Journal of Applied Technology and Innovation
Vol. 10, Issue 1, 2026, pp. 68-90
e-ISSN:2600-7304-ISSN
doi: 10.65136/jati.v10i1.329

# E-Learning Challenges and Preparedness among Malaysian Frontline Students during COVID-19: A Mixed-Methods Study.

**Nik Norliati Fitri Md Nor[1,2], Milad Bagheri[1,2,3*], Mehdi Soltanzadeh[4], Izham Mohamad Yusoff[1,2], Siti Masayu Rosliah Abdul Rashid[1,2], Iraj Gholami[5]**

[1]Geography Section, School of Distance Education, Universiti Sains Malaysia, Pulau Penang, Malaysia
[2]Transdisciplinary Research on Environmental Science and Occupational Health (Trees @ USM) section, School of Distance Education, Universiti Sains Malaysia, Pulau Pinang, Malaysia
[3]Institute of Oceanography and Environment, Universiti Malaysia Terengganu, Terengganu, Malaysia
[4]Department of Socioculture, Academy of Malay Studies, Universiti Malaya, Kuala Lumpur, Malaysia
[5]Division of Science, New York University Abu Dhabi (NYUAD), Abu Dhabi, United Arab Emirates

*Corresponding author: milad.b.g@usm.my

Received: 2026-03-23; Accepted: 2026-04-15; Published: 2026-04-20

## Abstract

This study examines the preparedness and challenges of Malaysian frontline students in adapting to e-learning during the COVID-19 pandemic. A mixed-methods design was employed, integrating descriptive statistics, inductive thematic analysis, and Exploratory Factor Analysis (EFA) using Principal Component Analysis (PCA). The quantitative results identified five principal components, which explained 76.3% of the total variance, reflecting major challenges related to scheduling and course materials, technical and logistical barriers, environmental disruptions, personal-life constraints, and combined contextual factors. Qualitative findings further revealed recurring issues including unstable internet access, financial burden, home distractions, and psychosocial stress. Overall, the findings indicate that students particularly struggled with missed scheduled sessions, the need for recorded online classes, poor internet connectivity, and disruptive learning environments. These results highlight the importance of strengthening digital infrastructure, improving scheduling flexibility, and providing greater academic and psychosocial support to enhance equitable and resilient e-learning systems.

**Keywords:** *Remote learning; Educational resilience; Online learning challenges; EFA and PCA methods; Thematic Analysis.*

## 1. Introduction

The COVID-19 pandemic triggered an unprecedented transformation in higher education systems worldwide, compelling universities to shift rapidly from conventional face-to-face teaching to emergency remote and online learning modalities (Dereso et al., 2021; UNESCO, 2020). Although this transition enabled academic continuity during lockdowns and movement restrictions, it simultaneously exposed structural inequalities in students' access to stable internet, digital devices, and supportive learning spaces (World Bank, 2021; OECD, 2020). These challenges were particularly severe in developing countries, where disparities in socioeconomic conditions and digital infrastructure remain significant (Helsper, 2021; Ahuja, 2023). In Malaysia, the sudden move to e-learning intensified longstanding inequities among postgraduate and distance learners, especially those who were simultaneously serving as frontline workers during the health crisis (Othman et al., 2022; Onyema et al., 2020; Yeap et al., 2021).

Malaysian frontline postgraduate students represent a unique and underexplored population within the broader e-learning literature. Unlike traditional learners, these students had to balance demanding professional roles in sectors such as healthcare, education, logistics, and public administration while sustaining academic progress in fully online environments. The intersection of occupational fatigue, unpredictable work schedules, family responsibilities, and limited study spaces created a highly complex learning context. In many cases, unstable internet connectivity, data limitations, and the financial burden of maintaining digital access further constrained their participation in synchronous platforms such as Webex and other learning management systems (Tan & Lim, 2021; Jones & Brown, 2022). In this study, "frontline students" refers to postgraduate students who were simultaneously enrolled in higher education and actively employed in essential service sectors, including healthcare, education, logistics, and public administration, during the COVID-19 pandemic.

Beyond technological barriers, the psychosocial and environmental dimensions of online learning emerged as equally critical. Household distractions, caregiving duties, noise disturbances, and the absence of dedicated study environments reduced concentration and negatively affected engagement with course materials. For working adult learners, these issues were compounded by emotional stress, burnout, and anxiety associated with frontline service during the pandemic (Lee et al., 2020; Greenhow & Chapman, 2020). Such realities suggest that e-learning preparedness extends beyond technical readiness alone and should be understood as a multidimensional construct encompassing cognitive, behavioral, emotional, and contextual factors.

To address this complexity, the present study adopts a mixed-methods framework that integrates descriptive statistical analysis, inductive thematic analysis, and exploratory factor analysis using PCA. This design allows the study to capture both measurable patterns and lived experiences, thereby providing a holistic understanding of how Malaysian frontline students adapted to crisis-driven digital education. While the quantitative strand identifies latent factors such as technological barriers, scheduling conflicts, and environmental disruptions, the qualitative strand contextualizes these findings through students' personal narratives, coping strategies, and resilience mechanisms (Creswell & Plano Clark, 2018; Braun & Clarke, 2006; Field, 2018).

The main objective of this research is to investigate the challenges, preparedness, and adaptation strategies of Malaysian frontline postgraduate students engaged in e-learning during the COVID-19 pandemic. Specifically, the study seeks to identify the major technological, occupational, environmental, and psychosocial factors influencing learning continuity and to evaluate how these dimensions interact within a broader preparedness framework. By focusing on this highly specific cohort, the study addresses an important gap in the literature concerning educational resilience among working and crisis-exposed learners.

This study is guided by four clearly defined research questions that align with the objectives, methods, and findings of the mixed-methods design. First, it examines the major technological, environmental, occupational, and psychosocial challenges faced by Malaysian frontline postgraduate students in adapting to e-learning during the COVID-19 pandemic (RQ1). Second, it investigates the key preparedness factors influencing students' readiness, engagement, and continuity in online learning environments (RQ2). Third, the study explores how demographic, socio-economic, and occupational characteristics shape the e-learning adaptation process among frontline students (RQ3). Finally, the research seeks to identify the latent structural dimensions of e-learning barriers through exploratory factor analysis using PCA (RQ4). Together, these research questions establish a clear analytical pathway connecting the study objectives with the descriptive statistics, thematic analysis, and PCA findings.

The significance of this study is both practical and theoretical. From a practical perspective, the findings provide evidence-based recommendations for strengthening institutional flexibility, improving digital infrastructure, supporting mental well-being, and promoting equitable access to online learning resources. From a theoretical perspective, the study advances current discourse on e-learning preparedness by linking digital knowledge, behavioral adaptation, and contextual resilience within a unified analytical framework. In line with the reviewer's suggestion, the Introduction is now presented as a single coherent section without subsections, improving clarity, readability, and alignment with the Journal of Applied Technology and Innovation format.

## 2. Materials and Methods

### 2.1. Research Design and Approach

This study adopted a mixed-methods research design that integrated both quantitative and qualitative approaches to gain a comprehensive understanding of Malaysian frontline students' preparedness and challenges in adapting to e-learning during the COVID-19 pandemic. The rationale for using a mixed-methods design lies in its ability to combine numerical data with rich narrative insights, allowing for a more holistic exploration of complex educational phenomena. Quantitative analysis included descriptive statistics to summarize patterns of e-learning readiness and EFA using PCA to identify underlying dimensions influencing students' preparedness. Meanwhile, qualitative data were examined through inductive thematic analysis to capture the contextual and emotional aspects of students' experiences.

By integrating these complementary methods, the study ensured methodological triangulation, enhancing the reliability and depth of the findings. This approach provided a balanced understanding of both the measurable and interpretive dimensions of e-learning adaptation. Ultimately, the mixed-methods framework enabled the researchers to not only identify structural and behavioral factors affecting learning continuity but also uncover the personal and institutional dynamics that shaped students' engagement with digital education under the unique pressures of a global health crisis.

### 2.2. Sampling and Participants

A purposive maximum variation sampling strategy was employed to ensure broad representation of participants with diverse demographic and socio-economic backgrounds. This sampling technique allowed for the inclusion of students across different gender, age, marital status, field of study, and employment categories, thereby capturing a wide range of perspectives on e-learning adaptation. The study focused on master's students in geography from Universiti Sains Malaysia (USM), who were actively engaged in online learning during the COVID-19 pandemic. These students represented a unique cohort of frontline learners balancing academic responsibilities with essential service roles, making them particularly relevant to the study's objectives.

The final sample consisted of 471 valid responses, an adequate size for ensuring statistical robustness in EFA and thematic data saturation for qualitative interpretation. Data collection followed strict ethical protocols approved by the USM Ethics Committee. Participants were fully informed about the study's purpose, and voluntary participation was ensured through informed consent. Anonymity and confidentiality were maintained throughout the research process. This sampling approach ensured inclusivity and reliability, providing a comprehensive dataset to examine the diverse experiences, preparedness levels, and contextual challenges of Malaysian frontline students in transitioning to e-learning environments.

