Utilising digital technology to personalise learning: How to influence Non-urban East Malaysian undergraduates' intention?

Noraisikin Sabani[1*], Sallimah Salleh[2], Anita Jimmie[3], Shamsul Kamariah Abdullah[4]

[1]Faculty of Humanities and Health Sciences, Curtin University Malaysia, CDT 250, 98009, Miri, Sarawak, Malaysia
noraisikin.s@curtin.edu.my
[2]Sultan Hassanal Bolkiah Institute of Education, Universiti Brunei Darussalam, Jalan Tungku Link, Gadong BE1410, Brunei
sallimah.salleh@ubd.edu.bn
[3]School of Pre-U and Continuing Education, Curtin University Malaysia, CDT 250, 98009, Miri, Sarawak, Malaysia
anita.jimmie@curtin.edu.my
[4]Faculty of Business, Curtin University Malaysia, CDT 250, 98009, Miri, Sarawak, Malaysia
shamsul.a@curtin.edu.my
**Corresponding Author*

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Abstract: *The focus of this study is to investigate East Malaysian undergraduates' behavioural intentions in personalising their learning using technology to promote learning inclusion. It is part of a project highlighting the accessibility and means of students of various backgrounds, particularly those deemed disadvantaged. The study's participants are students from rural or semi-rural areas, pursuing their studies in public higher education institutions in Sarawak or Sabah. The paper's main aim is to explore the use of personalised learning technologies among these students, as there is a lack of research examining behavioural intentions and how this demographic background affects their usage. Using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) as its theoretical framework, a quantitative approach was employed using questionnaires distributed to undergraduates in four public higher education institutions throughout Sarawak and Sabah. A total of 220 responses were collected,* *and the researchers employed the AMOS version 24 software to establish the reliability and validity of the questionnaire items, check the model fit, measure structural equation analyses, and examine the primary hypotheses of the theoretical framework. The findings indicate that a good model fit was obtained, with the Performance Expectancy and Student Agency construct demonstrating considerable influence in affecting the behavioural intentions of rural and semi-rural students in personalising their learning using digital technology.*

Keywords: *Behavioural intention, Digital equity, Personalised learning, Structural equation modelling*

1. INTRODUCTION

Technology empowers learners by creating a conducive, engaging, and interactive learning environment. Using and utilising technology as a medium for teaching and learning has afforded learners the relevant skills and knowledge required to perform better in their studies. Another crucial aspect in enhancing skills development is allowing students to use digital technologies to personalise their learning (Baba Yidana et al., 2023). The ability to personalise is a key factor that influences sustained interest in usage intention and positively impacts the continued use of a product or innovation (Cheng et al., 2020), as users have control over the content and resources to meet their needs. In addition, the rapid development and abundant access to various online education applications have impacted how students approach learning. The availability of mobile applications makes learning more accessible and convenient due to the ease of obtaining information online. While there is significant interest in examining student's behavioural intentions, there needs to be more information on the relationship between behavioural intention and socioeconomic background, focusing on students from rural and semi-rural areas.

Student's willingness to accept and adopt the use of technology in learning is impacted by several significant factors. Venkatesh et al. (2012) examine behavioural intentions and technology acceptance using the UTAUT2 model in their study. According to this model, technology adoption can be measured using seven variables, which include Performance Expectancy

(PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Learning Value (LC), Habit (H), and Hedonistic Motivation (HM) and Student Agency (SA).

In a study by Abbad (2021) on Jordanian students at Hashemite University, it was discovered that the students were motivated to use the Learning Management Platform, Moodle, to personalise their learning. Using the UTAUT framework, he examined the effects of four variables: Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions, to investigate the student's usage and behavioural intentions. He found that student's acceptance and subsequent adoption of e-learning platforms are influenced by performance expectancy and effort expectancy. Sharif et al.(2019) studied learner's acceptance of learning management systems among 178 university students in Pakistan using the UTAUT2 model. They discovered that the task technology fit and facilitating conditions play a significant role in the usage of learning management systems. This is supported by a study conducted by Bervell et al. (2022), where evidence suggests a predictive relationship between facilitating conditions and effort expectancy, hedonic motivation, habit, and social influence in adopting technology for learning. Rudhumbu (2022), in a study on 432 Zimbabwean postgrad students, revealed that performance expectancy, effort expectancy, social influence, facilitating conditions and hedonic motivation positively impacted technology acceptance.

