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Analyzing Learning Persistence Determinants in Virtual Learning Environments Using Mixed Methodology

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Abstract **– This research analyzes the impact of various factors and their relatable aspects, such as contextual (academic), external (environmental), and internal (personal) of students' learning persistence in virtual environments as critical aspects of online learning advancement and academic success. Utilizing a mixed methodology approach that combines qualitative and quantitative methods, this study leverages an educational dataset from Harvard and MIT, employing a multinomial logistic regression (MLR) model to detect the correlation among diverse learning factors and online persistence classes with the triple class label (positive persistence, negative persistence, and absence of persistence). The classification accuracy achieved in the MLR model reached 96%. Supporting evidence from online surveys and expert interviews further underscores the combined influence of academic, demographic, and environmental factors on learning persistence. The quantitative analysis highlights the significant influence of contextual factors, particularly achievements and activities, on learning persistence, while internal factors like gender and birth year have minimal impact. Qualitative analysis reveals a mix of internal, external, and contextual factors affecting persistence, including academic support, peer communication, and family support. Expert interviews confirm the importance of multidimensional features and highlight challenges ranging from technological access to varied learning styles. Suggestions for enhancing persistence include implementing supportive online tools and intelligent tutoring systems.**

This research's contribution lies in its holistic examination of online persistence-influencing factors through a mixed methodology lens, facilitating the identification of learning persistence; it aims to enhance support mechanisms for students in virtual learning environments, potentially improving educational outcomes and online learning experience. This innovative approach underscores the importance of understanding and addressing the various influencers of learning persistence to foster more successful outcomes in digital education contexts.

Keywords **– Learning persistence, virtual learning environments, mixed methodology approach, digital education contexts.**

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1. Introduction

Students in virtual learning environments (VLEs) exhibit diverse learning patterns that transcend time and space constraints, thus enabling them to pursue subjects at their own pace [1]. VLEs have gained tremendous popularity in recent years, with educational institutions worldwide adopting various e-learning platforms to deliver content and ensure uninterrupted learning amidst recent and unforeseen challenges [2].

Education is a multifaceted process that varies from one student to another, particularly in VLEs where spatial barriers exist between students and teachers. The design aspects of these educational environments, such as content complexity and exam difficulty, will significantly affect students' outcomes [3].

Integrating technology, mainly through interactive platforms such as social media, enhances the online learning experience. This shift aligns with the modern lifestyles of students, thus illustrating the meaningful harnessing of social media in higher education and its potential impact on academic success [4].

Active learning approaches empower students to connect their studies with real-life experiences, igniting motivation and engagement. The engagement extends to personality development and essential life skills such as communication, problem-solving, self-motivation, decision-making, and time management [5].

Considering this changing landscape, teachers are increasingly called upon to employ creativity and innovation. Especially in delivering knowledge through online learning; digital game-based learning emerges as a valuable tool for enhancing motivation among trainee teachers and making the online learning process more effective [6].

The demands of remote learning show that gamification influences motivation, classroom dynamics, and student engagement, highlighting the transformative impact of gamification on the psychology classroom and creating an enriched learning environment [7]. Although VLEs accommodate diverse learning patterns among students, they often provide the exact content to all types of learners, disregarding individual knowledge levels, learning styles, and preferences [8]. This practice highlights the significant impact of instructor presence on students' persistence and emotions in online learning settings [9].

The increasing complexity of current teaching proved that academic knowledge alone is no longer sufficient. In a constantly evolving society, multidimensional factors, including adaptability and innovative models such as Addie, are essential for designing practical blended learning applications, even in vocational colleges in Malaysia [10].

A factor is defined as a more general or broad element that influence outcomes in various contexts. Features are specific characteristics or aspects that describe or elaborate on the factor, providing more detail about how the factor manifests or operates [11]. In the context of the factors in the educational sector, diverse factors can affect students' online learning outcomes. For instance, the diverse insights and the conceptual framework recognize that understanding student learning in online environments requires an exploration of both internal and external factors [12], [13].

Internal factors, or the learners' characteristics, include students' innate qualities and attitudes, such as their engagement styles with learning tools, their existing knowledge base, and their level of motivation. These aspects significantly influence how students approach and interact with course materials and activities [12], [13].

Contextual factors, on the other hand, define specifically the broader learning environment. These encompass the course's mode of delivery, the course contents, the technology used for instruction, and the instructional strategies employed. The elements collectively shape the educational experience and outcomes for students in online learning settings [12], [13].