A purposive sampling method was employed to identify and select participants who met specific inclusion criteria directly aligned with the objectives of this research. This non-probability sampling approach was chosen because it enables the intentional selection of individuals possessing distinctive experiences and insights relevant to the study's focus (Creswell & Plano Clark, 2018). In this context, purposive sampling ensured that participants represented a clearly defined population frontline postgraduate students whose dual engagement in essential work and higher education during the COVID-19 pandemic provided valuable perspectives on e-learning adaptation and preparedness.

The participants were postgraduate students enrolled in the Master of program at USM between 2020 and 2022, a period marked by extensive reliance on online education. These individuals simultaneously served in essential sectors such as healthcare, education, logistics, and public administration. Their unique circumstances offered meaningful insights into how academic continuity and work-related obligations intersected amid pandemic-induced disruptions. The quantitative phase included 471 valid survey responses, which formed the dataset for descriptive statistical analysis and exploratory factor analysis using PCA. In addition, 18 participants were purposively selected for semi-structured interviews to provide qualitative depth through inductive thematic analysis. Eligibility for participation required individuals to meet three key criteria: (1) current enrollment in an accredited postgraduate program during the pandemic years (2020–2022); (2) active engagement in frontline or essential service occupations during this period; and (3) completion of at least one semester of online learning under pandemic-related movement restrictions.

Recruitment was conducted through academic networks, departmental announcements, and online communication platforms. Participation was entirely voluntary, and informed consent was obtained before data collection. Ethical approval for the study was secured from the Universiti Sains Malaysia Research Ethics Committee. This purposive sampling strategy ensured that the study captured a rich, contextually grounded understanding of the challenges faced by frontline students balancing work responsibilities and academic commitments within a remote learning environment.

### 2.3. Data Collection Instruments and Procedures

Data collection for this study was conducted through a combination of structured online surveys, interactive sessions, and semi-structured in-depth interviews. These methods were designed to capture both quantitative and qualitative dimensions of postgraduate students' e-learning experiences during the COVID-19 pandemic. The data collection process utilized online platforms, including Google Forms for surveys and Webex for interviews, ensuring accessibility and safety during movement restrictions. Participants were postgraduate students from the master of Geography program at USM, representing diverse academic years and professional sectors such as healthcare, education, logistics, and public administration. This diversity allowed for a comprehensive understanding of how students from different backgrounds adapted to e-learning while managing frontline work responsibilities. The online survey consisted of both closed- and open-ended questions to facilitate mixed-methods analysis. It covered five main dimensions: (1) demographic and socio-economic characteristics; (2) technological readiness and digital accessibility; (3) e-learning experiences and associated challenges; (4) psychological and environmental factors influencing learning performance; and (5) perceptions of institutional support.

The survey responses provided the foundation for identifying key trends, while follow-up semi-structured interviews with 18 volunteer participants provided deeper insights into individual coping strategies, motivations, and lived experiences. A maximum variation sampling approach ensured the inclusion of participants across gender, age, and employment sectors. The sample size was determined by the principle of data saturation, ensuring both breadth and depth in the findings. Prior to full implementation, all instruments were pilot-tested to ensure clarity, reliability, and content validity. To further establish internal consistency reliability, Cronbach's alpha was calculated for the multi-item survey constructs. The overall instrument demonstrated strong reliability, with a Cronbach's alpha value of 0.86, exceeding the recommended threshold of 0.70 for acceptable internal consistency (Field, 2018). In addition, construct validity was supported by the Kaiser–Meyer–Olkin (KMO) measure of 0.81 and the statistically significant Bartlett's Test of Sphericity ($p < 0.001$), as reported in the PCA section. The study adhered strictly to ethical standards approved by the Universiti Sains Malaysia Research Ethics Committee. Participants provided informed consent, and data were anonymized, securely stored, and used solely for research purposes. These comprehensive procedures enhanced the validity, reliability, and ethical rigor of the research, ensuring trustworthy and meaningful results.

### 2.4. Data Analysis Methods

#### 2.4.1. Theoretical Framework

This study employed a mixed-methods research design, integrating both quantitative and qualitative approaches to achieve a comprehensive understanding of Malaysian frontline students' preparedness for and challenges in adapting to e-learning during the COVID-19 pandemic. The mixed-methods design was chosen to combine the strengths of both numerical analysis and narrative interpretation, allowing for triangulation of findings and a more holistic exploration of the research objectives. Quantitative methods provided measurable evidence on variables such as demographic influences, internet accessibility, technological readiness, and academic outcomes, while qualitative methods offered deeper insights into students' lived experiences, emotions, and coping strategies in navigating remote learning under pandemic-related restrictions. The quantitative strand utilized structured online surveys to capture patterns and relationships among variables, which were analyzed using descriptive statistics and EFA through PCA. These techniques helped identify the underlying dimensions of e-learning challenges and preparedness factors.

The qualitative strand, on the other hand, employed semi-structured interviews to explore personal narratives, perceptions, and behavioral adaptations that could not be fully captured through numerical data alone. This combination enabled the study to uncover both the structural and experiential aspects of e-learning adaptation among postgraduate students. The integration of quantitative and qualitative data followed a convergent parallel design, in which both datasets were collected and analyzed separately but merged during the interpretation phase to identify points of convergence, divergence, and complementarity. This design strengthened the study's validity and depth by cross-verifying statistical results with narrative accounts. Furthermore, the adoption of a mixed-methods framework aligned with the study's goal of understanding the multifaceted challenges faced by frontline students balancing professional obligations and academic responsibilities, ultimately providing a robust and contextually grounded understanding of e-learning preparedness in times of crisis.

#### 2.4.2. Descriptive Statistical Analysis

The adoption of a mixed-methods research design in this study was motivated by the need to obtain a comprehensive and multidimensional understanding of Malaysian frontline students' preparedness for e-learning during the COVID-19 pandemic (Fig. 1). Mixed-methods research effectively integrates the quantitative rigor of numerical data with the qualitative richness of personal experiences, offering both breadth and depth in analysis (Creswell & Plano Clark, 2018). Quantitative data provide statistical generalizability and allow researchers to identify significant trends and relationships, while qualitative insights contribute contextual meaning, interpretation, and explanation for these observed patterns. This complementary integration enhances the robustness and credibility of the findings through methodological triangulation. In this study, the quantitative component involved descriptive analysis and EFA using the PCA method to uncover underlying structures and interrelationships among key variables such as digital readiness, psychological resilience, and institutional support. The qualitative component, comprising semi-structured interviews and open-ended survey responses, offered nuanced insights into students' lived experiences, emotional challenges, and adaptive strategies in balancing frontline duties with academic obligations. Together, these methods provided a holistic perspective on both the empirical (measurable) and experiential (perceptual) dimensions of e-learning adaptation.