Educational technology has been seen as an opportunity to manage educational challenges related to digital divide and inequality (Major et al., 2021). Research has shown that students have benefitted academically from receiving personalised instructions as they can cater to the learner's needs, pace and learning style, which in turn enhances motivation and behaviour (Krasodomska & Godawska, 2021; Zhang et al., 2020; Jones et al., 2013). Che Aziz et al.'s (2020) study on the effectiveness of E-learning among students in higher education institutions in Malaysia supports this theory. Their research discovered that students could personalise their learning content, making learning more flexible and easily accessible. This allowed the students to obtain learning resources in their own time, at their own pace. Similarly, Mat Salleh et al. (2019) also found that personalised learning, aided by digital technology, facilitated easier and more convenient learning for undergraduate students, thus enhancing the learning process. Similar findings were also reported on the positive role of digital technologies and increased motivation to personalise learning (Chatterjee et al., 2020; Wan Hamzah et al., 2020)

Based on the literature, it is evident that digital technology provides the opportunity to influence acceptance and subsequent intention to personalise learning. Thus, in this study, we investigate how personalised learning impacts learner's behavioural intentions, particularly among undergraduate students from rural and semi-rural areas in Borneo. This research focuses on filling in the information gaps and contributes to understanding how learners from lower household incomes utilise technology to personalise their learning. We also aim to test the conceptual model, UTAUT2, to determine the fit and explain how personalised learning affects technology acceptance and use among our respondents.

2. METHODS

The main project utilised a mixed methods approach, using a survey questionnaire supported by in-depth interviews. This paper reports on the findings from the quantitative analysis. The respondents were from four public universities in Sabah and Sarawak, resulting in 406 surveys and 43 interview responses. For this paper, the discussion will be based on 220 responses retrieved, focusing on undergraduates from non-urban demographic origins.

2.1 RESEARCH HYPOTHESES

The relationship between the latent variables was tested based on the research hypothesis based on the theoretical framework. These relationships' significance of probability values of less than 0.05 will be accepted inferences. Based on this, conclusions will be drawn, highlighting the statistical justifications extracted. Table 1 will highlight the initial research hypotheses proposed.

Hypothesis	Description
H1	Performance Expectancy will positively affect non-urban undergraduates' behavioural intention of digitalised personalised learning.
H2	Social Influence will have positive effects on non-urban undergraduates' behavioural intention of digitalised personalised learning.
H3	Hedonic Motivation will positively affect non-urban undergraduates' behavioural intention of digitalised personalised learning.
H4	Student Agency will have positive effects on non-urban undergraduates' behavioural intention of digitalised personalised learning.
H5	Effort Expectancy will positively affect non-urban undergraduates' behavioural intention of digitalised personalised learning.
H6	Facilitating Conditions will positively affect non-urban undergraduates' behavioural intention of digitalised personalised learning.

Table 1: Initial Research Hypotheses

2.2 STUDY CONTEXT AND SAMPLING SELECTION

As the focus of the research is to study the behavioural intention and adaptation of undergraduates from non-urban areas and lower household income brackets in personalising their studies with digital technology, criterion sampling was utilised to reflect the nature of the studied phenomenon. Additionally, based on the initial research objectives, the study only limits its participants to those of Sabah and Sarawak origin.

2.3 DATA COLLECTION TOOLS

Two research instruments were utilised based on the UTAUT 2 theoretical framework. However, an added variable, Student Agency (Vaughn, 2020), was included, as the researchers perceived it as an essential element to consider. The first instrument, the questionnaire survey, was distributed online via Qualtrics. The participating universities' officials acted as gatekeepers, distributing the invitation email and the survey link for the students to fill in. However, due to poor response, the team distributed the survey on-site. This has proven to be a more practical approach, with a collection of 406 responses after data cleaning. The on-site data collection span was also shorter than the online distribution. After data cleaning, the researchers identified and invited rural or semi-rural origin participants to participate in the in-depth interviews. The participation was voluntary, and the team managed to secure 43 responses.

2.4 ETHICAL CONSIDERATION

Prior to data collection, the team applied for ethical clearance and approval, which was granted and noted as HRE2021-0498. As the study involves data relating to human ethics, several considerations were focused on (Creswell, 1998). Among others, the priority was focused on the anonymity of the respondents. While their details were obtained for honorarium payment purposes, data cleaning was conducted to erase all identifiable data and was secured through aliases and participant numbering. They were also provided with details of the research's intention and nature. For every participant, a consent form was also provided, that indicates their rights and limits in the usage data for the research. All participants were given six months to withdraw entirely or partially (by omitting certain content), among which none of them did. Almost 500 survey responses were obtained from these four universities, of which 406 were accepted after data cleaning. Meanwhile, 43 agreed to be interviewed, and these responses are discussed in a different paper.

