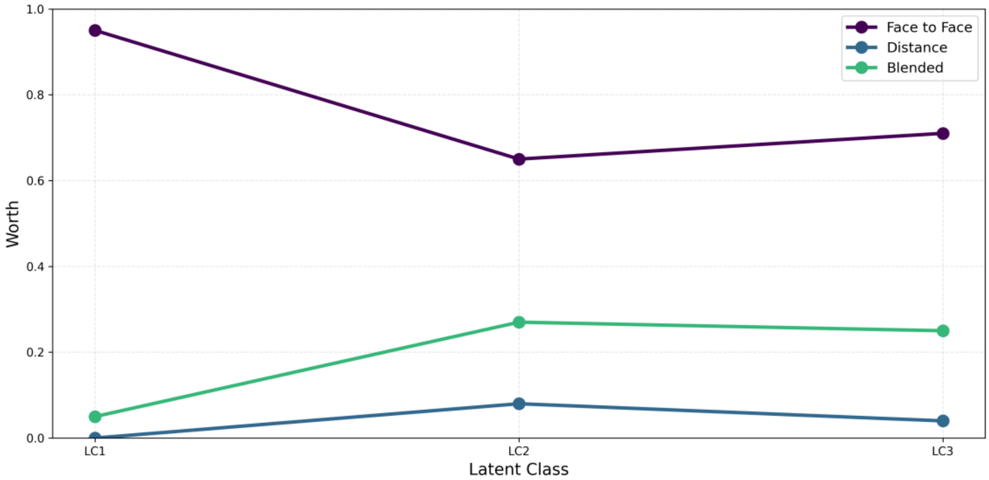
Table 9
Explanatory Model Parameters for Teaching Delivery Mode Preferences in the Context of Teaching Presence

					Worth		
Mode: Coefficient	*Estimate*	*Std. Error*	*z value*	*Pr(>|z|)*	*LC1*	*LC2*	*LC3*
Face to face:LC1	1.51	0.23	6.59	0.00*	0.95	0.65	0.71
Face to face:LC2	−1.08	0.25	−4.32	0.00*			
Face to face:LC3	−0.99	0.26	−3.83	0.00*			
Distance:LC1	−1.32	0.2	−6.75	0.00*	0.00	0.08	0.04
Distance:LC2	0.69	0.22	3.12	0.00*			
Distance:LC3	0.44	0.24	1.83	0.07			
Blended†:LC1	-	-	-	-	0.05	0.27	0.25
Blended†:LC2	-	-	-	-			
Blended†:LC3	-	-	-	-			

Note. * p < .05, †blended mode is reference, LC:latent class.

Conversely, when examining Figure 4, which is constructed using worth values reflecting relative preference probabilities, it is evident that in all three classes LC1 (worth = 0.95), LC2 (worth = 0.65), and LC3 (worth = 0.71) the face-to-face mode was the most preferred, while the distance mode was the least preferred ($worth_{LC1} = 0.00$, $worth_{LC2} = 0.08$, $worth_{LC3} = 0.04$). In all three classes, the preference for face-to-face mode exhibited a remarkably higher worth value compared to the other two teaching delivery modes.

Figure 4
Explanatory Model worth Values for Teaching Delivery Mode Preferences in the Context of Teaching Presence



3.3.3 Students' preferences for mode of teaching delivery in the context of cognitive presence

To ascertain which teaching delivery mode students exhibited a stronger preference for in supporting their cognitive presence, and how these preferences varied among latent classes, two models were estimated. According to the results shown in Table 10 the explanatory model differs significantly from the base model in terms of model fit ($\chi^2 = 60.79$, $p < .05$). This - indicates a significant improvement in explanatory power.

Table 10
LLBT Model Comparison of Teaching Delivery Mode Preferences in the Context of Cognitive Presence

	AIC	*Resid. df*	*Resid. Dev*	*df*	*Deviance*	*Pr(>Chi)*
Base Model	179.97	7	68.13			
Explanatory Model	127.18	3	7.33	4	60.79	0.00*

Note. *$p < .05$

Table 11 and Figure 5 present the parameter estimates related to students' preferences of mode of teaching delivery across latent classes in the context of cognitive presence. As shown in Table 11, individuals in Latent Class 1 significantly preferred face-to-face mode over blended learning, with a positive and statistically significant coefficient (β = 1.40, p < .05). Similarly, their preference for distance learning was significantly lower compared to the reference category, blended learning (β =−1.50, $p < .05$).