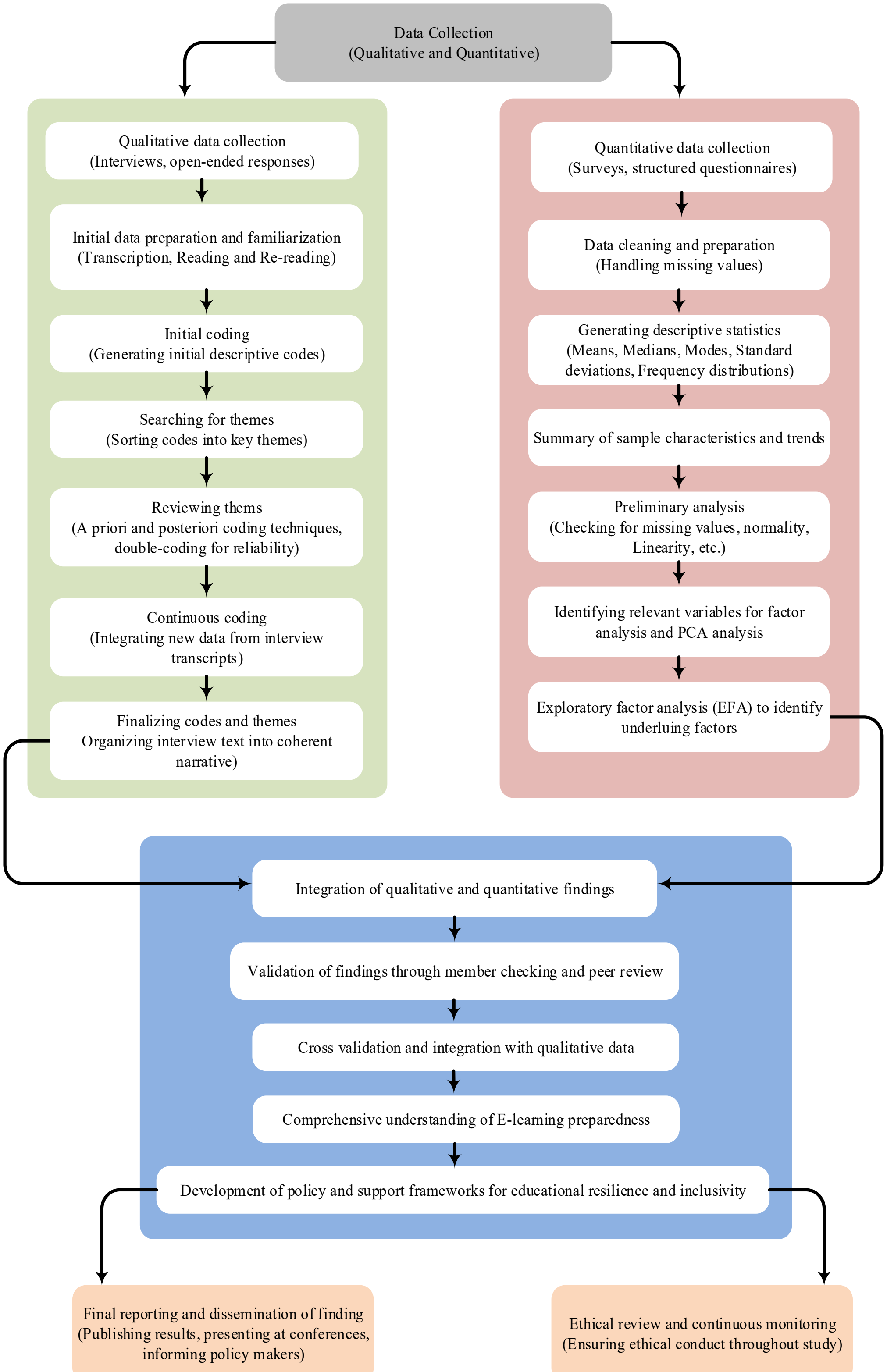


***Fig 1. Comprehensive approach for hybrid analysis in E-Learning preparedness study.***

The rationale for integrating both approaches was to ensure complementarity, triangulation, and validation of findings allowing quantitative results to be interpreted through qualitative evidence and vice versa. The inductive thematic analysis of interview data supported the interpretation of statistical patterns, thus enhancing the internal validity and depth of the study's conclusions. Conducted in Malaysia during the post-peak phase of the pandemic, the study specifically targeted master's students in geography at USM. By using this mixed-methods framework, the research not only captured the complex realities of e-learning among frontline students but also provided evidence-based recommendations for policy, institutional support, and digital education resilience.

This study is grounded in the KPR theoretical framework, which serves as the core conceptual foundation for understanding Malaysian frontline students' preparedness for e-learning during the COVID-19 pandemic (Fig.2). The framework conceptualizes e-learning preparedness as a dynamic and interdependent process involving three primary dimensions Knowledge, Practice, and Readiness that collectively determine students' capacity to adapt, engage, and succeed in digital learning environments under crisis conditions. Knowledge represents the cognitive and technical dimension of preparedness, encompassing students' understanding of digital platforms, online pedagogical tools, and communication technologies (Smith & Kumar, 2021). This component highlights how both formal education and informal learning experiences contribute to building the digital literacy required for effective online engagement. Practice, on the other hand, refers to the behavioral execution of this knowledge manifested in students' ability to apply digital skills in real-world learning scenarios, manage coursework, and participate in interactive online settings (Nguyen et al., 2021). Practice functions as a bridge between knowledge acquisition and readiness, allowing learners to refine their abilities through continuous engagement and feedback. Readiness reflects the affective and motivational dimension, defined as the degree to which students feel psychologically, emotionally, and materially prepared to sustain e-learning amidst disruptions (Mohammed et al., 2021). This component integrates students' confidence, self-efficacy, and resilience, which are critical for maintaining learning continuity during uncertainty.

The KPR model is further supported by established theoretical perspectives that enhance its explanatory depth. The Online Learning Readiness Model emphasizes the significance of self-directed learning, motivation, and computer/Internet self-efficacy constructs that closely align with the Knowledge and Practice dimensions of the present framework. Similarly, the Community of Inquiry (CoI) Framework contributes to the understanding of how cognitive, social, and teaching presence shape engagement and reflection in online environments, corresponding to the Practice and Readiness dimensions of this study. Moreover, the Educational Resilience Theory introduces the affective element of perseverance and adaptability, explaining how students' psychological resilience mediates the relationship between stressors such as poor connectivity, workload, and emotional fatigue and overall readiness for digital learning. Within this study, the KPR framework functioned as both a conceptual lens and analytical foundation. Quantitatively, EFA and PCA were employed to identify the underlying structural relationships among variables representing the three domains. Components such as course design, internet accessibility, time management, and institutional support were mapped onto the framework to reveal how knowledge and practice interact to influence readiness. Qualitatively, thematic analysis illuminated the lived experiences of students, capturing narratives of coping mechanisms, motivation loss, and adaptive learning behaviors. These qualitative findings substantiated the statistical patterns identified through PCA, reinforcing the theoretical assumption of interdependence among the three dimensions.

By integrating cognitive (knowledge), behavioral (practice), and affective (readiness) elements, the KPR framework offers a comprehensive and empirically grounded explanation of e-learning preparedness among Malaysian frontline students. It advances theoretical discourse by linking digital self-efficacy, active learning engagement, and educational resilience, providing a nuanced understanding of how learners navigate crises while maintaining academic continuity. Ultimately, this theoretical integration strengthens the explanatory power of the study and contributes to broader discussions on sustainable digital education and crisis-responsive pedagogy. This integration not only grounds the study in established theory but also advances the conceptual understanding of digital and educational resilience in crisis-driven learning contexts, particularly among working and frontline student populations.

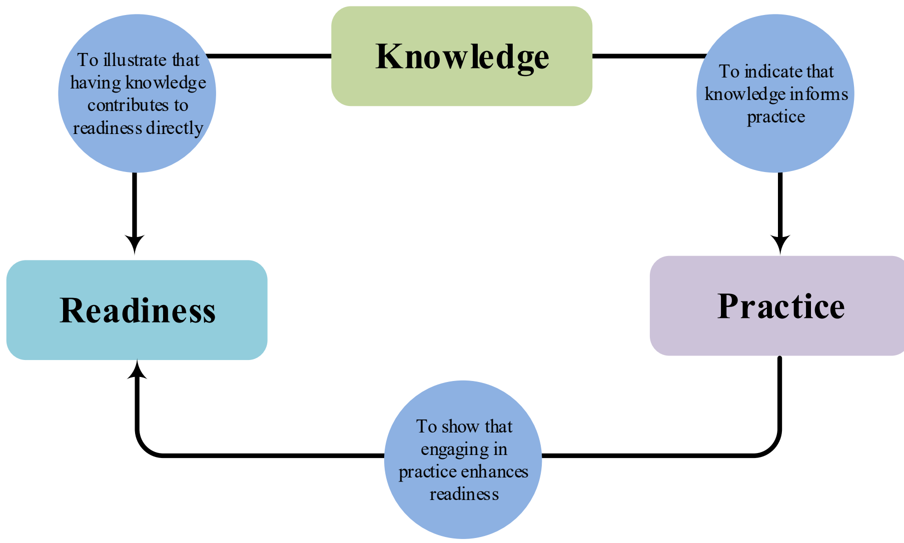


***Fig 2. A theoretical framework for investigating the perceived preparedness of Malaysian frontline students for covid-19 and e-learning in public spaces.***

Quantitative data in this study were analyzed using descriptive statistical methods, including measures such as mean, median, mode, standard deviation, and frequency distribution. These tools were used to summarize demographic patterns and identify key challenges faced by students in adapting to e-learning during the COVID-19 pandemic. Descriptive statistics serve as a foundational step in data analysis by organizing and presenting data in a clear and interpretable manner, allowing for an initial understanding of the dataset before applying more complex analytical techniques. The main components of descriptive statistics include measures of central tendency, variability, and distribution shape. Measures of central tendency mean, median, and mode help identify the central or typical value within a dataset, while measures of variability, such as range, variance, standard deviation, and Interquartile Range (IQR), indicate the degree of dispersion among data points. The IQR, in particular, provides a robust measure of variability less influenced by extreme values or outliers. In addition, distributional characteristics such as skewness and kurtosis describe the symmetry and "tailedness" of the data, respectively, offering insight into whether data points are concentrated around the mean or spread across the distribution. Frequency distributions, often illustrated through tables, histograms, or bar charts, further help visualize how frequently each response category occurs, thereby simplifying interpretation of large datasets.

Collectively, these techniques provide an essential overview of the dataset's structure and patterns, forming a statistical foundation for subsequent inferential analyses. In this study, descriptive statistics were particularly useful in capturing demographic variations and outlining major e-learning difficulties among students, setting the stage for deeper correlation and comparative analyses that examined how factors such as socioeconomic status, internet accessibility, and institutional support influenced e-learning preparedness and adaptation.

