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Exploring Factors that Predict Undergraduates' Behavioural Intention to Digitalised Personalised Learning

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Abstract: The study explores factors that may predict undergraduates' behavioural intention to personalise their learning through utilising digital technology, which is accessible to them both in their homes and at university. The research design is non-experimental and employs a research questionnaire survey as a research instrument. Twenty-two items have been included, based on the Unified Theory of Acceptance and Use of Technology 2 theoretical framework. The responses from 203 undergraduates from East Malaysia studying in two public universities in Sarawak have been analysed descriptively, illustrating the respondents' varying backgrounds. Additionally, factor analysis was conducted, indicating an extraction of six out of seven variables originally anticipated, excluding Facilitating Conditions from the equation. Multiple linear regression analysis revealed that four of the five independent variables signified in factor analysis significantly correlate to the behavioural intention of utilising digital technology to personalise learning. These factors are student agency, performance expectancy, social influence and effort expectancy.

Keywords: *Personalised learning, digital divide, students' intention, students' behaviour, factor analysis, multiple linear regression*

1. Introduction

Learning and teaching have undergone many phases of delivery modes, from chalk-and-talk, with teachers being the leading actors and students being the audience listening to instructions. In the digital era, where most activities happen with a click of a button, it has also impacted the Education industry, where technology is becoming increasingly an essential tool in assisting learners in their learning process. As technology continues to move to the next level, learners need to be more knowledgeable about using it for their learning. Technology is no longer one of the motivating factors in learning. It is an element that needs to be included to ensure learners are equipped with the skills to cope with the world of technology. The future of education will need to make sure that technology can be used to learners' benefit and educate future generations in managing the challenges that may arise from it.

In Higher Education, technology is the key to assisting learners in their learning journey. Technological advancements it has improved the way learners handle their learning. Learners have started to adapt and adopt the learning materials, group learning and group discussion using digital tools to help them process information and demonstrate their understanding in their preferred way. Technology has not just changed the way learners learn and retrieve data. Also, technology has driven learner engagement and has encouraged educators to re-design their teaching materials. A study [1] indicated the possibility of utilising infographics to self-learn digital marketing is due to the learner's confidence in independently using the digital platform. Another study [2] found a positive relationship between digital equity and inclusion with learning personalisation. From a personalised learning perspective, it shows that learning personalisation can empower learners to improve their learning. Some aspects should be addressed, including the learners' human factors and socioeconomic

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conditions. Finally, another research [3] highlighted that digital technologies and emerging pedagogies in learning and teaching are becoming paramount, and these technologies can potentially improve education.

2. Literature Review

2.1. Personalised Learning

The COVID-19 pandemic has transformed the educational system toward using more ICT tools in higher education. With this, E-learning is becoming the trend which somehow impacts the learners' personalised learning [4].

Personalised learning is an educational approach that considers each learner's specific needs, interests and strengths of each learner; where teachers/educators can then provide a unique learning experience based on individual traits [5]. Personalised learning is based on the learner's capability, and their responsibility is to create and maintain their learning. Their personal learning environment supports their learning activities, informal interaction and discussion that build their learning network. This will help to improve the application of the principles of constructivism and connectivism [6]. In addition, technological advances have resulted in the increased use of mobile applications in the education industry, mainly at the university level. Therefore, higher educational institutions have started using various learning methods and incorporating mobile phones as part of the tools. More developed countries are now practising e-learning concepts in their learning and teaching activities. The idea of Bring Your Own Devices (BYOD), using online sources and social media, is used by learners to respond to classroom activities [7]. Using the digital platform in personalised learning has facilitated a deeper understanding of the subject matter [8].

As mentioned earlier on the trend towards E-learning, it was noted in a study that E-learning provides students with relevant, personalised learning content that can be accessed remotely at their own time, using resources readily available to them [9]. According to Qing [10], personalised learning can be used as a mediating tool by utilising digital technology to learn a second language, as it allows access to the grammatical nuances of the language and the social and cultural artefacts that the language possesses. However, it was noted that more needed to be done to study the usage of these mediating tools as personal media in their language learning. The findings revealed that all the students possess similar ICT platforms to access the information: e-resources and e-tools. The students also indicated the differences in materials and media accessed based on their personal, cultural and social interests. Furthermore, students who plan to use digital technology for specific learning purposes indicated a higher level of metacognitive skills, which correlates to their learning autonomy.