By synthesizing the above perspectives, it is evident that a nuanced understanding of the interplay between internal learner characteristics and the contextual learning environment is essential for the effective design and delivery of online education. This approach highlights the need to address the diverse needs and backgrounds of students while optimizing the structural components of online courses to enhance learning outcomes and student performance [12], [13].

External factors are essential factors affecting online learning. It was defined as the influences outside of classroom activities, such as family dynamics, internet accessibility and its associated costs, and broader environmental conditions [14], [15]. External factors include environmental and demographical aspects, which extend to financial challenges. Such external variables significantly impact students' ability to persist while learning online [14], [15]. On the other hand, students' negative emotions, such as stress, were valuable in measuring a combination of efforts and interests in online education settings [16].

Anxiety was also related to students' self-efficacy in measuring learning persistence [17]. Students' motivation, academic performance, and attitude can be positively adjusted when intelligent software is available to help students facing difficulties when seeking help [18].

Students' grades and overall achievements can be affected by contextual interactions such as several student communications by posts and replies [19]. On the other hand, students' demographics such as gender prior-knowledge level, can reveal how learning performance is improved [20].

Previous studies conducted in digital learning environments have examined learners' challenges. Among these difficulties are technical issues, the absence of a supportive community, motivational obstacles, struggles with self-regulation, concerns regarding self-efficacy, social anxiety [21], disengagement, and negative persistence patterns [22].

1.1. Students Learning Persistence in Online Learning

Investigating learning behaviours, engagement, and persistence has become the core of many academic studies that focus on integrating students' achievements with factors that affect online learning outcomes by seeking adequately defined features that significantly improve student success [23]. The online learning management systems can be utilized to extract academic datasets as contextual factors to investigate course perception according to students' activities and outcomes [24].

Other studies focus on social and behavioural factors and their importance in increasing cognitive engagement in online learning environments [25]. One deeply studied behavioural factor was online learning persistence, defined as working hard to reach academic goals despite many challenges. Learning persistence is an essential part of life's success [26]. It is also viewed as the determination of the learners to complete the learning process and overcome obstacles to achieve academic success [27]. Students learning persistence in VLEs appears to be an essential learning construct that helps students succeed when learning new materials [28], [29].

Table 1 shows the classes of online learning persistence according to the most related studies and the definition of each class. It is noticeable that these definitions came from the contextual factors (academic achievements) and internal factors (students' behaviours).

Table 1. Definition of online learning persistence classes according to the most related literature

Persistence Class	**Definition**
Positive persistence [26], [27], [28]	The student scored a grade equal to or greater than the passing rate and earned a certificate at the end of the course (if any).
Negative persistence [26], [27], [30]	The student who scored a grade less than the passing rate grade did not earn a certificate, but the behaviours of that student show signs of engagement.
No persistence [27]	The student scored a grade less than the passing rate grade, did not earn a certificate, and the behaviour showed no signs of engagement.

1.2. Factors Affecting Online Learning Persistence

Different factors affecting students' learning and various techniques used to find the features that affect online learning persistence were studied. Previous investigations proved that online persistence plays an essential role in student academic outcomes and students' achievements [31], [32], [33], [34].

The investigations have indicated that various factors, which may be related to the course content and the technology used, potentially affect the steadiness of students' persistence. It may also be directly related to the student's cultural and behavioural aspects [35], [36].

Table 2 shows the factors and related features that influence learners' decision to persist according to the works of literature explained earlier.

Table 2. Online learning factors and related features affecting online persistence

Factor	**Features**
Internal [37],[38], [39],[40], [41],[42], [43]	Students' skills include previous knowledge and experiences, aspirations, time management skills, learning styles, personal attributes, and technological expertise. Students interact from the perspective of academic emotions and attitudes such as enjoyment, anxiety, and boredom.
Contextual [14], [20] [44], [48] [49], [50]	Course-related issues include course design, course difficulty, and course time. Institutional facilities include faculty support, teachers' presence, facilitating conditions, and academic feedback. Students' self-efficacy, task value, and achievements.
External [30],[44], [45],[46], [47], [48]	Students' characteristics and demographics include gender, age, family and work responsibilities, other commitments, maternal educational level, and social interactions.

The organization of this paper is as follows: section 22 outlines the data samples and research methodology, section 3 shows the results, section 4 illustrates the discussion, and section 5 highlights the conclusion.