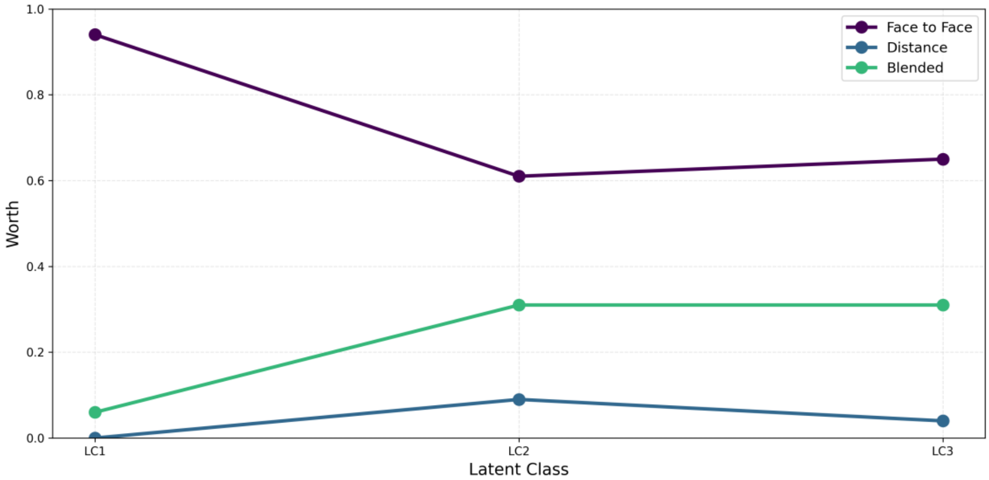
Table 11
Parameter Estimates of the Explanatory Model for Teaching Mode Preferences in the Context of Cognitive Presence

					Worth		
Mode: Coefficient	*Estimate*	*Std. Error*	*z value*	*Pr(>|z|)*	*LC1*	*LC2*	*LC3*
Face to face:LC1	1.40	0.21	6.67	0.00*	0.94	0.61	0.65
Face to face:LC2	−1.06	0.23	−4.58	0.00*			
Face to face:LC3	−1.03	0.24	−4.31	0.00*			
Distance:LC1	−1.50	0.23	−6.57	0.00*	0.00	0.09	0.04
Distance:LC2	0.86	0.25	3.43	0.00*			
Distance:LC3	0.50	0.27	1.83	0.07			
Blended†:LC1	-	-	-	-	0.06	0.31	0.31
Blended†:LC2	-	-	-	-			
Blended†:LC3	-	-	-	-			

Note. * $p < .05$, †blended mode is reference, LC:latent class.

According to the worth values presented in Figure 5, the probability of preferring face-to-face mode in LC1 was remarkably high (0.94), while distance learning had the lowest worth value (0.00). Blended learning was also low, with a worth value of 0.06. For Latent Class 2, both face-to-face ($\beta = -1.06$, $p < .05$) and distance learning ($\beta = 0.86$, $p < .05$) modes significantly differed from the blended mode. In Latent Class 3, only the face-to-face preference differed significantly from the reference category ($\beta = -1.03$, $p < .05$), while the preference for distance learning did not differ significantly ($\beta = 0.50$, $p > .05$). An examination of the worth values in Figure 5 reveals that face-to-face mode had the highest preference probability in all three classes: LC1 (0.94), LC2 (0.61), and LC3 (0.65). In contrast, distance learning consistently received the lowest worth scores across all classes: LC1 (0.00), LC2 (0.09), and LC3 (0.04).

Figure 5
Explanatory Model worth Values for Teaching Delivery Mode Preferences in the Context of Cognitive Presence



4. Discussion and Conclusion

The increasing diversity of educational programs, coupled with the imperative for student retention and catering to varied learner requirements, underpins the need for flexible and adaptable teaching modes in higher education (Imran et al., 2023). Against this backdrop, a significant determinant in responding to this evolving demand is the ascertainment of learner preferences. Our research endeavored to delineate a preference profile through an examination of learner preferences in relation to the CoI framework and autonomous learning. The results derived from this investigation are subsequently presented and discussed.

In this research, we first used LCA to classify the participants into homogenous classes according to their autonomous learning characteristics, which resulted in three different classes, or in other words, student profiles. LC1 comprised students who exhibited high self-directed learning and learner control (typically scoring within categories 5-7), but who also demonstrated notably low e-learning motivation (scoring within categories 1-3). In contrast, LC2 demonstrated high self-directed learning and learner control (categories 5–7) and a medium-to-high level of e-learning motivation (categories 4–7). Finally, LC3 was characterized by moderate levels across all factors, with responses concentrated primarily in the middle categories (3–5). These results highlight the diverse learning landscape in higher education and suggest that a one-size-fits-all approach to teaching mode delivery may not effectively address students' varied needs and motivations. Indeed, Callo and Yazon (2020) stated that pedagogical competencies and technology experience have a decisive role on teaching mode preferences. Students' e-learning readiness is an important factor that positively affects their engagement, motivation, and overall experience in online learning (Çebi, 2023).