### 2.4.3. Thematic Analysis

Qualitative data were analyzed using inductive thematic analysis as outlined by Braun and Clarke (2006), which enabled a systematic exploration of students' lived experiences, challenges, and coping strategies related to e-learning during the COVID-19 pandemic. Thematic analysis is a widely used qualitative method that identifies, examines, and interprets recurring patterns or themes within textual data. Unlike quantitative techniques that focus on numerical representation, thematic analysis aims to uncover the meanings, perspectives, and emotions embedded in participants' narratives. This approach is particularly suitable for interpreting open-ended survey responses and interview transcripts, as it allows researchers to derive insights grounded in participants' own words and experiences.

The analysis followed several key stages to ensure methodological rigor. First, the researcher immersed in the data by repeatedly reading the transcripts and responses to gain a deep understanding of their content. This stage facilitated familiarization with the breadth and depth of the data. Next, initial codes were systematically generated to label meaningful segments of text that reflected important aspects of the participants' experiences. These codes were then examined and grouped to identify broader patterns or potential themes that captured shared meanings across the dataset. Each emerging theme was carefully reviewed to ensure internal coherence and external distinctiveness, guaranteeing that it accurately represented the dataset as a whole. In some cases, themes were refined, merged, or redefined to achieve conceptual clarity. Once finalized, each theme was named and defined, and its relevance to the research objectives was articulated.

The final stage involved reporting the themes with supporting evidence, such as direct quotations from participants, to illustrate key findings and ensure authenticity. Although thematic analysis is primarily qualitative, frequency counts were occasionally used to indicate how often particular themes, such as "technological barriers" or "academic workload stress," appeared in the data, providing a sense of prevalence without reducing the richness of the qualitative insights. This method provided a nuanced understanding of the psychological, social, and institutional dimensions shaping students' e-learning experiences. Even though thematic analysis is qualitative, to provide an idea of how common a theme is, you may use a simple descriptive statistic like frequency (Equation 1):

$$Frequency\ of\ Theme = \frac{Number\ of\ Instances\ of\ Theme}{Total\ Number\ of\ Istances\ in\ Dataset} \tag{1}$$

An inductive thematic analysis was carried out following the six-phase framework developed by Braun & Clarke (2006). This approach was selected because it enables patterns, meanings, and themes to emerge organically from participants' responses without being constrained by pre-existing theoretical assumptions or categories. The method facilitated a detailed and nuanced understanding of Malaysian students' preparedness for e-learning, their perceived challenges, and the strategies they adopted to adapt during the COVID-19 pandemic.

- Phase 1 (Familiarization): In the initial stage, all interview transcripts and open-ended survey responses were read multiple times to achieve deep immersion in the data. This process allowed the researchers to gain a holistic sense of participants' perspectives and to note preliminary ideas relevant to e-learning readiness, technological adaptation, and emotional resilience.

- Phase 2 (Generating Initial Codes): Open coding was then conducted manually, supported and verified using NVivo 12 software to ensure analytical consistency and transparency. Each meaningful data segment such as statements reflecting barriers, motivations, or coping strategies was assigned a concise code that represented its core meaning. This systematic labeling laid the groundwork for the identification of broader conceptual patterns.

- Phases 3-4 (Searching and Reviewing Themes): The initial codes were subsequently collated into potential themes through iterative comparison and pattern recognition. These emerging clusters were continuously refined and cross-checked against the full dataset to ensure that each theme was internally coherent yet distinct from others. The reviewing stage ensured that the themes accurately reflected the participants' collective experiences and were empirically grounded in the data.

- Phases 5-6 (Defining and Naming Themes): In the final stages, themes were clearly defined, named, and described to capture their conceptual essence and relevance to the study objectives. The interpretation of each theme was collaboratively reviewed by two researchers to enhance inter-coder reliability and minimize subjective bias.A simplified example of the coding and theme development process is presented in Table 1, demonstrating the progression from raw data to higher-level thematic constructs.

**Table 1: A simplified example of the coding process.**

| Raw Data (Participant Excerpt) | Initial Code | Category | Emergent Theme |
|---|---|---|---|
| "My internet always drops during Webex sessions, and I miss important explanations." | Poor internet stability | Technical issues | Internet Access and Connectivity |
| "I can't focus when my children are around; it's very hard to manage both." | Home distractions | Learning environment | Environmental and Domestic Disruptions |
| "Working at the hospital means I sometimes join class after my shift ends; it's exhausting." | Work-study conflict | Fatigue and scheduling | Workload and Scheduling Challenges |
| "I felt anxious about exams online; I wasn't confident using new platforms." | Anxiety, digital confidence | Psychological factors | Psychosocial and Emotional Impact |

### 2.4.4. Exploratory Factor Analysis Using PCA

EFA using the PCA model was employed to identify the underlying dimensions influencing Malaysian frontline students' preparedness and challenges in e-learning during the COVID-19 pandemic. PCA was chosen for its efficiency in data reduction and its ability to transform correlated variables into a smaller number of uncorrelated components that explain the maximum variance in the dataset (Field, 2018). The analysis was conducted using SPSS software, and factor extraction was guided by the Kaiser criterion (eigenvalues greater than 1), ensuring that only the most significant factors were retained. To enhance interpretability and achieve a clearer separation of factors, varimax rotation was applied. This process yielded five principal components, each representing a distinct domain of e-learning challenges and preparedness. The identified components included:

1. Scheduling and course material issues, reflecting difficulties in managing online coursework, deadlines, and content accessibility;

2. Technical and logistical barriers, capturing issues related to internet connectivity, digital infrastructure, and platform usability;

3. Environmental and personal disruptions, representing distractions, home responsibilities, and stress factors affecting concentration;

4. Psychological and motivational readiness, encompassing self-efficacy, learning motivation, and emotional resilience; and

5. Combined contextual factors, integrating institutional and social elements influencing the overall e-learning experience.

This quantitative analysis complemented the qualitative findings derived from inductive thematic analysis, which explored students' perceptions, coping mechanisms, and adaptive strategies in greater depth (Braun & Clarke, 2006). Together, these methods provided a comprehensive mixed-methods approach, integrating both numerical trends and experiential insights. Descriptive statistics (mean, median, mode, standard deviation, and frequency distributions) were used to summarize key demographic characteristics and provide a contextual basis for the EFA results (Creswell & Poth, 2018). The PCA results not only validated the thematic patterns identified through qualitative analysis but also revealed statistically robust dimensions of e-learning preparedness, such as technological proficiency, access to digital resources, and psychological adaptability. By integrating EFA-PCA findings with qualitative insights, this study establishes a multidimensional understanding of e-learning readiness. PCA was used primarily to simplify the interpretation of multiple interrelated e-learning challenges into a smaller number of meaningful dimensions. The extracted five components provided a clearer understanding of the dominant barriers affecting Malaysian frontline students, including scheduling issues, technical barriers, environmental disruptions, personal-life constraints, and contextual factors. This component-based interpretation strengthens the practical relevance of the findings for institutional policy and digital learning support. It demonstrates how structural, technological, and psychosocial variables interact to influence students' capacity to adapt to remote learning environments during crisis conditions, offering valuable implications for future digital education policy and institutional support frameworks. The factor analysis model can be expressed as (Equation 2):

$$x_i = \lambda_{i1}F_1 + \lambda_{i2}F_2 + \ldots + \lambda_{im}F_m + \epsilon_i \tag{2}$$

where $\lambda ij$ are the factor loadings, Fj are the common factors, and $\epsilon i$ are the unique factors (errors).

Factors are extracted using techniques like Maximum Likelihood Estimation (MLE) and Principal Axis Factoring (PAF) (Novak et al., 2020), and rotated for interpretability, often using varimax rotation (Tabachnick & Fidell, 2019). The final solution provides a multi-dimensional understanding of the data. Factor loadings are organized in a matrix (Equation 3):

$$X=\Lambda F+E \tag{3}$$

where X is the matrix of observed variables, $\Lambda$ is the factor loadings matrix, F is the matrix of factor scores, and E is the matrix of unique factors. Factor scores are calculated for interpretation (Equation 4):

$$F = \Lambda T(\Sigma-1)\ X \tag{4}$$

where $\Sigma$ is the covariance matrix of the observed variables.

PCA reduces the dimensionality of large datasets by converting original variables into a new set of uncorrelated variables, ordered by the variance they explain (Abbas et al., 2023). PCA in this study identifies primary characteristics influencing e-learning experiences, including scheduling and course material challenges, logistical and technical difficulties, environmental disruptions, and personal life impacts. Addressing these areas with targeted interventions can significantly improve the e-learning experience, equipping students with the tools and resources needed to succeed academically during and after the pandemic. A mathematical method known as PCA reduces the dimensionality of a dataset by splitting the data into a new set of orthogonal (uncorrelated) variables called principal components, which are then arranged according to how much variance they are able to extract from the original data. An explanation of the PCA approach and the essential equations are provided below. Standardizing the dataset is the first step of PCA, which makes sure that every variable contributes equally to the analysis. To do this, take each variable's mean and subtract it from the data points, then divide the result by the standard deviation. The steps and equations in PCA include standardizing data (Equation 5):

$$Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j} \tag{5}$$

where zij is the standardized value of the i-th observation of the j-th variable, xij is the original value, μj is the mean of the j-th variable, and σj is the standard deviation of the j-th variable.