2. Data Samples and Methodology

This section provides a comprehensive overview of the data samples and the mixed-methods approach utilized in this research. It outlines the quantitative dataset sourced from the edX learning platform, including the selected attributes that inform the analysis of online learning persistence. Additionally, it details the qualitative components, such as expert interviews and student surveys, designed to enrich the findings. Together, these methodologies create a robust framework for exploring the factors influencing student persistence in online learning environments.

2.1. Data Samples

The quantitative approach comprised a total of (N=16,425) records; it is extracted from the edX learning platform [51]. The original data has five courses from both Harvard and MIT institutes with (N=20) attributes as follows: course id, user id, registered, viewed, explored, certified, country, level of education, year of birth, gender, grade, start time, last event, number of events, number of active days, number of played videos, number of completed chapters, number of forum posts, roles of staff and instructors, flag of inconsistent records.

In this research, only (N=10) attributes were utilized regarding their relevance to the proposed work such as: grade, certified, number of chapters explored, number of events, number of active days, number of videos, number of forum posts, gender and year of birth. Other attributes were removed due to their minimal relevance and lack of contribution to the study's objectives.

75% of the data were used for training the model, while the remaining 25% were reserved for testing. In defining the class labels, learning persistence was classified as (positive, negative, and no persistence) as illustrated in Table 1.

On the qualitative front, the suggested approach consists of two distinct components. First, in-depth interviews were conducted with five esteemed experts selected based on their extensive experience and background in online education. These experts' detailed profiles are in Appendix A, and interview questions are in Appendix B.

Second, an online survey targeting higher education students was conducted to collect responses from (N=30) participants. The participants' characteristics are outlined in Appendix C, offering a comprehensive understanding of the demographic landscape and ensuring transparency in the qualitative methodology.

2.2. Research Methodology

This research employed a mixed methodology approach to provide a robust framework for delving into the various factors that affect online learning persistence, offering valuable insights into student motivation and success. The proposed mixed methodology is structured into three distinct phases: Phase (1) Data Collection and Classification, Phase (2) Innovation and Model Development, and Phase (3) Validation.

Each phase incorporates a blend of qualitative and quantitative. Furthermore, the outputs from each phase seamlessly transition into an input to the other, fostering cohesive and rigorous research development.

2.2.1. Phase (1) Data Collection and Classification

A. Quantitative Approach:

Input: Collecting the most related factors impacting learning persistence from previous works of literature.
Activities: Exploring an educational dataset, classifying online learning factors into internal (self-related), external (environmental), and contextual (course-related), classifying persistence into (Negative, Positive, and Absence).
Outcomes: Defining each persistence class and each learning factor's characteristics and features.

B. Qualitative Approach:

Input: Collecting insights from experts and higher education students.
Activities: Preliminary study including designing the experts' interview questions, aims, and the online survey setting.
Outcomes: Identification of impactful learning factors and their characteristics regarding learning persistence.

2.2.2. Phase (2) Dataset Analysis and Model Development

A. Quantitative Approach:

Input: Extract the knowledge from the factors related to persistence.
Activities: Pre-process dataset of (16,425) samples, selecting (10) attributes for the analysis and excluding the rest, splitting the data into training (75%) and testing (25%), employ multinomial logistic regression (MLR) algorithm to illustrate persistence classifications and correlate them with student factors and their related features.
Outcomes: Correlations results among learning persistence class label and internal, external, and contextual factors.

B. Qualitative Approach:

This part involves qualitative methods to complement the quantitative analysis.
Input: Students' and experts' insights Analysis.
Activities: Conduct in-depth interviews with five online learning experts and a survey of 30 international postgraduate students.
Outcomes: Interview and survey analysis results of the responses using a five-point Likert scale, determining average survey scores and validating them with experts' outcomes.

2.2.3. Phase (3) Validation

A. Quantitative Approach:

Input: Findings from the innovation phase to affirm the impact of identified factors (internal, external, contextual) on learning persistence.
Activities: Classification report using confusion matrix to validate the correlation outputs, confirming the role of internal, external, and contextual factors in influencing online learning persistence, ensuring consistency with prior studies' current quantitative results, and qualitatively highlighting their importance.
Outcomes: Confirm the findings derived from the quantitative analysis and their alignment with prior research and the results of the conducted (MLR) model.

B. Qualitative Approach:

Input: Collecting and validating the online survey outcomes with experts' contributions.
Activities: Confirm the findings derived from the surveys and interviews.
Outcomes: Validation of the quantitative analysis findings and assurance of validity through experts and students.