2.5 DATA PROCESSING ANALYSIS

As previously indicated, this paper focuses on the statistical analysis of the survey questionnaire. The data was initially analysed through SPSS to evaluate the factor loading of the questionnaire results based on seven variables provided in Figure 1. Principal Component Analysis was utilised, with rotation of Promax with Kaiser Normalisation of 0.4, producing the cleanest factor loading distinction. Due to the paper's brevity and objective, only the factor loading analysis results are provided. It was noted that through factor loading, 5 components were identified: Performance Expectancy, Social Influence, Student Agency, Hedonic Motivation and Behavioural Intentions.

Meanwhile, Effort Expectancy and Facilitating Conditions components failed to be identified in the factor loading stage. The Cronbach Alpha test was also conducted, resulting in a 0.878, deemed a good value (Pallant, 2020). Figure 1 illustrates the proposed conceptual framework for the study based on the UTAUT 2 model. Student Agency is an added motivation-based construct. The label and definition of theoretical framework constructs, based on post-factor loading, are provided in Table 2.

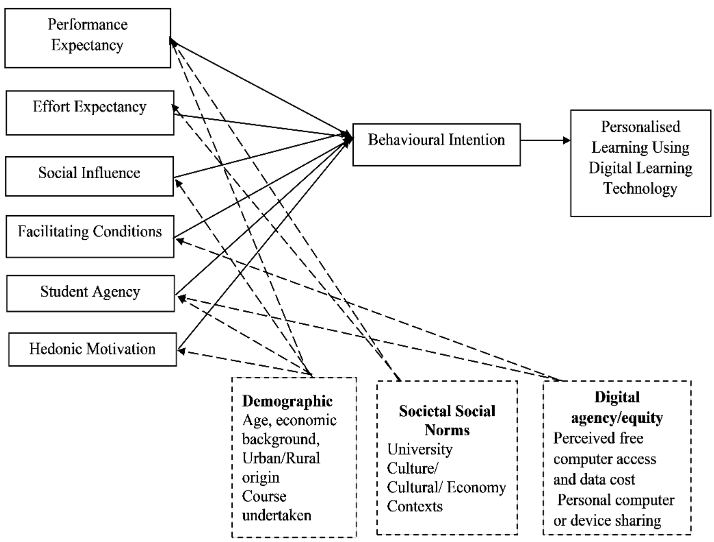

Figure 1: Proposed conceptual framework, an extended UTAUT2 model (Venkatesh et al., 2012)

3. RESULT AND DISCUSSION

3.1 SOCIODEMOGRAPHIC PROFILING

The sociodemographic analysis illustrated that of the 220 respondents, 124 of 56% were from Sabah, while 44% were from Sarawak. Meanwhile, regarding study majors, only 45% were taking Science, Engineering, Technology and Mathematics (STEM) based subjects. Slightly more than half of them were aged between 22 to 23 years old, followed by one-third of them aged between 20 to 21 years old. 22 or 20% of them were of the youngest category of 18 to 19 years old, and finally, only 7% or 16 of them were aged 24 years old and above. In terms of monthly household income, an overwhelmingly 78%, or 173 of the respondents, were from the B40 group, with a monthly income of a maximum of RM4849 (USD 1115)(Malaysian Department of Statistics, n.d.).

Regarding accessibility to digital technology, many respondents own a laptop, smartphone, and personal internet data packet, at 88%, 98% and 76%, respectively. Meanwhile, in terms of university facilities, the most common facility accessible is the university-wide Wi-Fi, at 66%, followed by computer labs, at 50%, and printing services, at 46%, respectively. Further details relating to their access to personal and university-based digital gadgets and facilities are demonstrated in Table 4.

In both cases of having no access to digital technology facilities at home or university, one person reported such restriction for each scenario. Table 3 provides the demographic information of the respondents.