The covariance between each pair of variables in the dataset is captured by the covariance matrix, which is a measure of how much two variables change together (Equation 6):

$$C = \frac{1}{\mathrm{n} - 1} \sum_{i=1}^{n} z_i z_i^T \tag{6}$$

where:

- $C$ is the covariance matrix.
- $Zi$ is the vector of standardized values for the $i$-th observation.
- $n$ is the number of observations.

The covariance matrix is used to calculate the eigenvectors and eigenvalues. The directions (principal components) in which the data fluctuates most are represented by the eigenvectors, and the degree of the variance in these directions is shown by the eigenvalues. The following equation is satisfied by the eigenvalues $\lambda$ and eigenvectors $v$ (Equation 7):

$$C_v = \lambda_v \tag{7}$$

where:

- $C$ is the covariance matrix.
- $v$ is the eigenvector.
- $\lambda$ is the eigenvalue corresponding to eigenvector $v$.

Then, the eigenvectors are arranged in descending order by the matching eigenvalues. The first principal component is the eigenvector with the highest eigenvalue, followed by the second principal component and so on. The original standardized data are projected onto the eigenvectors to create the major components (Equation 8):

$$PC_i = Zv_i \tag{8}$$

where:

- $PC_i$ is the $i$-th principal component.
- $Z$ is the matrix of standardized data.

- $v_i$ is the $i$-th eigenvector.

Ultimately, choose the highest $k$ principal components (determined by the biggest eigenvalues) and eliminate the other ones. Now that the dataset has been reduced, the majority of the variance present in the original data is captured in terms of these $k$ primary components (Equation 9):

$$Y = ZV_k \tag{9}$$

where:

- $Y$ is the matrix of the reduced data.
- $Vk$ is the matrix of the top.
- $k$ eigenvectors.

## 3. Results

This study employs a mixed-methods approach, using maximum variation sampling and saturation criteria to assess the experiences and preparedness of Malaysian frontline students for e-learning during the COVID-19 pandemic. By gathering a broad range of perspectives, the research aims to inform the development of more effective educational policies and support systems tailored to the needs of these students. The survey, which covered topics such as internet access, e-learning experiences, and demographics, received responses from 471 participants, with most questions achieving a 97% to 100% response rate, highlighting the relevance of the issues addressed (Table 2). Key areas explored included learning challenges, distractions, practical work, employment and financial status, and demographic data. Understanding these demographic factors, such as age, gender, marital status, and employment as frontline workers, was crucial in contextualising their e-learning experiences and identifying patterns or correlations. The study found that financial strain, particularly in pandemic-affected sectors, exacerbated e-learning challenges, such as securing adequate internet connectivity. The importance of reliable internet access was underscored, with recommendations for financial support or discounts. Additionally, difficulties in the home learning environment and managing online sessions were highlighted, emphasising the need for recorded sessions and improvements in scheduling and interactive components. The findings offer critical insights for enhancing educational programmes.

**Table 2. Summary of survey questions, number of responses, and response percentages.**

| Index | Theme | Responses | Percentage |
|---|---|---|---|
| 1 | Gender | 467 | 99% |
| 2 | Age | 470 | 100% |
| 3 | Race | 470 | 100% |
| 4 | Marital Status | 468 | 99% |
| 5 | Year of Study | 470 | 100% |
| 6 | Field of Study | 468 | 99% |
| 7 | Major/Minor in Geography | 459 | 97% |
| 8 | Are you a frontline? | 470 | 100% |
| 9 | Employment sector | 471 | 100% |
| 10 | Monthly income (MYR) | 470 | 100% |
| 11 | Are you facing problems with internet access? | 471 | 100% |
| 12 | Is your internet access sufficient to attend Webex meetings? | 471 | 100% |
| 13 | Internet bill per month | 471 | 21% |
| 14 | As a Distance Education student, does providing sufficient internet access burden you? | 470 | 100% |
| 15 | Are you facing problems in learning during the COVID-19 pandemic? | 468 | 99% |
| 16 | Can you attend scheduled Webex meetings? | 469 | 100% |

| | | | |
|---|---|---|---|
| 17 | Constraints on work, unpredictable schedules | 469 | 100% |
| 18 | Difficulty focusing due to disruptions from children | 466 | 99% |
| 19 | Not being familiar with the scheduled learning topics | 469 | 100% |
| 20 | Feeling the importance of recorded Webex sessions because instructors will provide them | 470 | 100% |
| 21 | Often forget the date and time of scheduled Webex sessions | 470 | 100% |
| 22 | Does attending Webex sessions help you understand the content better? | 470 | 100% |
| 23 | Internet access issues | 468 | 99% |
| 24 | Disturbance from noise made by other students | 469 | 100% |
| 25 | Difficulty understanding what the instructor is conveying | 471 | 100% |
| 26 | Do you face challenges in completing assignments given by instructors? | 471 | 100% |
| 27 | Given the choice, would you prefer to complete individual assignments or group assignments? | 471 | 100% |
| 28 | Does group assignment pose constraints for you in completing it? | 467 | 99% |
| 29 | Do you have sufficient internet access during Practical Work sessions? | 470 | 100% |
| 30 | Can you complete Practical Work within the given timeframe? | 470 | 100% |
| 31 | Given the choice, would you prefer to answer Physical Continuous Assessment or online? | 467 | 99% |
| 32 | Device used to answer daily Practical Work | 469 | 100% |
| 33 | The location where you answer daily Practical Work | 469 | 100% |
| 34 | Does your employer provide leave for scheduled Practical Work sessions? | 467 | 99% |

### 3.1. Descriptive Statistics Analysis

The descriptive statistics analysis offers a comprehensive overview of Malaysian frontline students' e-learning experiences during the COVID-19 pandemic, providing valuable insights into the sample characteristics, including demographics, internet access, learning challenges, and preferences. This analysis utilized key statistical measures such as mean, median, mode, standard deviation, and frequency distributions, which were visually represented in Fig. 3 to provide a clear summary of the data.

The study's results provide a comprehensive view of the e-learning experiences of Malaysian frontline students during the COVID-19 pandemic, highlighting diverse aspects of their academic journeys. The age distribution among students was notably varied, with the largest group being 31-40 years old, followed by those in the 21-30 age bracket. This diversity includes both traditional undergraduates and older, non-traditional learners who may be part-time or returning students. The presence of older students indicates a blend of life experiences and expectations, which could affect their e-learning engagement. Older students, balancing academic work with family and job responsibilities, face unique challenges that younger students might not encounter. Gender distribution revealed a significant imbalance, with a higher proportion of male students. This skew suggests that male perspectives might dominate the study, highlighting the need for future research to ensure a more balanced representation of genders to fully capture the diverse experiences and needs in e-learning contexts.

The majority of students were married, reflecting their older age group and indicating that many are managing academic responsibilities alongside family obligations. This dual pressure can lead to increased stress and suggests the need for flexible scheduling and targeted support to help these students manage their commitments effectively. Student distribution across academic years showed significant concentrations in the second and third years. This variation implies that students at different stages of their studies face distinct challenges. For example, third-year students might experience heightened academic pressures and more complex course material, necessitating tailored support strategies to address their specific needs. Internet access was generally adequate for most students, though some faced connectivity issues.

