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What drives the shift? A data mining approach to understanding student preferences for digital learning in post-pandemic Malaysia

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ABSTRACT

The rapid evolution of post-pandemic education has highlighted a significant shift toward online platforms. However, the specific emotional factors and core competencies driving university students to choose digital over traditional education remain largely unexplored. Therefore, this study aims to identify the underlying criteria that differentiate traditional from digital learning and determine the key drivers of students' shifting preferences. Methodologically, a quantitative data mining approach was employed, using secondary data from the Department of Statistics Malaysia, comprising data on 432 university students. The data were analyzed in Orange software using linear regression and the *RReliefF* feature selection method to extract predictive patterns. The results indicate that students distinguish between the two learning modes primarily based on their study skills, feelings of academic overload, and a lack of interaction. Furthermore, a preference for digital education is significantly influenced by personal interest, problem-solving abilities, and managerial/entrepreneurial skills. In conclusion, these data-driven insights emphasize that successful digital learning environments must actively support student well-being and interactive engagement. This study equips educational policymakers and instructional designers with the targeted data needed to optimize future educational environments.

Keywords: Digital education, student preferences, data mining, e-Learning, traditional learning

INTRODUCTION

Traditionally, education has taken place in physical classrooms where students and instructors interact physically. However, the accelerated development of technology and the global disruptions caused by the COVID-19 pandemic have positioned digital education as a highly viable alternative. Digital education offers profound benefits, including geographical flexibility, access to vast resources, and personalized learning trajectories (Basak et al., 2018).

Despite its growing prevalence, a comprehensive understanding of what specifically drives students to prefer digital education over traditional methods remains scarce. Existing literature frequently focuses on isolated variables, such as technological infrastructure, while overlooking the multifaceted emotional and skill-based criteria influencing students. Without this understanding, institutions struggle to design effective programs that maintain student engagement.

This study bridges the gap by systematically evaluating the criteria that shape student preferences. By employing advanced data mining techniques on comprehensive student datasets, this research highlights distinct variables, ranging from individual discipline to psychological stress, that shape the future of educational delivery.

PROBLEM STATEMENT

The rapid acceleration of digital education, driven by technological advancements and the COVID-19 pandemic, has fundamentally altered the educational landscape. While digital platforms offer significant flexibility and access to resources, the comprehensive factors driving students' shifting preferences between digital and traditional classroom environments remain poorly understood. Existing research frequently examines these variables in isolation, focusing solely on technological infrastructure or specific demographics, which makes it difficult to draw generalizable conclusions.

This fragmented understanding creates a critical gap: without a holistic view of student preferences, educational policymakers, administrators, and instructional designers struggle to develop programs that sustain student engagement and motivation. Therefore, a systematic investigation is necessary to pinpoint the exact criteria and external factors (such as infrastructure, family income, and training support) that dictate whether students prioritize digital or traditional education.

Research Questions

1. What criteria differentiate traditional learning from digital learning from the students' perspective?
2. What specific factors drive a student's priority and preference for digital versus traditional learning?

Research Objectives

1. To investigate how students perceive the characteristics and differences between traditional and digital learning.
2. To identify the primary factors influencing students' preference for traditional learning or digital learning.

Understanding these criteria can shed light on the factors that influence students' preferences for digital education versus traditional classroom instruction. These criteria can assist educational institutions and policymakers in making informed decisions about adopting and implementing digital education. In addition, understanding students' preferences can inform instructional design and pedagogical strategies, better aligning with their requirements and preferences and resulting in enhanced learning outcomes.

However, despite the increasing prevalence of digital education, there is a paucity of research that examines in depth the factors influencing students' shifting preferences between digital and classroom education. Existing research frequently focuses on isolated factors or is limited to specific contexts, making it difficult to generalize findings. Consequently, additional research is required to systematically investigate the criteria that influence students' preferences for digital or classroom education, taking into account a variety of factors and contexts.