3. Results

The results section presents findings derived from quantitative and qualitative approaches to examine factors influencing students' persistence in online learning environments. The quantitative approach involved using an educational dataset from edX to classify persistence into three categories: no persistence, negative persistence, and positive persistence, which were analyzed using a multinomial logistic regression (MLR) model. This approach highlights external and contextual factors related to online learning outcomes. The qualitative approach complements the quantitative analysis by exploring internal factors through Students' online surveys and experts' interviews, offering a deeper understanding of the challenges and features impacting students' learning persistence. Both approaches provide a comprehensive view of the influences on students' engagement, challenges, and persistence in the online learning context.

3.1. Quantitative Approach Results

From the obtained dataset, students' profiles have been defined regarding each dataset attribute; each definition represents a specific aspect of students' outcomes, intent, or engagement in the online learning setting along with persistence, which is classified into three classes as defined previously in Table 1. Persistence classes were given a code-based representation in the conducted (MLR) model as follows: (0: no persistence, 1: negative persistence, and 2: positive persistence).

The quantitative approach dataset only provides contextual and limited external factors related to online learning persistence. Hence, the absence of internal factors will be covered later in the qualitative approach. The correlation results are illustrated in Table 3.

Table 3. Quantitative dataset correlation results

Factor	Dataset Attribute	Correlation Score
Contextual	Grade	0.960732
	Certified	0.791441
	Number of chapters	0.842195
	Explored	0.801222
	Number of events	0.736942
	Number of active days	0.760852
	Number of videos	0.438177
	Number of forum posts	0.083884
External	Gender	0.014318
	Year of birth	0.007261

The contextual factors encapsulate academic achievements, delineating the relationship between academic performance and persistence. On the other hand, the external factors encapsulate students' demographics.

The correlation scores show that academic achievements, such as grades and certification, exhibited strong positive correlations with persistence. Active engagement metrics, including the number of chapters explored, active days, and event participation, also showed significant positive associations with persistence.

However, specific engagement metrics like video consumption and forum activity demonstrated weaker correlations with persistence. Demographic factors, such as gender and birth year, displayed minimal correlations with persistence.

The employed model underwent testing using a confusion matrix, where out of (16,425) instances, the overall accuracy stands at (96%); the confusion matrix results are illustrated in Table 4.

Table 4. Confusion matrix results

Class	Precision	Recall	F1-Score	Support
0	1	0.97	0.98	3194
1	0.73	0.96	0.83	365
2	1	0.96	0.98	547

3.2. Qualitative Approach Results

The qualitative method contained two parts (Expert interview with N=5 and student online survey with N=30); in the following sections, students' survey results will be illustrated, and then interviews with experts' results will be viewed.

3.2.1. Students' Surveys Results

The survey consisted of four main questions, each with sub-questions to capture participants' opinions in detail, focusing on (internal, external, and contextual) factors. Table 5 shows the students' survey results, presenting the calculated mean for each question.

Table 5: Students' online survey results

Question	Feature	Score
Do you agree that the absence or the lack of one or all of these features may affect your online learning journey?	Funding	3
	Family Support	4.5
	Academic Support	4
	Communications with peers	4.5
	Computer skills	3.5
	Time management skills	3.5
	Background knowledge	5
Do you agree that these features directly influence your online learning achievements?	Course Design	4
	Teaching Style	4
	Student Responsibilities	4
	Student Commitment	4.5
	Student Motivation	3.5
	Student Engagement	4.5
	Student Self-esteem	4.5
	Student Interest	4
	Relationships with peers	4.5
Do you agree that these emotions can distress your learning persistence in an online learning course?	Feel of Isolation	4.5
	Feel of Disengagement	4.5
	Feel of Boredom	4.5
Do you agree that the presence of these features can help you develop a positive persistence behaviour?	Online Forums	4.5
	Instructor's Support	4.5
	Clarity of the Online Learning Program (Course Aims/Goals)	4
	Availability of Academic Services	5
	Ease of Access to the Academic Resources	4.5
	Diversity of the Educational Content	4.5
	Persistence Prediction model	5

3.2.2 Experts' Interviews Results

The expert interviews aim to validate factors and their related features investigated in previous works of literature regarding online persistence. These interviews offer valuable insights into challenges faced by students in online learning environments, as perceived by experts. They also validate quantitative findings on significant factors impacting learning persistence and engagement, contributing further to the quantitative outcomes. Appendix B contains interview questions addressing various factors affecting online learning persistence. Tables 6 and 9 show each part of the experts' interview answers.