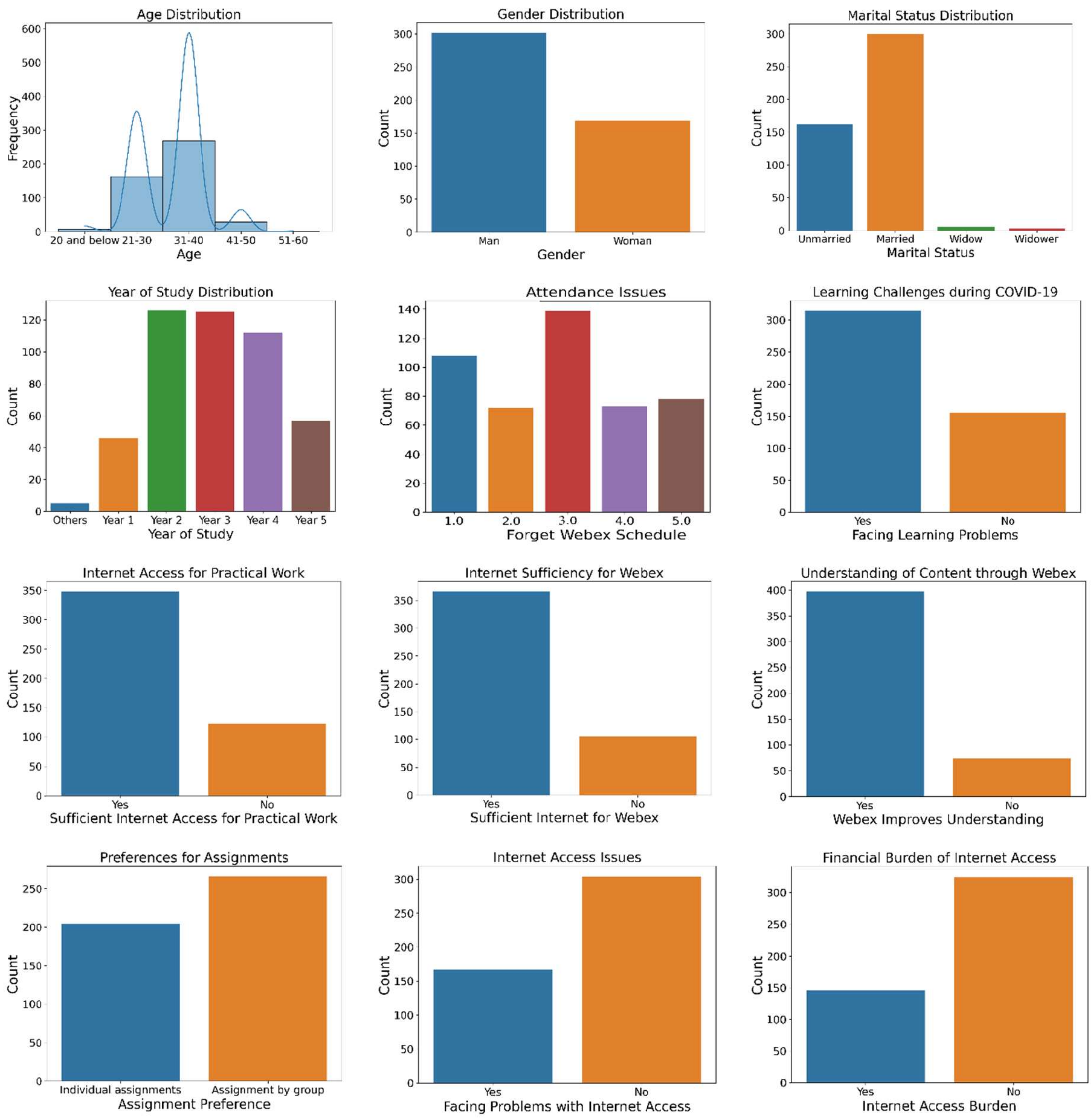


***Fig 3. An overview of the descriptive statistics analysis.***

This gap underscores the need for improved digital infrastructure to ensure that all students can fully participate in online education. Continuous enhancements in internet accessibility and reliability are essential for providing equitable learning opportunities. Learning challenges during the pandemic were prevalent, with many students struggling to understand course material and maintain motivation. These difficulties are critical for intervention, highlighting the need for additional support such as tutoring, counselling, and motivation-building activities to improve academic performance and satisfaction. Students showed a strong preference for group assignments due to the benefits of collaborative learning. However, group work presents coordination and communication challenges, particularly in an online setting. Educators should design assessments that leverage the advantages of collaborative work while addressing these challenges. Attendance issues were significant, with many students forgetting their scheduled Webex sessions. This indicates a need for better scheduling tools and reminders. Implementing consistent routines and automated reminders could reduce missed sessions and enhance participation.

While most students found Webex sessions useful, some struggled with engagement. Enhancing interactive elements in online sessions, such as incorporating polls, breakout rooms, and live chats, could help maintain engagement and improve comprehension. Practical work, essential in many courses, posed challenges, especially for those with inadequate internet access. Although most students managed practical sessions well, those with connectivity issues required targeted support, potentially including alternative assessment methods or improved internet services. The overall adequacy of internet access for Webex meetings was generally satisfactory, but a significant minority lacked sufficient connectivity. This gap is a major barrier to effective e-learning and requires solutions such as internet subsidies, enhanced broadband coverage, or on-campus access points. Financial burdens related to maintaining internet access were a substantial challenge for many students. This financial strain indicates a need for institutional support, such as financial aid or subsidies, to cover internet costs. Ensuring that all students can afford the necessary technology and services is crucial for promoting equitable access to education, particularly in e-learning contexts. The descriptive statistics provide a detailed snapshot of the e-learning experiences of Malaysian frontline students during the pandemic, highlighting critical areas for support and intervention. Addressing issues like internet access, financial support, learning challenges, and engagement strategies will help educators and policymakers better support students, ensuring they can thrive in a digital learning environment.

### 3.2. Inductive Thematic Analysis

The Inductive Thematic Analysis (ITA) provided an in-depth exploration of Malaysian frontline students' e-learning experiences during the COVID-19 pandemic, capturing the complexity of their narratives. This analysis followed a rigorous process of data coding, classification, and theme development, ensuring that themes emerged naturally from participants' responses. Data was collected through structured interviews and open-ended survey questions, offering a rich and authentic view of the students' perspectives. The coding process was conducted in several stages to ensure thoroughness. Initially, transcripts and survey responses were reviewed repeatedly to identify recurring ideas and significant statements, which were then used to generate preliminary codes reflecting the students' experiences. These initial codes were refined into descriptive codes, grouping similar concepts to identify broader patterns. The descriptive codes were analysed to uncover key themes based on their frequency and significance. These themes were then reviewed against the original data to ensure relevance and consistency, with adjustments made as needed. Finally, each theme was clearly defined and named to accurately capture the underlying patterns and meanings within the data. This meticulous approach ensured that the analysis faithfully represented the challenges and complexities of e-learning for frontline students during the pandemic.

### 3.3. Key Themes Identified

The ITA highlighted several key challenges faced by Malaysian frontline students in adapting to e-learning during the COVID-19 pandemic, emphasizing the urgent need for comprehensive support and resources. Internet Access and Connectivity were significant barriers, particularly for students from rural areas and lower-income families, who struggled with unstable connections and the financial burden of maintaining adequate internet service. The Learning Environment further compounded these challenges, as many students encountered frequent disruptions and distractions, such as noise and caregiving responsibilities, exacerbated by limited private space at home, making it difficult to focus on their studies.

In terms of Understanding and Comprehension, the shift to online learning posed difficulties, with many students reporting challenges in grasping course content due to the absence of face-to-face interaction. Although some students found Webex sessions beneficial, others faced technical issues and struggled with the impersonal nature of online communication. Assessment and Practical Work presented additional hurdles, as students encountered problems in completing assignments due to the lack of direct support and coordination in group tasks. The online format also hindered practical work, with difficulties in accessing necessary resources and maintaining engagement. The Psychosocial Impact of e-learning was profound, with students experiencing heightened stress and anxiety levels, coupled with a decline in motivation due to the absence of a structured learning environment and in-person interactions. The need for Support and Resources was a recurring theme, as students called for better institutional support, including financial aid for internet costs, mental health services, and enhanced online resources. The role of instructors was also critical, with effective communication and support being essential for a more positive learning experience. The ITA underscored the multifaceted challenges of e-learning for Malaysian frontline students, highlighting the necessity for targeted interventions to improve their preparedness, resilience, and educational equity in future crises.

### 3.4. Identified Themes and Supporting Evidence

The thematic analysis revealed four key themes that encapsulate the major challenges faced by Malaysian frontline students during e-learning in the COVID-19 pandemic highlighting the complex interplay between technological, occupational, environmental, and emotional factors. First, internet connectivity issues emerged as a dominant challenge, where participants frequently cited unstable connections and limited data access as barriers to effective learning. Many reported missing important explanations or being unable to participate in discussions, as one student explained, "Sometimes the connection drops, and I miss explanations. It makes me feel behind compared to others" (Participant 8). Second, work–study balance challenges were prevalent among students juggling professional duties and academic responsibilities. Frontline workers, particularly in healthcare, experienced exhaustion after long shifts, which affected focus and engagement during online classes. One participant stated, "After my hospital shift, I still had to attend classes. I was exhausted and couldn't concentrate well" (Participant 12).

Third, home and environmental disruptions were commonly mentioned, as students struggled to find quiet and organized spaces conducive to learning. Family responsibilities and noise frequently interfered with concentration, as reflected in the comment, "My kids were playing around while I was studying; there's no quiet space at home" (Participant 4). Lastly, psychosocial and emotional strain was a recurring theme, as isolation, anxiety, and reduced motivation negatively affected students' mental well-being and learning consistency. As one participant described, "I felt lonely and anxious. I couldn't interact with classmates like before" (Participant 15). Collectively, these themes illustrate the multidimensional barriers confronting frontline students in online education, emphasizing the urgent need for institutional support mechanisms that address technological inequities, flexible scheduling, home-based learning challenges, and mental health considerations to foster resilience and improve learning outcomes in crisis-driven digital education environments.