Indicator	**Detail**	**Percentage**
Origin	Sabah Sarawak	62.3 37.7
University's Site	Sabah Sarawak	56.4 43.6
Course Major	Science, Technology, Engineering and Mathematics (STEM) majors Non-STEM majors	45.0 55.0

Age group	18-19 years old 20-21 years old 22-23 years old 24 years old and above	10.0 30.9 51.8 7.3
Living Area	Rural Semi-Rural	57.3 42.7
Monthly household income bracket	Less than RM2500 RM2500-RM3169 RM3170-RM3960 RM3970- RM4849 RM4850-RM5879 RM5880-RM7099 RM7110-RM8699 RM8700-RM10959 RM11000 and above	50.5 20.5 5.5 2.3 6.4 6.8 1.8 3.6 2.7

Table 3: Respondents' demographic profiling

Home		University	
Item	**Percentage**	**Item**	**Percentage**
Personal Computer (PC)	20.5	Printing Services	45.9
Tablet	15.9	Computer Lab	50
Laptop	88.2	University-Wide Wi-Fi	66.4
Smartphone	97.7	Limited Access Wi-Fi	43.6
Wireless Internet	28.2	Others (digital library)	1.4
Personal Internet Data	76.4	No access to any facilities	0.5
No access to digital media	0.5		

Table 4: Access/Ownership to Digital Technology Gadgets/Facilities

3.2 MEASUREMENT MODEL

Five out of seven components were extracted from factor analysis, with 19 out of 22 items intact, based on their factor loading value, as the measurement model to identify a good model fit for the initial stage.

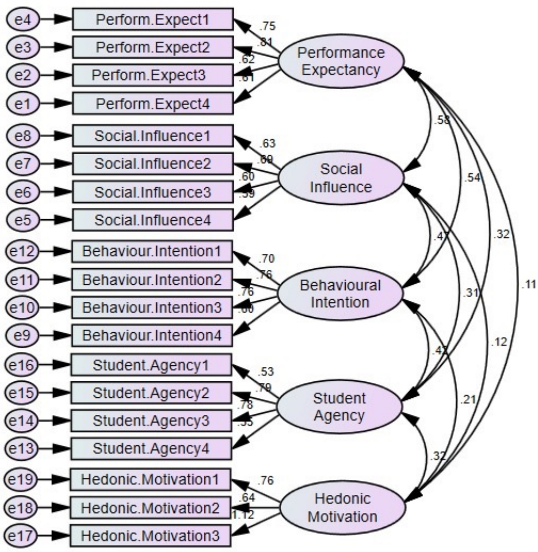

Fig. 2 Initial measurement model

3.3 MODEL FIT GOODNESS

The Lowry and Gaskin validity and reliability test (2014) was conducted to test and improve the reliability and validity of the model fit. The initial result indicated CR and AVE value issues, particularly for the Social Influence construct. While it met the minimum requirement of 0.6 CR value at 0.655, it failed to meet the minimum AVE value of 0.5 at 0.487 (Pahlevan Sharif & Sharif Nia, 2018). Therefore, while the initial measurement model was initially accepted, the Social Influence construct was levelled to increase the reliability and validity of a good model fit of the constructs. As a result, the CMIN/DF value is at 2.279. Figure 3 illustrates the outcome of the validity and reliability testing.

Meanwhile, most baseline comparisons increased to, or almost 0.9 value, where CFI at 0.939, IFI Delta 2 at 0.939, TLI rho2 at 0.919, NFI Delta 1 at 0.897, and RFI rho1 at 0.864. This implied that deleting the Social Influence construct from the analysis improved model fit reliability and validity. It is also important to note that out of the original 23 items representing seven constructs, the items were reduced to 13. Table 4 provides details of the final measurement scale from the total sample analysed.

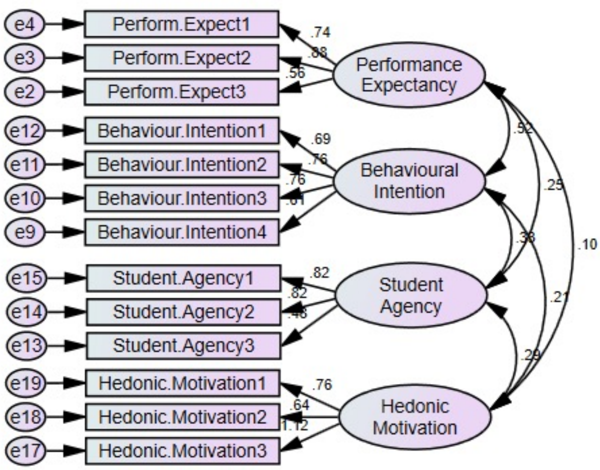

Figure 3: Measurement model recalibration as an outcome of reliability and validity testing.