Subsequent analyses used the Bradley-Terry model to make pairwise comparisons of teaching mode preferences. This analysis revealed a clear overall hierarchy of preference among teaching modes: blended learning was the most preferred, followed by face-to-face instruction and then online learning. These findings strongly align with recent literature suggesting the growing importance and effectiveness of blended learning (Imran et al., 2023). Blended learning's capacity to combine the strengths of both traditional and digital education, offering flexibility while encouraging student engagement and self-regulated learning, are likely the constructs that have influenced these choices. Blackford et al. (2022) revealed that despite the general convenience of online learning, it necessitates effective support and raises student privacy concerns, yet students generally preferred a mixed method of teaching. While some studies, such as Joji et al. (2022), have reported a predominant preference for purely face-to-face instruction with online as a complement, our overall results highlight blended learning as the primary choice, underscoring its growing acceptance and perceived benefits among students.

Delving deeper revealed differences in teaching mode preferences between different student profiles when latent classes were included in the preference model. LC1, with a high self-directed score and low e-learning motivation, showed a high preference for face-to-face learning followed by blended and minimal online preference. This finding suggests that having direct instructor guidance and structured environment in face-to-face teaching seems to be the most important element as having the potential to compensate for low e-learning motivations. These findings suggest that especially in distance education and online environments, motivation still needs to be addressed in detail as suggested by Chen and Jang (2010). Face-to-face education not only offers distinct benefits such as enhanced interpersonal interaction among students and with instructors, facilitation of social learning, and reduced distractions, but its educational quality can also be significantly improved by incorporating computer technology (Taylor et al., 2018). Unlike face-to-face learning environments, online learning environments lack face-to-face interaction and communication channels. Although social tools exist to overcome this deficiency, students prefer direct communication channels. According to Ng (2022), although students perceive online learning as an accessible teaching mode, the lack of physical interaction is an important barrier. The difference in the motivation dimension was reflected in preferences, with the LC1 group clearly preferring face-to-face education, while the LC2 and LC3 groups preferred the blended learning model. Students with relatively high learning motivation preferred guided participation with flexibility. Wright (2017) stated that highly motivated students especially prefer classroom interaction to better understand the lessons. Hence, it is a sign that the highly motivated participants of this study learn better in blended and face-to-face environments. Teacher-driven input and immediate feedback can be vital, especially for students such as LC1 students who have high levels of self-directed learning skills but low e-learning motivation.

Lee and Nuatomue (2021) revealed a significant relationship between the delivery modes of the CoI framework. The CoI framework was used in this study as a tool for students to evaluate their learning experiences. To examine learner preferences more deeply, the CoI framework was included in the pairwise comparison model. Analyses were repeated according to the framework's three sub-dimensions. Findings regarding social presence showed that LC1 had a clear preference for face-to-face learning while LC2 and LC3 had more evenly split. These results highlight the importance of face-to-face learning for social interaction in all groups and demonstrate its critical nature for LC1. These results align with literature highlighting the strong social aspects of traditional learning environments (Heilporn et al., 2021; Imran et al., 2023). In online learning, students can have more independence and control over their own learning process (Holmberg, 2005). However, rather than self-control, students with low motivation wanted their motivational gaps to be met in a face-to-face way.

The findings on teaching and cognitive presence are especially notable for LC1. For teaching presence, LC1 showed a strong preference for face-to-face learning. There was no preference for online learning and only a small preference for blended learning.

Similarly, for cognitive presence, LC1 showed a strong preference for face-to-face learning, while blended learning received minimal support. In LC2 and LC3, face-to-face learning was the most favored approach, followed by blended learning as the second choice. Online learning received the least preference across all learning components. Accordingly, while face-to-face was dominant in terms of other dimensions, LC1's extreme preference for face-to-face education in both teaching and cognitive presence is quite remarkable. These findings can be interpreted as students with low motivation do not prefer to engage in additional interaction other than classroom learning in terms of cognitive and teaching presence. On the other hand, although face-to-face learning is clearly the primary preference for other formal education students, additional learning opportunities also support their perceptions of presence. Examining student preferences for online and face-to-face teaching modes, Joji et al. (2022) found that face-to-face instruction was the most highly preferred, with online learning primarily viewed as a complementary tool. Consistent with their learning intentions at the start of university, formal education students primarily prefer the face-to-face mode of instruction, even when they have a choice (Wright, 2017). While a review of the literature suggests that the preference for face-to-face instruction stems from its strong emphasis on group participation and social aspects (Heilporn et al., 2021; Imran et al., 2023), surprisingly, in our investigation, both teaching and cognitive presence demonstrated relatively stronger contributions/salience to the observed preferences.