### 3.5. Factor Analysis

Factor analysis is a statistical method used to identify underlying relationships between variables, reducing the complexity of data by transforming many variables into a smaller set of latent factors. PCA is a widely used technique for this purpose. This study uses PCA to understand the preparedness and experiences of Malaysian frontline students for e-learning during the COVID-19 pandemic by identifying key influencing factors. PCA simplifies analysis by transforming a large set of variables into principal components, which are linear combinations of the original variables. This reduction allows for easier visualization and interpretation of complex datasets, helps remove noise, and enhances the efficiency and accuracy of machine learning algorithms by reducing the risk of overfitting. The process begins with data standardization, ensuring each variable has a mean of zero and a standard deviation of one. Then, the covariance matrix is calculated to understand how variables relate. Eigenvalues and eigenvectors of the covariance matrix are found, with the eigenvectors corresponding to the highest eigenvalues identified as the principal components. A feature vector is constructed to form a new dataset based on these principal components, transforming the original dataset into a new feature space. In this study, PCA identified the key factors influencing the e-learning preparedness and experiences of Malaysian frontline students during COVID-19 by reducing the number of variables while preserving data variability. The principal components captured the most significant patterns in the data. The PCA and scree plots (Fig. 4) show the eigenvalues associated with each principal component, with a steep decline indicating that the first few components capture most of the dataset's variance. This helps determine the number of principal components to retain for further analysis, focusing on those that explain the majority of the variance.

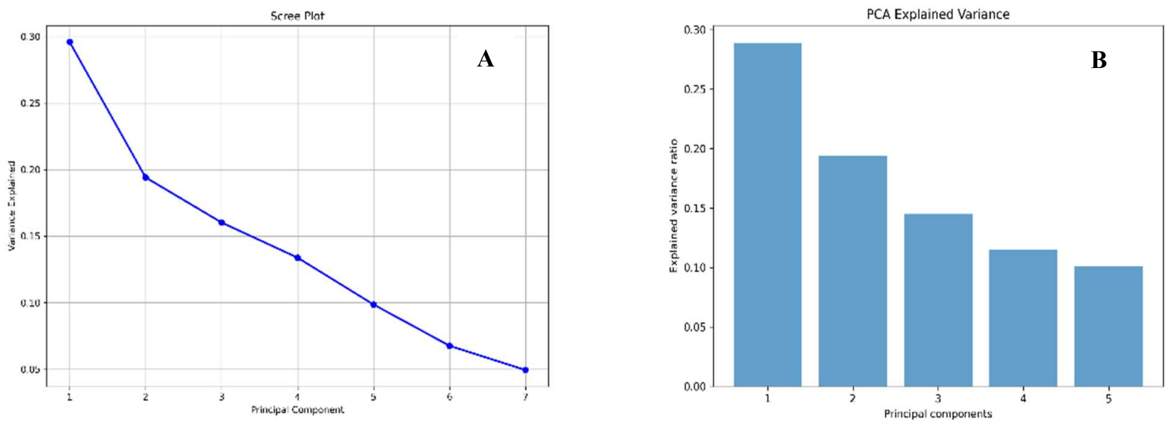


***Fig 4. Scree plot (A) and PCA (B). The scree plot displays the eigenvalues associated with each principal component. PCA plot is the selection of the first 5 PCs.***

Table 3 shows the loadings for each variable on the principal components. These loadings represent the correlation between the original variables and the principal components, indicating how much each variable contributes to the principal components.

***Table 3. Loadings for each variable on the Principal Components (PC).***

| Theme | PC 1 | PC 2 | PC 3 | PC 4 | PC 5 |
|---|---|---|---|---|---|
| Constraints on work, unpredictable schedules | 0.151541 | -0.712454 | -0.400477 | -0.385138 | 0.142011 |
| Difficulty focusing due to disruptions from children | 0.589954 | -0.178082 | -0.251174 | 0.565790 | 0.473725 |
| Not being familiar with the scheduled learning topics | 0.682353 | 0.356165 | 0.023138 | 0.060465 | -0.297318 |
| Feeling the importance of recorded Webex sessions | 0.733723 | 0.381640 | 0.063727 | -0.097569 | 0.055442 |
| Often forget the date and time of scheduled Webex sessions | 0.715409 | -0.067390 | -0.169834 | -0.418212 | -0.099354 |
| Internet access issues | 0.284263 | -0.683520 | 0.207151 | 0.342904 | -0.512545 |
| Disturbance from noise made by other students | 0.246329 | -0.274067 | 0.848209 | -0.176099 | 0.316557 |

The results of the study reveal a detailed understanding of the challenges faced by Malaysian frontline students in e-learning during the COVID-19 pandemic, captured through PCA. The analysis identified five principal components, each representing distinct aspects of the e-learning experience.

- Principal Component 1 (PC1) is characterised by high positive loadings on factors such as lack of familiarity with scheduled learning topics, the perceived importance of recorded Webex sessions, and frequent forgetting of session dates and times. This component highlights issues related to scheduling and understanding course material. Students who struggle with remembering session timings and who feel that recorded sessions are essential likely face difficulties in keeping pace with the course schedule.

- Principal Component 2 (PC2) reflects high negative loadings on constraints related to work schedules, unpredictability, and internet access issues. This component addresses the logistical and technical challenges that students encounter. Those with erratic work schedules and poor internet connectivity experience significant disruptions in their e-learning process, suggesting a need for enhanced technical and logistical support.

- Principal Component 3 (PC3) has a high positive loading on disturbances from noise made by other students. This component highlights environmental challenges, particularly noise in shared or public spaces, which impacts the learning experience. It underscores the necessity of creating a conducive learning environment to facilitate effective e-learning.

- Principal Component 4 (PC4) is associated with difficulty focusing due to disruptions from children. This component reflects challenges related to personal life and home environment, specifically the impact of children on study concentration. It suggests that students need support in managing home responsibilities alongside their educational commitments.

- Principal Component 5 (PC5) displays mixed loadings on both internet access issues and noise disturbances. This component indicates a combination of technical and environmental challenges affecting e-learning, pointing to the need to address both internet connectivity and noise-related issues.

The study highlights critical areas where educational institutions can improve e-learning effectiveness and ensure equitable opportunities for all students. By addressing issues such as internet access, financial support, and environmental challenges, and by enhancing interactive elements in online courses, institutions can better support students' academic pursuits during challenging times. Furthermore, the study revealed that older, married students between the ages of 31 and 40 face significant challenges balancing family and academic responsibilities, underscoring the need for tailored financial aid and flexible academic policies. Financial strain, particularly for those affected by the pandemic, exacerbates participation difficulties in e-learning. Reliable internet access remains a major concern, particularly for students from lower socio-economic backgrounds or rural areas. The study highlights the importance of addressing digital inequality through improved infrastructure and financial support for internet costs. Environmental factors, such as lack of private study spaces and distractions at home, also emerged as significant barriers.

Additionally, issues with engagement and communication in virtual education were noted. The study recommends providing recorded sessions for flexible learning, incorporating interactive elements like polls and real-time feedback, and enhancing support systems for assessments and practical work. Psychological impacts, such as increased anxiety and stress, were significant, indicating a need for robust support networks and mental health services. Addressing the digital divide, improving home learning environments, and supporting students' mental health are crucial for effective e-learning. These findings have important policy implications for education, particularly in the context of crises.

### 3.5.1. Exploratory Factor Analysis Using Principal Component Analysis

To validate the structure of e-learning challenges identified in the quantitative survey data, an EFA using the PCA method was performed. This statistical technique aimed to identify underlying dimensions that summarize and explain correlations among observed variables, thereby providing a clearer understanding of the latent factors influencing students’ preparedness for online learning.

Data Adequacy and Test of Factorability: Before factor extraction, data suitability was assessed through standard statistical tests. The KMO measure of sampling adequacy yielded a value of 0.81, which is well above the minimum acceptable threshold of 0.60 (Kaiser, 1974), indicating that the dataset was appropriate for factor analysis. Additionally, Bartlett's Test of Sphericity produced a statistically significant result ($\chi^2 = 382.14$, df = 21, $p < 0.001$), confirming that correlations among the items were sufficient to justify the use of PCA. These results collectively affirmed the robustness and suitability of the data for dimensional reduction.

Variable Selection and Extraction Process: Seven key survey variables were included in the PCA based on both conceptual relevance and empirical evidence from prior studies and the qualitative phase. These variables represented critical aspects of e-learning challenges: (1) unpredictable work schedules, (2) difficulty concentrating due to distractions at home, (3) lack of familiarity with learning topics, (4) the importance of recorded sessions, (5) forgetting session times, (6) internet connectivity issues, and (7) noise disturbances (Table 4). The PCA employed a Varimax rotation technique to optimize factor interpretability by maximizing the variance of factor loadings across variables. Components with eigenvalues greater than 1.0 were retained, following the Kaiser criterion, ensuring that each factor explained a significant portion of total variance. A scree plot further supported the extraction of five meaningful components, which collectively accounted for 76.3% of the total variance. These components represented distinct dimensions of e-learning challenges, including technological barriers, time management issues, environmental distractions, and cognitive preparedness, forming a solid statistical foundation for subsequent analysis and interpretation.