The transition to digital education has become a prominent trend in the contemporary educational landscape. Educational stakeholders must understand the factors that influence students' preferences for digital versus classroom education to effectively plan, design, and implement educational programs that meet students' needs and preferences. This study aims to address a research gap by examining the factors influencing students' shifting preferences between digital and traditional classroom education. The findings will contribute to the existing literature on educational technology, instructional design, and educational policy.

SCOPE OF THE STUDY

The purpose of the study was to determine the factors influencing students' preferences for digital versus traditional education. To achieve this objective, a quantitative methodology was employed, focusing on the statistical relationships between the criteria of interest and students' preferences for digital and classroom education. Age, gender, socioeconomic status, prior exposure to digital and classroom education, and other factors that may have influenced students' preferences were considered. These criteria were selected because prior research identified them as prospective determinants of students' preferences for digital education versus classroom education.

The analysis utilized secondary data from the Department of Statistics Malaysia. The data were collected by administering surveys and questionnaires to students who received both digital and traditional classroom education. Regression analysis, a statistical technique for determining the intensity and direction of the relationship between two or more variables, was used to analyze the study's data. Regression analysis was used to determine the extent to which the variables of interest influenced students' preferences for digital and classroom education. For instance, the study could determine whether age had a significant impact on students' preferences, or whether their prior experience with digital and classroom education affected those preferences.

The Department of Statistics Malaysia's secondary data provided a dependable and readily accessible data source for the study. However, the investigation had some limitations. For instance, the data may have been biased, and the study may not have accounted for all potential confounding variables.

THE TRANSITION TO DIGITAL LEARNING IN MALAYSIA

The COVID-19 pandemic necessitated a rapid and unprecedented transition to online education globally, a shift deeply felt within Malaysian higher education. In March 2020, the implementation of the Movement Control Order (PKP) forced the immediate closure of physical institutions, prompting the swift adoption of platforms like the Ministry of Education's e-Learning (*e-Pembelajaran*) system. Even prior to the pandemic, national initiatives such as the Malaysia Education Blueprint 2015–2025 aimed to integrate digital technology, including virtual and game-based learning, more deeply into the educational ecosystem. However, the abrupt pandemic-induced transition highlighted critical infrastructure gaps, forcing institutions to rapidly adopt emergency remote teaching models to ensure academic continuity (UNESCO, 2020).

Student Perceptions: Benefits and Barriers

Despite the initial hurdles of implementation, e-learning offers substantial benefits, including flexibility, personalized learning experiences, and access to diverse academic resources (Alsabawy et al., 2016; Fink et al., 2025; Majjate et al., 2025; Patil, 2025). Studies indicate that integrating mobile and online platforms can significantly enhance academic achievement and stimulate critical thinking among university students (Zhang et al., 2021).

Conversely, the literature also identifies severe barriers that shape students' perceptions of digital education. Online learning in Malaysia is frequently hindered by technical difficulties, inadequate infrastructure, and a lack of digital training (Zainuddin & Halili, 2016). Beyond technical issues, students face significant psychological and social challenges. The shift away from traditional classrooms has exposed vulnerabilities such as a lack of self-motivation, increased academic distraction, feelings of isolation, and limited peer-to-peer and student-instructor interaction. These emotional and competency-based factors play a crucial role in shaping students' perceptions of the efficacy of digital versus traditional learning environments.

E-Learning Implementation and Institutionalization

The successful integration of educational technology is best understood through models of organizational transformation, which progress from pre-implementation to full institutionalization (Sidhu & Gauge, 2021). For digital learning to be effectively institutionalized, it must evolve beyond emergency remote teaching (Shetu et al., 2021) to well-structured environments that prioritize interactivity and learner support (Illie & Frătineanu, 2019; Al-Maroof et al., 2021). The literature emphasizes that while digital platforms offer rich pedagogical experiences, their ultimate success depends heavily on user adaptability and alignment with learner preferences. Educational institutions must provide ongoing support and resources to ensure instructional designs meet students' evolving emotional and academic needs.