Latent Variable	Observed Variable	Validity (λ)	Reliability (R2)
Performance Expectancy (PE)	Perform.Expect1 Perform.Expect2 Perform.Expect3	.739 .876 .557	.547 .767 .310
Student Agency (SA)	Student.agency1 Student.agency2 Student.agency3	.820 .816 .482	.673 .665 .232
Hedonic Motivation (HM)	Hedonic.Motivation1 Hedonic.Motivation2 Hedonic.Motivation3	.759 .642 1.117	.576 .412 1.248

Behavioural Intention (BI)	Behaviour.Intent1	.693	.584
	Behaviour.Intent2	.764	.572
	Behaviour.Intent3	.756	.372
	Behaviour.Intent4	.610	.547

Table 4: Final measurement scale from the total sample (N=220): Validity and reliability

3.4 STRUCTURAL EQUATION MODELING

After establishing the validity and reliability of the theoretical constructs, Structural Equation Modeling was conducted to test the initial hypotheses, as indicated earlier. Based on the analysis, it can be noted that the Chi-square value is at 134.487, with the probability level of significance at 0.000, which means it met the minimum requirement of the default model. While it was noted that all three final constructs, Performance Expectancy, Hedonic Motivation and Student Agency, all correlated positively to the Behavioural Intention to personalised learning via digital technology, their significance level differed.

Table 5 illustrates that the model fit indices were within the accepted values. As Pahlevan Sharif and Sharif Nia (2018) highlighted, a CMIN/DF value below 3 is acceptable, which in this case is 2.279. Additionally, at least 3 baseline requirements were met, with CFI at 0.939, IFI Delta 2 at 0.939, and TLI rho2 at 0.919, respectively. Thus, the conceptual model is a good fit to demonstrate non-urban origin undergraduates' intentional behaviour in using digital technology to personalise their learning.

Index	Perfect Fit	Accepted Values	Model Result
Chi-Square	Chi-Square < 3	3 < Chi Square < 5	2.279
RMSEA	0 < AGFI < 0.05	0.05 < AGFI < 0.08	0.076
CFI	0.97 < CFI < 1	0.95 < CFI < 0.97	0.940
IFI	0.95 < IFI < 1	0.90 < IFI < 0.95	0.939
TLI	0.90 < TLI < 1	0.90 < TLI < 0.95	0.919

Table 5: Conceptual research model fit indices

4.0 DISCUSSION

To restate, at the initial stage, five hypotheses were to be tested against the conceptual model and its respective SEM. The structural equation modelling outcome to test the hypotheses is illustrated in Figure 5, while the findings of the hypotheses are provided in Table 6.

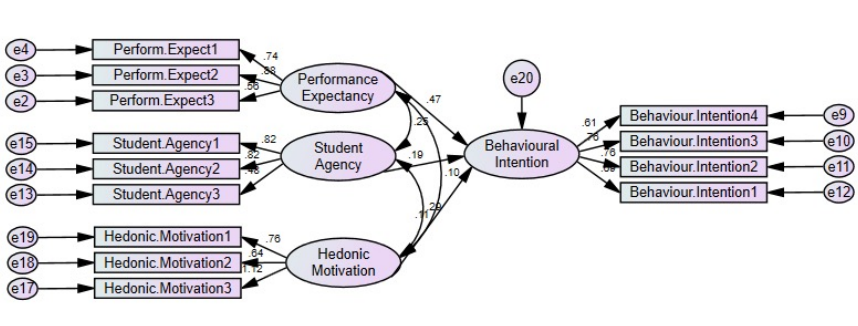

Figure 5: Structural equation model post good fit indices

Hypothesis	Description	β	p
H1	Performance Expectancy will positively affect non-urban undergraduates' behavioural intention of digitalised personalised learning.	0.465	0.000*
H2	Social Influence will have positive effects on non-urban undergraduates' behavioural intention of digitalised personalised learning.	Not tested as excluded during good fit model estimation	
H3	Hedonic Motivation will positively affect non-urban undergraduates' behavioural intention of digitalised personalised learning.	0.108	0.061
H4	Student Agency will have positive effects on non-urban undergraduates' behavioural intention of digitalised personalised learning.	0.189	0.026**

H5	Effort Expectancy will positively affect non-urban undergraduates' behavioural intention of digitalised personalised learning.	Not tested as excluded during the factor loading stage
H6	Facilitating Conditions will positively affect non-urban undergraduates' behavioural intention of digitalised personalised learning.	Not tested as excluded during the factor loading stage