***Table 4. Rotated Component Matrix.***

| Theme | PC 1 | PC 2 | PC 3 | PC 4 | PC 5 |
|---|---|---|---|---|---|
| Lack of familiarity with learning topics | 0.72 | 0.18 | 0.10 | 0.04 | -0.12 |
| Importance of recorded sessions | 0.76 | 0.31 | 0.05 | -0.09 | 0.07 |
| Forgetting session times | 0.70 | -0.12 | -0.19 | -0.36 | -0.04 |
| Work schedule conflicts | 0.15 | -0.69 | -0.39 | -0.30 | 0.16 |
| Internet connectivity issues | 0.27 | -0.71 | 0.20 | 0.33 | -0.49 |
| Noise from environment | 0.25 | -0.27 | 0.82 | -0.15 | 0.29 |
| Distractions from children | 0.59 | -0.18 | -0.24 | 0.57 | 0.45 |

## 4. Discussion

The findings of this study provide strong empirical support for the proposed KPR theoretical framework, demonstrating how cognitive, behavioral, and contextual dimensions interact to shape e-learning preparedness among Malaysian frontline students during the COVID-19 pandemic. Both the PCA and thematic analysis reveal a consistent pattern: deficiencies in digital knowledge and technological proficiency significantly constrain students' ability to engage in effective e-learning practices. The qualitative themes directly reinforced and contextualized the quantitative PCA structure. For example, the qualitative theme of "internet connectivity issues" strongly supported the PCA components associated with technical and logistical barriers, while the theme of "home and environmental disruptions" explained the high loadings related to noise disturbances and childcare-related distractions.

Similarly, narratives describing fatigue after frontline work shifts provided contextual depth for the quantitative component representing work-schedule conflicts. This explicit convergence between thematic evidence and PCA dimensions strengthens the study's mixed-methods inference by demonstrating how lived experiences explain the statistical structure of e-learning barriers. Limited familiarity with online learning platforms, inadequate exposure to digital tools, and challenges in accessing course materials reduced students' capacity to manage their study time efficiently, complete assignments, and sustain active participation. Consequently, these practical limitations diminished overall readiness to learn in virtual environments, confirming the interdependence between the framework's three domains. Personal and environmental disruptions emerged as critical moderating variables that further weakened the link between Practice and Readiness. Issues such as poor internet connectivity, household distractions, and competing professional responsibilities disrupted concentration and reduced engagement. These findings underscore the framework's assumption that e-learning readiness is not merely an individual attribute but a complex construct influenced by external circumstances. The interaction of cognitive knowledge, applied behavior, and contextual constraints illustrates that preparedness cannot be achieved through skill development alone it must be supported by enabling conditions that facilitate consistent access, focus, and motivation.

The statistical and thematic findings collectively indicate that technological barriers, environmental disruptions, and occupational fatigue are not isolated issues but interconnected factors shaping e-learning preparedness. These results suggest that institutional interventions should focus on flexible scheduling, digital infrastructure support, and psychosocial assistance to improve learning continuity among frontline students.

By integrating quantitative and qualitative evidence, this study refines theoretical understanding of e-learning preparedness in crisis contexts. The mixed-methods approach validates the K–P–R model's applicability, showing that effective online learning readiness involves a dynamic equilibrium between knowledge acquisition, behavioral adaptation, and environmental stability. For frontline students, whose dual roles in professional service and higher education amplify stress and fatigue, this balance is particularly fragile. Therefore, interventions must address not only technical literacy but also socio-emotional resilience and environmental support to promote sustained digital learning engagement. Beyond its immediate context, the study's implications extend to broader educational systems in developing regions. The challenges identified such as unstable digital infrastructure, limited institutional support, and high psychosocial stress reflect systemic vulnerabilities that hinder the scalability of online education. The COVID-19 experience revealed that digital inequities persist even among highly motivated learners, emphasizing the need for long-term structural reforms. Educational institutions should prioritize investment in stable internet infrastructure, user-friendly learning management systems, and digital literacy training for both students and educators.

Moreover, policies promoting hybrid and flexible learning can mitigate the tension between professional obligations and academic participation, particularly for working and frontline learners. Mental health support programs, time management workshops, and peer mentoring can further strengthen readiness and retention in online learning environments. Collectively, these measures advance institutional resilience and contribute to a sustainable educational transformation. Thus, the insights from this research not only validate the theoretical framework but also inform strategic directions for building adaptive, inclusive, and crisis-resilient education systems capable of enduring future disruptions.

## 5. Conclusion

This study synthesizes the multidimensional challenges affecting Malaysian frontline postgraduate students' e-learning preparedness during the COVID-19 pandemic through the lens of the KPR framework. The findings confirm that knowledge-related digital literacy, practice-oriented behavioral adaptation, and readiness shaped by psychosocial and environmental resilience are deeply interconnected.

Theoretically, the study strengthens the KPR framework by demonstrating how technological, occupational, and emotional dimensions jointly influence digital learning continuity. Practically, the results highlight the need for flexible scheduling systems, strengthened digital infrastructure, mental health support, and inclusive instructional design for working adult learners. From a policy perspective, the study underscores the importance of crisis-responsive higher education systems that promote digital equity, institutional resilience, and sustainable online learning ecosystems beyond pandemic conditions.

Despite its valuable contributions, the study has several limitations. The research sample was limited to postgraduate students enrolled in master's Geography programs at USM, which may restrict the generalizability of the findings to other disciplines and broader undergraduate populations. Additionally, although the mixed-methods approach enhanced the richness and validity of the analysis, reliance on self-reported survey and interview data may have introduced response bias or social desirability effects. Contextual factors, such as differences in socio-economic status, living arrangements, and internet access, may also have influenced responses. Moreover, the study's data were collected during a specific phase of the pandemic, reflecting temporary conditions that may not represent long-term developments in post-pandemic e-learning practices. Future research should address these limitations by broadening the sample across multiple universities, employing longitudinal designs, and integrating comparative approaches to explore evolving patterns in e-learning preparedness and adaptation.

## References

Abbas, F., Zhang, F., Iqbal, J., Abbas, F., Alrefaei, A. F., & Albeshr, M. (2023). Assessing the Dimensionality Reduction of the Geospatial Dataset Using Principal Component Analysis (PCA) and Its Impact on the Accuracy and Performance of Ensembled and Non-ensembled Algorithms. https://doi.org/10.20944/preprints202307.0529.v1

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Creswell, J. W., & Poth, C. N. (2018). Qualitative Inquiry and Research Design: Choosing Among Five Approaches (4th ed.). Sage Publications.

Dereso, C. W., Omprakash, H. M., Chandra, K. R., Alam, J., Rani, K. M., & Nagalakshmi, V. (2021). Education beyond covid-19–the world academic coalition. Annals of the romanian society for cell biology, 2062-2076. (Retrieved from http://annalsofrscb.ro/index.php/journal/article/view/1151)

Field, A. (2018). Discovering Statistics Using IBM SPSS Statistics (5th ed.). Sage Publications.

Greenhow, C., & Chapman, A. (2020). Learning to adapt to a new reality: Student and teacher attitudes toward online education after COVID-19. Educational Researcher, 49(7), 432-441.

Lee, K., Choi, H., & Kim, J. (2020). *The Impact of COVID-19 on Student Experiences and Expectations: Evidence from a Survey*. Journal of Higher Education Policy and Management, 42(3), 320-338. https://doi.org/10.1016/j.jpubeco.2020.104271

Mohammed, S., Tilahun, B., & Deressa, W. (2021). *Mental health impacts among students due to the COVID-19 pandemic in Ethiopia: A cross-sectional study*. PLOS ONE, 16(9), e0256415.

Nguyen, T., Nguyen, T. D., & Lai, Q. (2021). Challenges to the network infrastructure of developing countries amid the COVID-19 transition to online learning. Journal of Network and Computer Applications, 174, 102917.

Novak, M., Šlibar, B., Kermek, D., & Begičević, N. (2020). Evaluation of factor analysis methods: Student feedback case study. In INTED2020 Proceedings (pp. 8208-8216). IATED. https://doi.org/10.21125/inted.2020.2241

OECD. (2020). The impact of COVID-19 on education: Insights from Education at a Glance 2020. OECD. https://doi.org/10.1787/69096873-en.

Smith, J., & Kumar, P. (2021). Digital divide: Impact on student engagement and learning in the age of COVID-19. Journal of Educational Technology Systems, 49(3), 414-435. https://doi.org/10.17576/JEM-2021-5503-07

Tabachnick, B. G., & Fidell, L. S. (2019). Using Multivariate Statistics (7th ed.). Pearson.

UNESCO. (2020). *Education: From disruption to recovery*. (Retrieved from https://en.unesco.org/covid19/educationresponse)

World Bank. (2021). *The COVID-19 Pandemic: Shocks to Education and Policy Responses*. (Retrieved from https://www.worldbank.org/en/topic/education/publication/the-covid-19-pandemic-shocks-to-education-and-policy-responses)