Identification of the Knowledge Gap

While existing literature extensively documents the broad advantages and infrastructural challenges of digital learning, there remains a notable gap regarding the specific, student-centric criteria that dictate educational preferences in a post-pandemic context. Previous studies frequently examine technological factors in isolation or rely on broad qualitative observations. Few studies have employed advanced quantitative data-mining approaches to isolate the core competencies (e.g., study skills, problem-solving, entrepreneurial skills) and emotional factors (e.g., feelings of academic overload) that drive these shifting preferences. A systematic investigation into these underlying variables is necessary to equip educational policymakers and instructional designers with the specific data required to optimize future digital learning ecosystems.

METHODOLOGY

To investigate shifting preferences among university students between digital and traditional education, this study employed a quantitative data-mining approach. The methodology encompasses data collection, hypothesis formulation, data preprocessing, and predictive modelling using the Orange data-mining toolkit.

Figure 1

Research Framework

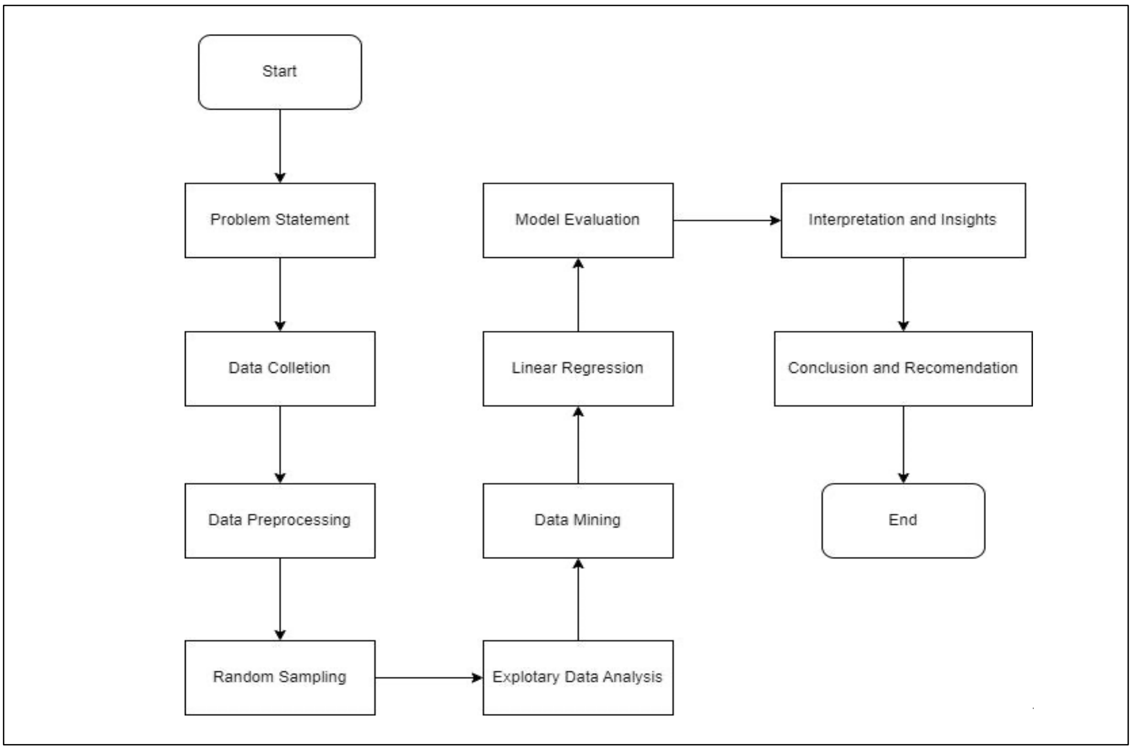

Figure 1 illustrates the research framework, from problem formulation to conclusion, using the effective technique of data mining. It involves analyzing data using algorithms and other statistical techniques to identify patterns and correlations that can be used to predict the future. Data mining is a powerful technique that permits researchers to extract valuable insights and knowledge from large datasets. It is necessary to employ a systematic, well-structured research methodology to conduct research in this field effectively~~.~~