The autonomous learning and CoI framework provide valuable outputs in understanding students' learning environment preferences. This approach provides diagnostic information for designing instructional environments suitable for changing learner needs and demands. Although blended learning was generally preferred, the preference for face-to-face teaching mode came to the fore when CoI was considered. Especially low motivated students did not prefer fully online learning environments. These students overwhelmingly prefer to be in the same physical environment with the instructor and their peers. An important reason for the low preference for online learning is that students feel that they have learning difficulties in this environment (Lee & Nuatınue, 2021). This situation reveals the close correlation between learners' motivation, communication needs and preferences.

5. Practical Implications

This research offers practical findings to help higher education institutions to improve their teaching methods. Across different student profiles, the blended learning model is clearly preferred. This shows that hybrid models, combining the benefits of synchronous and asynchronous learning, need to be developed. Technology should be used effectively to boost student engagement, self-directed learning, and interaction among students. The research also highlights the need for different teaching strategies, especially for students (LC1) who have low e-learning motivation but strong self-directed learning skills. For this group, face-to-face learning is a clear preference. To address motivational gaps and improve the learning experience, direct instructor support, immediate feedback, and a structured physical environment are important. Therefore, institutions should consider more interactive in-person or hybrid options for these students. Social and instructional presence plays a crucial role, especially for students with low motivation. Learning activities must be thoughtfully designed to provide strong communication, peer interaction, and clear teaching support. It is clear that a uniform approach doesn't work for today's diverse student body. Universities should instead employ more flexible and responsive teaching strategies which meet the needs of different learners. In this way, positively reinforcing students' motivation sources such as their interest and desire toward the lessons may increase their engagement in these lessons (Aydoğan, 2024).

Future research could examine these preferences over time, incorporate qualitative data to gain a deeper understanding, and study larger, more diverse student groups across different educational levels. Digital competencies and issues related to technology access can also be considered significant reasons why students do not prefer online learning (Mudau et al., 2022).

6. Limitation

As a matter of fact, the current study was conducted in a university with a relatively lower socio-economic environment. Low digital competencies and difficulties in accessing the internet and computers may have been a determining factor in students not preferring technology-oriented learning environments.

Author contributions: Both authors contributed equally to the design, implementation, analysis, and writing of this study. All authors have read and approved the final manuscript.

Declaration of interest: The authors declared that there were no potential conflicts of interest.

Data availability: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethical statement: This study was approved by the Ethics Committee of Van Yüzüncü Yıl University on October 23, 2024 with the decision number 2024/22-22.

Funding: No funding was received to assist with the preparation of this manuscript.

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Appendix 1. Learners' Mode of Teaching Delivery Preference Pairwise Comparison Form

Community of Inquiry Content	*Items*	*Paired Comparison*
	1. Which teaching delivery mode do you prefer generally?	Face to face vs. Blended Face to face vs. Distance Blended vs. Distance
Social Presence	2. In which environment do you feel more comfortable participating in discussions?	Face to face vs. Blended Face to face vs. Distance Blended vs. Distance
	3. In which environment can you communicate more easily with other students?	Face to face vs. Blended Face to face vs. Distance Blended vs. Distance
	4. In which environment do you feel a greater sense of cooperation and togetherness?	Face to face vs. Blended Face to face vs. Distance Blended vs. Distance
Cognitive Presence	5. In which environment does the instructor encourage student participation more?	Face to face vs. Blended Face to face vs. Distance Blended vs. Distance
	6. In which environment do you communicate better with the instructor?	Face to face vs. Blended Face to face vs. Distance Blended vs. Distance
	7. In which environment is the instructor more encouraging in exploring new concepts/ideas?	Face to face vs. Blended Face to face vs. Distance Blended vs. Distance
Teaching Presence	8. Which environment's learning activities help you learn more?	Face to face vs. Blended Face to face vs. Distance Blended vs. Distance
	9. In which environment do the questions/problems raised increase your interest in the course topics?	Face to face VS Blended Face to face vs. Distance Blended vs. Distance
	10. Which environment's course activities make you more curious?	Face to face vs. Blended Face to face vs. Distance Blended vs. Distance