In the digital era, technology heavily supports personalised learning, which has made learning more flexible in terms of time, content, delivery, instructional approach, and assessment [11]. It was mentioned that using technology to support personalised learning increases learner access to their learning both in and out of the classroom [12]. Major, Gill and Tsapali [12] also agreed that technology could assist personalised learning among learners in low- and middle-income countries (LMICs). This can be essential in ensuring more comprehensive and equitable access to education, particularly in the aftermath of COVID-19.

2.2. UTAUT 2 Model and Learning Personalisation

Emerging literature has yielded various aspects of the acceptance of online learning platforms. Raffaghehelli et al. [13] explored the use of an early warning system, which is a tool that monitors students' progress and identifies students at risk of failing. The researchers utilised the UTAUT model to explore students' perceptions and acceptance of this phenomenon. The findings indicate that when the students expect highly on the usefulness of technology, the post-usage experience showed lower technology acceptance. The researchers noted that the study might suggest that learners may have different or unreal expectations towards AI, particularly in their academic activity support. This, in turn, affects their acceptance of technology. Consequently, their intentions to use technology to personalise learning are negatively affected.

Abbad [14] studied the effects of principal factors or components of intentional behaviour, including performance expectancy, effort expectancy, social influence and facilitating conditions. Results indicated that students' adoption of and use of e-learning platforms is influenced by behavioural intentions, which are affected by performance expectancy and effort expectancy. The students at Hashemite University in Jordan were driven to use the Learning Management Platform Moodle to facilitate their learning experience. Thus UTAUT provides valuable feedback on factors that influence students' acceptance and adoption of personalised learning tools.

Kim et al. [15] applied the UTAUT model to study the determinants driving students' behavioural intentions to use online learning systems. The findings show that students' perceived ease of use of a learning tool affects their perceived usefulness. In turn, their perceived usefulness is significantly correlated to their attitude. In contrast, it was noted that perceived ease of use is not significantly correlated with or affects their attitude. In addition, attitude and subjective norms correlated positively towards behavioural intention, while perceived behavioural control did not.

An examination of the usage of online learning and blended learning was conducted by Arnesen et al. [16]. They highlighted that undergraduates' preservice teachers were willing to adopt personalised learning as they understood the results and benefits of applying the teaching method in their online classes. Based on both studies, personalised learning plays a vital role in student's education when they have access to the appropriate digital technology. Another finding reveals that user innovativeness mediates between subjective norms and behavioural intention.

In this research, not only the four main independent factors in UTAUT 2, which are performance expectancy, effort expectancy, social influence and facilitating conditions, are explored. In addition, two other independent variables are included, hedonic motivation and student agency, which focus on the intrinsic motivation of utilising technology, as well as students' preference and interest in their choice of learning, respectively [17].

3. Methods

This section will focus on the research design, data collection procedure and data analysis based on the feedback provided by the respondents.

3.1. Research Design

The study is non-experimental, based on a comparative case studies design. It is part of a larger-scale research project that focuses on the 4 public universities in Sabah and Sarawak, the two states of East Malaysia. However, this report only focuses on the findings based on the two public universities studied in Sarawak. The study focuses on finding factors that may contribute to the behavioural intention of the respondents in utilising digital technology in personalising their learning, whether at home or their respective universities. The researchers also focus on finding personal aspects that may contribute to the findings, including their demographic profiling. These data include their age, family income, area of origin and courses undertaken. The respondents' access to digital technology is also examined.

3. 2. Research Respondents

Undergraduates from the two universities were invited to participate by filling in an online survey questionnaire via Qualtrics in December 2021. As criterion sampling is utilised, part of the requirement is that the respondents can only be undergraduates studying at the sites studied, and they can only be of the origin of East Malaysia. This is done purposely, as only a little research on this phenomenon focuses on students of this origin. The survey was distributed only after approval to conduct the study in the respective universities. Nonetheless, due to poor participation, a printed version of the questionnaire was distributed on-site in June 2022. According to Stevens [18], the formula for sample number calculation is N>50+8m. Therefore, as the theoretical framework indicate the possibilities of 6 independent variables, the minimum number of sampling per analysis is 98 respondents. Meanwhile, after data cleaning, the respondents consisted of 203 undergraduates, which exceeded the minimum requirements.