Problem Statement

In the problem formulation phase, researchers must explicitly define the research problem they intend to address and the objectives of their study. This involves comprehending the problem's domain and context and defining the study's scope. For instance, if the research problem is to predict customer attrition at a telecommunications company, the goal could be to develop a predictive model that accurately identifies customers at risk of leaving. Defining the objectives helps guide the entire research process and establish clear outcome expectations. To further refine the problem formulation, researchers may conduct a comprehensive literature review to identify relevant existing studies, methodologies, and theories. This literature review helps clarify the current state of knowledge and identify the research gaps this study seeks to fill. It also aids in formulating research questions or hypotheses that guide the data mining process.

Data Collection and Data Preprocessing.

Administration of an Online Questionnaire Survey

Recognizing the need to collect university students' firsthand experiences and perspectives, the Department of Statistics Malaysia conducted an online questionnaire survey. The purpose of the survey was to obtain primary data on the challenges Malaysian students face in e-learning, as well as their attitudes and future objectives toward this mode of education. Google Forms, a popular online survey platform, was selected for its convenience and accessibility.

Hypotheses Development

Hypothesis development is a crucial phase in the research process. It entails developing precise statements or hypotheses that reflect the anticipated relationships or differences between variables. There is a standard method for developing hypotheses.

Recognize the Variables

This phase starts by obtaining a thorough understanding of the research's variables, including identifying the dependent variable, which in this case is students' preference (category: digital education or classroom education), as well as the independent variables, such as demographic factors, access to technology, and reasons for students' preferences.

Evaluate Current Literature

Conduct a literature review to gain insight into prior research on students' educational preferences and the factors influencing them. This summary will help you understand the existing theories, concepts, and empirical evidence related to the topic. It may also serve as a foundation for developing research hypotheses.

Formulate Hypotheses

There are numerous arguments against e-learning. Arguments of online pedagogy include accessibility, affordability, adaptability, learning pedagogy, lifelong education, and policy. According to Mrudula (2020), online education is readily accessible and can even reach rural and remote areas. It is considered a relatively inexpensive mode of education due to reduced transportation, lodging, and overall institutional costs. Another intriguing aspect of online learning is its adaptability; learners can schedule or plan their time to complete online courses.

Hypothesis development establishes the anticipated relationships between the identified variables. The dependent variable in this study is the student's learning preference (categorized as digital education or traditional classroom education). The independent variables consist of demographic factors, technological access, study skills, and emotional factors (e.g., feelings of overload).

The literature highlights numerous factors influencing these preferences. For instance, arguments supporting online pedagogy emphasize accessibility, affordability, and adaptability. As noted by

Mrudula (2020), online education is highly accessible and reaches rural and remote areas. It is a cost-effective mode of learning due to reduced transportation and institutional costs, while also offering learners the flexibility to schedule their own time.

Based on the literature and the dataset variables, the following hypotheses were formulated:

Null Hypothesis (H0a): There are no specific criteria that differentiate traditional learning from digital learning from the student's perspective.

Alternative Hypothesis (H1a): There are specific criteria that differentiate traditional learning from digital learning from the student's perspective.

Null Hypothesis (H0b): There is no significant relationship between the identified independent factors and the students' preference for digital over traditional education.

Alternative Hypothesis (H1b): There is a significant relationship between the identified independent factors and the students' preference for digital over traditional education.

Random Sampling and Exploratory Data Analysis

To ensure that the results were representative of the broader university student population in Malaysia, both cluster and systematic random sampling techniques were used. Cluster sampling divided the population into distinct categories by university or faculty. Considering the diversity of educational institutions across the nation, clusters were then randomly selected. This strategy sought to incorporate diverse perspectives and experiences. Systematic random sampling was utilized within each designated cluster to guarantee randomness and reduce bias. This involved selecting every nth student from a student catalog or database within each cluster to participate in the survey. Using this method, each pupil had an equal probability of being included in the sample, regardless of their position in the catalog or database.