Note:
* significant at 0.000;
** significant at below 0.05

Table 6: Regression coefficients (**β**) and probability values (p) or the research hypotheses

Table 6 indicates two hypotheses of significant value, H1 and H4, at (b= 0.465, p=0.000) and (b=0.189, p=0.02) respectively. Meanwhile, H3 was found to be non-significant at (b=0.108, p= 0.06). Finally, while two constructs (H5 and H6) were rejected from the initial model due to factor loading issues, H2 could not be tested after reliability and validity testing. Based on these findings, it can be argued that Performance Expectancy and Student Agency positively affect these undergraduates' behavioural intention in personalising their learning through digital technology. On the other hand, the result indicated that Hedonic Motivation has no significant relationship with non-urban undergraduates' decision to use digitalised personalised learning. It was also important to note that the three original constructs, namely Effort Expectancy, Facilitating Conditions and Social Influence, had to be excluded, as the data indicated that these constructs did not contribute to the model's validity and reliability.

5.0 CONCLUSION AND RECOMMENDATION

The statistical analysis indicated that the conceptual model illustrates a good fit with high internal consistency and reliability. This means the UTAUT2 components provided strong explanatory power for the studied phenomenon.

In the case of non-urban undergraduates in East Malaysia studying in Sabah and Sarawak, it was noted that Performance Expectancy and Student Agency positively influence their behavioural intention to personalise their learning via digital technology. Concurrently, while it was perceived that hedonic motivation impacts their behavioural intention at the initial stage, it was proven otherwise through the structural equation modelling analysis.

While the study only found two constructs or factors to positively affect the behavioural intention of non-urban undergraduates in personalising their learning experiences using digital technology, the study could be replicated on a larger scale to substantiate further the conceptual framework suggested by the researchers. Furthermore, as indicated in the earlier part, the findings in this paper are part of a larger-scale project, which is supported by qualitative findings as well. Further analysis makes it viable for the researchers to understand further the undergraduates' perceived experiences of the studied phenomenon.

Based on these findings, the researchers would argue that adding Student Agency as one of the constructs in the UTAUT2 model, particularly for the phenomenon studied, has indicated benefits, as the result illustrated a significant positive impact of student agency, which is allowing the learners to have decision-making power in their learning experience in influencing the usage extent of digital technology to personalise their learning (Tsai et al., 2020). Additionally, the researchers agree with Archambault, Leary, and Rice (2022) that there is a need to increase student agency in digital-based learning by allowing these learners to assess their circumstances and have autonomy by making a decision based on the facilities and support that they have around them, they will be able to thrive better in their learning experiences.

Additionally, heightened student agency correlates to these undergraduates' performance expectancy and drive. Ley, et. al. (2022) highlight the importance of meaningful technology integration to benefit learners and improve their performance. As such, it could be implied that if undergraduates see the value of digital learning in personalising their learning experience thus, enabling them to improve their learning performance, they are more inclined to utilise it. Simultaneously, personalised digital learning would be more fruitful by heightening student agency through the allowance of selecting the appropriate technology based on their circumstances and needs. As indicated through a systematic review by Stenalt and Lassesen (2022), it was noted how student agency plays a role in personalised learning and learning analytics, as through the data obtained from their online activities, students have the opportunities to cultivate self-regulation and learning efficacy. It is to be noted, though, that such self-empowerment cannot be done in isolation, without support from their teachers, through feedback and assessment. This will aid students in measuring their performance and monitoring their achievement and understanding of the subject content (Zheng et al., 2022).

Through the findings of the demographic data, it can be noted that the Malaysian Government have benefitted the undergraduates through digital gadgets initiatives as a mean to heighten ICT (Information and Communications Technology) literacy among youths as part of SDG (sustainable development goals) 4 (quality education) initiative (Malaysian Department of Statistics, n.d.). However, it was also noted that there is a discrepancy between Wi-Fi and personal data access for these learners, which could be considered a sign of the digital divide (Jaggars et al., 2021). This may have been perceived by the Malaysian Government as well, as there is a newly noted initiative of providing cheaper internet access catered for the less privileged (Bernama, 2023). Such initiatives are evidently significant, as found in Guo, Huang, Lou and Chen's (2020) study that indicated the importance of supporting disadvantaged groups, including students from rural areas or those of lower-income households.

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