Table 6. Experts' agreement and disagreement regarding internal, external, and contextual factors affecting learning persistence

Expert Number	Result
1, 2, 3, 4, and 5	All experts unanimously agree that internal, external, and contextual factors and their related features significantly affect learning persistence.

Table 7. Experts' point of view regarding the challenges affecting online learning persistence and their related influencers

Expert Number	Result	
	Online Learning Challenges	Related Influencers
1	Not every student has access to the internet and electronic devices.	Lack of commitment, collaboration, and involvement.
2	No direct interaction with the teacher.	Absence of instructor support and students' feeling of isolation.
3	Easily distracted in online learning environments.	Students' self-discipline and personal skills.
4	Lack of interaction with peers.	Students' commitments and intent to achieve academic goals.
5	Different learning styles make assessment challenging.	Different environmental and cultural values are extracted from various demographical aspects affecting learning styles.

Table 8. Experts' point of view regarding the requirements for an effective online learning environment

Expert Number	Result
1	Peer collaboration with an interactive learning environment
2	Intelligent learning environment that detects early academic achievements
3	Flexible content design with the feedback system
4	Instructors' presence and guidance
5	Interactive e-content design and ease of content delivery

Table 9. Experts' suggestions for enhancing learning persistence

Expert Number	Result
1	Supportive online tools and collaborative features.
2	Accessible and approachable online academic services.
3	Learning persistence detection tools to help struggling students.
4	An intelligent tutoring system is embedded within the online learning environment.
5	Increase students' academic engagement and commitment via all the suggestions mentioned above.

4. Discussion

The quantitative analysis conducted in Table 3 (Quantitative dataset correlation results) revealed that contextual factors, particularly achievements and activities, are the most influential contributors to learning persistence. Within this category, attributes such as grades, certificates, course exploration, the number of viewed chapters, and forum posts emerged as the highest contributors. Additionally, factors like the number of active days and events closely follow. Conversely, external factors related to students' demographics, such as gender and year of birth, were found to have minimal impact on persistence in online learning environments.

In parallel, the qualitative analysis results from Table 5 (Students' online survey results) exposed a mix of internal, external, and contextual factors influencing student persistence in online learning environments.

Key factors contributing to persistence include academic support, communication with peers, family support, background knowledge, student commitment, student engagement, student self-esteem, relationships with peers, availability of educational services, and the possibility of advanced tools such as the online learning persistence prediction model.

Equally, reasonable factors related to online persistence from the student's point of view have encompassed course design, teaching style, student responsibilities, feelings of isolation, disengagement, boredom, online forums, instructor support, and clarity of the online learning program.

Finally, factors with the lowest impact on online persistence are funding, computer skills, time management skills, student motivation, and student interest.

Experts' interviews, discussed in Table 6 (Experts' agreement and disagreement regarding internal, external, and contextual factors affecting learning persistence), confirm the significance of multidimensional features in influencing persistence in virtual learning environments (VLEs).

Furthermore, expert insights from Table 7 (Experts' point of view regarding the challenges affecting online learning persistence and their related factors) highlight challenges ranging from technological access issues to varied learning styles, emphasizing the need for adaptive and inclusive VLE designs.

In Table 8 (Experts' point of view regarding the requirements for effective online learning settings), experts underscore the importance of interactivity, intelligent design, flexibility, instructor presence, and content delivery methods for effective online learning environments.

Lastly, Table 9 (Experts' suggestions for enhancing learning persistence) outlines suggestions such as supportive online tools, accessible academic services, learning persistence detection systems, intelligent tutoring, and enhancing students' management skills and commitment.

Integrating these findings into the design and implementation of online learning programs is crucial for fostering positive student persistence and enhancing the effectiveness of VLEs.

Prioritizing interactivity, flexibility, personalized support, and student engagement can create conducive online learning environments that promote sustained learning and academic success.

Moreover, considering various features like cultural backgrounds, emotions, motivation, and skills is essential for understanding and enhancing student persistence in VLEs. Effective course design, social interaction, and self-directed learning play critical roles in maintaining student engagement and positive persistence, given the various nature of academic, cultural, and personal factors impacting online learning outcomes.

5. Conclusion

In conclusion, this research has significantly advanced our understanding of student persistence in virtual learning environments (VLEs). A mixed methodology approach has generated a comprehensive and validated outcome that elucidates the complex dynamics of factors influencing student persistence in online learning.