The online questionnaire survey was administered to a random sample of 432 Malaysian university students from various backgrounds. This sample size was determined based on statistical power and practical constraints within the study. The researchers aimed to obtain a representative cross-section of the student population, including a range of demographic characteristics, academic disciplines, and geographic locations. The questionnaire was meticulously crafted to encompass numerous dimensions of e-learning. It included questions regarding the availability of infrastructure, the quality of instruction and support, challenges associated with discipline and self-regulation, the perceived benefits and drawbacks of e-learning, and the effect on learning outcomes. The survey questions were formulated based on a comprehensive literature review, expert input, and consideration of the unique circumstances of the COVID-19 pandemic.

This study investigated the impact of e-learning on university students in Malaysia during the COVID-19 pandemic by combining secondary data analysis with primary data collected through an online questionnaire survey. Using cluster and systematic random sampling techniques, a sample representative of the diverse backgrounds and experiences of Malaysian students was obtained. The questionnaire survey focused on various aspects of e-learning and provided vital insights into infrastructure, instruction and support, discipline, benefits, drawbacks, and learning outcomes. These findings will contribute to a deeper understanding of the challenges and opportunities posed by e-learning in times of crisis, thereby informing educational policies and practices in Malaysia and beyond.

The goal of data analysis in scientific research is to extract meaningful insights, recognize patterns, and derive conclusions from collected data. Data analysis is essential to the research process because it enables researchers to make informed decisions, validate hypotheses, and address research objectives. This study involves random sampling and exploratory data analysis. By analyzing quantitative data, researchers can identify relationships between variables, test statistical hypotheses, and generalize about the studied population. Using appropriate techniques for analyzing quantitative data is vital for several reasons:

Accuracy

Appropriate analysis methods guarantee the precision of the results. By employing the appropriate statistical methods, researchers can minimize errors, reduce biases, and produce trustworthy results.

Validity

Using appropriate methods enhances the reliability of the research. Robust statistical methods increase the probability of drawing valid conclusions and making sensible inferences about the target population.

Interpretation

Selecting appropriate techniques enables researchers to interpret the data correctly. Different types of data and research queries are suited to distinct analytic approaches. Choosing the appropriate method ensures that the findings align with the research objectives and yield insightful conclusions.

Generalizability

Appropriate data analysis techniques facilitate generalization. Researchers can make reliable generalizations from sample data to the larger population by employing statistical methods that account for variability and sampling errors.

Reproducibility

Using appropriate methods helps ensure the reproducibility of research. When researchers use well-established analytical methods and provide explicit documentation of their procedures, other researchers can replicate the analysis and verify the results, thereby increasing the credibility of the research.

The dataset for this analysis was obtained from the Department of Statistics Malaysia. The dataset includes demographic and behavioral information on consumers from various Malaysian universities. The dataset was chosen for its applicability to the research problem of identifying the factors that drive shifts in students' preferences between digital and traditional classroom education. The Department of Statistics Malaysia is renowned for providing trustworthy and exhaustive datasets, assuring the quality and veracity of the data. After obtaining the dataset, it was preprocessed to guarantee its integrity and usability. Included in the preprocessing stages were the elimination of duplicates, errors, and missing values. Additionally, anomalies were identified and treated appropriately. The dataset was then transformed to ensure all variables were on the same scale by standardizing them. This normalization procedure helps eliminate potential measurement-unit-related biases. In addition, feature selection techniques were employed to reduce dimensionality, keeping only the most pertinent and informative features for the analysis.

Data Mining, Linear Regression, and Model Evaluation

In this study, the analysis software used was "Orange." Orange is an open-source data mining and machine learning toolkit that provides a vast array of data analysis and modeling techniques and algorithms. It provides a user-friendly interface that enables researchers to investigate and analyze data interactively, construct models, and visualize results. Various data mining techniques were utilized within the Orange framework to analyze the preprocessed dataset. These methods included regression analysis, classification and clustering algorithms, and association rule mining. In this study's specific analysis, however, linear regression played a crucial role.

A dependent variable and one or more independent variables are intended to be related using the statistical modeling approach known as linear regression. It helps explain how variations in the independent variables affect the dependent variable. In the context of predicting consumer churn, linear regression can be used to identify the main contributors to student preferences and develop a predictive model for the likelihood of those preferences. Various evaluation metrics, such as mean squared error, root mean squared error, and R-squared, were used to evaluate the linear regression model's performance. These metrics provide insight into the model's precision and goodness of fit. The interpretation of the linear regression results included examining the coefficients of the independent variables to determine their impact on the dependent variable (factors), identifying significant predictors, and understanding the direction and magnitude of their influence.

In summary, the data mining research methodology includes problem formulation and objective definition, data acquisition and preprocessing, and the application of data mining techniques, utilizing software such as Orange, to extract insights from the data. Using Orange, researchers employed a variety of techniques, including linear regression, to analyze the dataset and derive meaningful insights into students' preferences for digital education versus classroom education.

Data Preprocessing and Feature Selection

Data analysis was conducted using Orange, an open-source data mining and machine learning software, due to its robust capacity for interactive data visualization and predictive modeling. Before modeling, the dataset underwent rigorous preprocessing to ensure data integrity. This involved handling missing values, eliminating duplicates, and treating identified outliers. To eliminate potential biases arising from different measurement units, all variables were standardized to a common scale. Subsequently, a feature selection model was applied to reduce dimensionality and isolate the most informative variables. Specifically, the *RReliefF* (*Regressional ReliefF*) algorithm was used to rank and extract the strongest predictive features for student preferences, ensuring that the subsequent predictive model was built only on the most significant data points.

Predictive Modeling and Data Analysis

To test the hypotheses and understand the relationships between the selected features, Linear Regression was employed as the primary predictive model within the Orange framework. The Linear Regression model was used to map the relationship between the dependent variable (student preference) and the independent variables extracted during the feature selection phase. By examining the regression coefficients, the study identified the main contributors to student preferences and determined the direction and magnitude of their influence. The performance and accuracy of the linear regression model were systematically evaluated using standard goodness-of-fit metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2).

Assumptions and Limitations

Assumptions

1. The secondary data utilized in the analysis are assumed to be of high quality. This assumption is contingent upon the accuracy, dependability, and totality of the original data source. Since the data source is the government, the credibility and reputation of the source are trustworthy.
2. The assumption is that secondary data is representative of the population or phenomenon under investigation. This presupposes that the original data collection process utilized appropriate sampling techniques or that adjustments have been made to account for any potential sampling-related biases or limitations.

Limitations

Since secondary data are collected by someone else for a different purpose, researchers have no control over the data collection process. This lack of control may result in limitations such as missing variables, inadequate measurement instruments, and inconsistent data-collection procedures. These limitations may impact the analysis's precision and dependability. Secondary data may be derived from multiple sources or distinct datasets, each with varying variable definitions, measurement scales, and coding systems. These inconsistencies may pose difficulties when merging or harmonizing the data, potentially affecting the validity and reliability of the analysis. When utilizing secondary data, researchers are restricted to the variables already present in the dataset. It may not be possible to modify or validate variables to align them with the research objectives better or to test specific hypotheses.

ANALYSIS AND DISCUSSION OF RESULTS

This section presents the findings from the linear regression and *RReliefF* feature selection models built in Orange. To ensure the reliability of the predictive model and eliminate bias, the analysis was iterated ten times. The analysis evaluates a comprehensive profile of 43 distinct criteria ranging from demographic factors (e.g., family income, home location) to psychological and competency-based factors (e.g., study skills, stress, problem-solving) to address the two primary research objectives. The application of the *RReliefF* feature selection algorithm represents a novel methodological step in educational research, enabling precise, mathematical ranking of emotional and cognitive variables rather than relying solely on broad qualitative observations.

Criteria Differentiating Digital and Classroom Learning (Objective 1)

To address the first objective, the model isolated the primary criteria students use to distinguish between digital and traditional learning modes. Table 1 integrates the *RReliefF* selection frequency with the individual regression coefficients (t-statistics) to demonstrate the significance of each criterion.