An essential contribution is the introduction of comprehensive overall factors and their related features, which integrate internal, external, and contextual factors, providing a holistic perspective on student learning experiences in online settings.

Moreover, the research has successfully demonstrated the association between multidimensional factors and established persistence class labels using a multinomial logistic regression model (MLR); the extracted correlation scores verified the importance of the educational dataset in extracting the related results to online learning persistence, but it lacks students' opinions and experts visions on how other factors such as internal factors also have a pivotal role in advancing positive learning behaviour when learning remotely. Therefore, the statistical validation and the qualitative approach establish a robust framework for the model's applicability across various educational and non-educational factors.

Additionally, the qualitative data obtained from online surveys and interviews reinforces the significance of the study, highlighting the complex relationship among internal, external, and contextual factors affecting learning persistence. These qualitative insights complement and enrich the quantitative analysis, offering a more nuanced understanding of the factors influencing students' learning persistence.

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Data Availability

The qualitative dataset presented in this research is available upon request from the corresponding author. The data are not publicly available due to privacy regulations. On the other hand, the quantitative dataset is available online at the open source from the following link: https://dataverse.harvard.edu/dataverse/mxhx.

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Appendices

Appendix-A expert biography

Expert Number	Biography
1	Expert 1 is an Associate Professor and a Strategic Informatics Research Group member at University Kebangsaan Malaysia. His research interests include Human-Computer Interaction, E-Learning Technology, Quality Models and Impact Study & Strategic Planning for Information Systems. He has led several funded research projects and published numerous academic publications. Besides that, he is also keen on quality assurance for academic programmers.
2	Expert 2 is a Post-Doctoral Researcher Software Technology & Management Research Center (SOFTAM), Faculty of Technology & Information Science, at UITM University, Malaysia
3	Expert 3 is currently an Associate Professor with the Faculty of Information Science and Technology (FTSM), University Kebangsaan Malaysia (UKM). She is also a member of the Asian Language Processing (ASLAN) Research Group, Centre of Artificial Intelligence (CAIT). She is the Head of the CAIT Postgraduate Program at UKM. Her research interests include natural language processing and computational linguistic-to-speech processing.
4	Expert 4 is a lecturer at the Artificial Intelligence Technology Research Center (CAIT), University Kebangsaan Malaysia. She was Chairman of the Artificial Intelligence Technology Research Center (CAIT) from 2013 to 2019.
5	Expert 5 has received his master's degree in computer science; his specialty is Artificial intelligence, Deep learning, and Data mining, He is a previous lecturer at Al-Esraa University, Baghdad, Iraq.

Appendix-B Questions of the experts' interview

Questions
1- Do you agree that students' characteristics, such as age, gender, academic performance, and academic preparation, may influence their learning persistence patterns?
2- Do you agree that internal factors, including study habits, course availability, commitments, and learning styles, may impact students' learning persistence patterns?
3- Do you agree that students' time management and computer skills could affect their persistence patterns?
4- Do you agree that students' needs, such as clarity of the educational program, self-esteem, and accessibility to services, may play a role in their persistence patterns?
5- Do you agree that external factors, such as financial constraints and family responsibilities, may influence students' learning persistence patterns?
6- Do you agree that contextual factors, such as the design of the learning environment, course design, and instructor presence, may affect students' learning persistence patterns?
7- Can you briefly describe the challenges and the related factors that the students may face in online learning programs that can affect their learning persistence?
8- From your practical experience, what key components are essential for designing an effective online learning program that fosters positive student persistence?
9- Drawing from your expertise in online education, could you contribute any insights or suggestions to enhance learning persistence VLEs?

Appendix-C Online survey participant demographics

The survey engaged (30) international postgraduate students, ranging in age from (25 to 35), with a gender distribution of (21) males and (9) females. These students hailed from various universities, including (13) students were from (UKM) university, (10) students from (UPM) university, and the remaining students from (U.M., USM, UTM, and UiTM) universities, bringing diverse educational backgrounds predominantly in the Information Technology field. (27) respondents were enrolled in full-time research programs, while (3) respondents were pursued part-time research. The academic standing of these students was primarily in their third or fourth semesters, with (24) registered in PhD programs and (4) registered in MSc. programs. Funding sources varied, with most students being self-funded, one receiving a grant, and the remainder supported by governmental funds. Additionally, the respondents' circumstances varied; most were married with family responsibilities, half had part-time jobs outside their studies, and half dedicated more than (6) hours daily to their studies. The others spent less diverse regarding their personal preferences and learning styles.