Table 1

Key Criteria Differentiating Digital and Classroom Learning

Criteria	*RReliefF* Top-5 Frequency	Critical value	t-statistic value	Confidence Interval (95%)
Study skills of students	5	± 2.6633 $(t_{0.005, 58})$	9.233349216	0.620833333 ±0.0632 (±10.2%) [0.558 – 0.684]
Overloaded	5	± 2.6633 $(t_{0.005, 58})$	-6.100261273	0.558333333 ±0.0802 (±14.4%) [0.478 – 0.638]
Lack of interaction	3	± 2.6633 $(t_{0.005, 58})$	-6.095234837	0.7 ±0.0744 (±10.6%) [0.626 – 0.774]
Social isolation	2	± 2.6633 $(t_{0.005, 58})$	-5.256423407	0.6375 ±0.0731 (±11.5%) [0.564 – 0.711]
Stress of students	2	± 2.6633 $(t_{0.005, 58})$	-4.636838575	0.4625 ±0.0780 (±16.9%) [0.385 – 0.540]

The data clearly indicate that psychological and competency-based factors overwhelmingly define how students differentiate the two learning environments. *Study skills* ($t = 9.23$) and *feelings of being overloaded* ($t = -6.10$) emerged as the most critical differentiating factors, closely followed by a *lack of interaction* ($t = -6.10$). These findings align with existing theories of self-directed learning, which posit that online education demands a higher degree of autonomy and time management than traditional classrooms (Illie & Frătineanu, 2019). Furthermore, the prominence of overload, lack of interaction, and social isolation echoes the barriers identified during the COVID-19 emergency remote teaching phase (Zainuddin & Halili, 2016). Students do not primarily differentiate the platforms based on technology itself, but rather on the emotional toll and the independent academic rigor required to succeed in a digital space.

Factors Influencing Student Preferences (Objective 2)

The second objective examined the specific factors driving a student's preference for digital learning over traditional classroom education, as summarized in Table 2. The analysis reveals that a student's preference for digital education is significantly driven by intrinsic motivation and high-level cognitive competencies. *Student happiness* ($t = 9.39$), *personal interest* ($t = 6.04$), and *problem-solving skills* ($t = 3.78$) are the strongest predictors of a preference for e-learning. This supports the notion that learners strongly favor digital learning environments that provide the managerial and problem-solving skills needed to navigate flexible, self-paced ecosystems (Alsabawy et al., 2016). Interestingly, the data dismantled several common assumptions. Variables such as *family household income* ($t = -2.48$) and *existing digital skills* ($t = 2.27$) yielded t-statistics below the critical threshold, indicating they are not statistically significant drivers of preference in this context. This suggests a paradigm shift: access to technology and baseline digital literacy are no longer the primary barriers or motivators for university students. Instead, emotional engagement (happiness/interest) and cognitive adaptability dictate their educational choices.

Table 2

Factors Influencing Educational Preferences

Criteria	***RReliefF*** **Top-5 Frequency**	Critical value	t-statistic value	Confidence Interval (95%)
Interest of students	4	± 2.6633 ($t_{0.005, 58}$)	6.037644847	0.416666667 ±0.0778 (±18.7%) [0.339 – 0.495]
Managerial and entrepreneur skill	5	± 2.6633 ($t_{0.005, 58}$)	3.40356779	0.5875 ±0.0667 (±11.4%) [0.521 – 0.654]
Problem solving skill	5	± 2.6633 ($t_{0.005, 58}$)	3.78231973	0.5 ±0.0689 (±13.8%) [0.431 – 0.569]
Happiness of students	5	± 2.6633 ($t_{0.005, 58}$)	9.388015028	0.579166667 ±0.0654 (±11.3%) [0.514 – 0.645]
Social skill	4	± 2.6633 ($t_{0.005, 58}$)	3.138265294	0.5125 ±0.0776 (±15.1%) [0.435 – 0.590]
Communication, leadership and team skill	3	± 2.6633 ($t_{0.005, 58}$)	2.526430721	0.525 ±0.0743 (±14.2%) [0.451 – 0.599]
Family's household income	1	± 2.6633 ($t_{0.005, 58}$)	- 2.482576712	0.575 ±0.0801 (±13.9%) [0.495 – 0.655]
Digital skills of students	1	± 2.6633 ($t_{0.005, 58}$)	2.269261092	0.6 ±0.0725 (±12.1%) [0.527 – 0.673]

Overall Hypothesis Testing (Model Significance)

To validate the overall reliability of the models used for Objectives 1 and 2, F-tests were conducted to measure the collective significance of the independent variables against the dependent variable, as shown in Table 3.

Table 3

Overall Regression Model Significance (F-Test)

Objective	Critical value	F-statistic value	Confidence Level (95%)	Result
RO1: Differentiate digital learning and classroom learning	3.38 ($F_{5,54,0.01}$)	32.38365321	0.595833333 ±0.0763 (±12.8%) [0.520 – 0.672]	Null Hypothesis (H_{0a}) Rejected
RO2: Changing on students' preferences for digital learning and classroom learning	2.88 ($F_{8,51,0.01}$)	12.7183188	0.536979167 ±0.0740 (±13.8%) [0.463 – 0.611]	Null Hypothesis (H_{0b}) Rejected

The regression model for Objective 1 yielded an F-statistic of 32.38, far exceeding the critical value of 3.38. Similarly, the model for Objective 2 generated an F-statistic of 12.72, surpassing the critical value of 2.88. Both results are statistically significant at a 95% confidence level. Consequently, we reject both null hypotheses. The data conclusively prove that (1) there are specific, measurable criteria students use to differentiate traditional from digital learning, and (2) there is a highly significant relationship between specific intrinsic competencies (interest, problem-solving, happiness) and the shifting preference toward digital education.

CONCLUSION

This analysis rigorously examined the factors driving students' preferences for digital versus traditional classroom education. By using an iterative Linear Regression model to ensure statistical robustness, the study revealed critical insights into the specific variables shaping educational choices.

Objective 1 (Differentiating Criteria): Study skills and feelings of academic overload emerged as the strongest criteria students use to distinguish between learning modes, followed closely by a perceived lack of interaction. Stress and social isolation also played notable, albeit secondary, roles. Conversely, structural variables such as family household income and baseline digital skills were not statistically significant, indicating they do not primarily determine how students differentiate between the two environments.

Objective 2 (Drivers of Preference): The strongest predictors of a student's preference for digital education are personal interest, managerial/entrepreneurial competencies, and problem-solving skills. Student happiness and social skills also serve as significant secondary drivers. Notably, household income and existing digital proficiency showed a limited impact on these specific preferences.

Ultimately, this comprehensive analysis demonstrates that psychological well-being (e.g., happiness, academic overload) and intrinsic cognitive competencies (e.g., study skills, problem-solving) dictate educational choices far more than financial status or baseline technical proficiency. These findings provide educational policymakers and instructional designers with the precise, data-driven insights necessary to optimize student-centric learning environments in the digital age. The novel findings of this study prove that emotional engagement and self-directed cognitive skills now outweigh baseline digital literacy and household income in shaping educational preferences. These data-driven insights provide a new framework for educational policymakers, shifting the focus from purely infrastructural investments to targeted, student-centric support systems.

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CONFLICT OF INTEREST

The authors declare no conflict of interest regarding the publication of this paper.

DECLARATION OF GENERATIVE AI USE

I acknowledge that Grammarly (https://www.grammarly.com) was used solely to improve grammar, readability, and language. All AI-assisted content was reviewed and edited by the authors. No AI tools were used to generate data, conduct analyses, modify research results, or draw conclusions. The authors take full responsibility for the content of the manuscript.

DATA AVAILABILITY

All data are available under the following repository:
https://data.mendeley.com/datasets/p8d75psxk4/2

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