3.3. Research Instruments

The use of a survey questionnaire is one of the instruments that is being used in this research project, alongside semi-structured interview questions. These instruments have been designed based on the UTAUT 2 (Unified Theory of Acceptance and Use of Technology 2) model. Nonetheless, for this paper, the researchers will discuss only the findings related to the survey questionnaire.

The research questionnaire consists of twenty-two items, highlighting one independent variable: a behavioural intention to use digital technology to personalise learning. It is then aligned against 6 independent variables: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation and student agency. The respondents must also fill in their demographic data, as their background may influence their responses. The information includes their State of origin, age, monthly household income, the course undertaken and digital amenities that the respondents have access to at home and university.

The reliability of the instruments was tested utilising Alpha Cronbach, with an expected coefficient range between 0 to 1. Based on the test, Cronbach's value is .869, which is deemed a good value. According to Pallant [19], the closer the value to 1, the instrument exhibits higher reliability.

4. Data Analysis

There are three stages of analysis that are described in this paper, which are descriptive analysis, factor analysis and multiple linear regression analysis. These analyses were conducted sequentially.

4.1. Descriptive Analysis

Firstly, descriptive analysis was done to study the respondents' backgrounds. The analysis indicated that out of 203 respondents, 170 undergraduates, or 83.7 per cent of them, are from Sarawak, while the rest, 33 people, or 16.3 per cent, is from Sabah. Out of these respondents, only 34 per cent are currently undertaking STEM (Science, Technology, Engineering and Mathematics) based courses, while the other 66 per cent are undertaking non-STEM courses. Almost half of these respondents are in the age group of 22 to 23 years old (46.8 per cent), followed by 20 to 21 years old at 31 per cent, then 12.3 per cent are undergraduates aged 18 to 19 years old, and only 9.9 per cent of them are aged above 24 years old at the time of data collection. As for their area of origin, 24.1 per cent indicated that they are from rural, 23.2 from semi-rural, while the rest, 52.7 per cent, are from urban areas. Despite having an almost balanced division between rural/semi-rural and urban respondents, 70.9 per cent of them belong to the B40 (monthly household income of less than RM4850), and 25.6 are from the M40 group (less than RM11000 per month). Only 3.4 per cent are in the T20 group, with an average monthly household income above RM11000.

As for access to digital amenities at home and at universities, the respondents noted that their most common devices accessible at home are smartphones and laptops, and most of them owned SIM-based or personal internet data. Meanwhile, the more common facilities that the respondents access on campus are computer labs and access to Wi-Fi, whether university-wide or limited space access. Further details are provided in table 1.

TABLE I. PERCENTAGE OF RESPONDENTS WITH DIGITAL TECHNOLOGY ACCESS

Digital Access/ Internet access at home/residence	Percentage of respondents with access	Digital Access/ Internet access at the university	Percentage of respondents who have access
Personal Computer	26.6	Computer lab	53.7
Tablet	18.2	Printing Services	47.3
Laptop	89.2	University-Wide Wi-Fi	50.2
Smartphone	95.1	Limited Area Wi-Fi	53.2
Personal Internet (SIM card)	74.9	Other digital access (Digital library)	2.5
Internet/ Home Wi-Fi	48.2	No access at all	2.5
No access at all	0		

4.2. Factor Analysis

Factor analysis for the twenty-two items constructed in the survey is then conducted, which is an important step before running multiple linear regression. This ensures that the items with an acceptable factor loading are assigned to their respective components or variables to increase their reliability. This is done to determine which variables are perceived as a predictor of the behavioural intention and usage of digital technology to personalise learning. Based on KMO and Bartlett's test, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy was .834 and Bartlett's Approx. Chi-Square was 1618.716, which was significant, at .000. These findings indicate that the number of respondents was sufficient. The variance explained suggested that the cumulative percentage of factor loading is 61.89 per cent, deemed valid [20]. Based on the initial Eigenvalues of above 1, 6 components were extracted. The total variance table is provided in table 2.

TABLE II. TOTAL VARIANCE

Component	*Initial Eigenvalues*			*Extraction Sums of Squared Loadings*			*Rotation Sums of Squared Loadings*
	Total	*% of variance*	*Cumulative %*	*Total*	*% of variance*	*Cumulative %*	*Total*
1	6.473	29.421	29.421	6.473	29.421	29.421	5.137
2	2.002	9.100	38.521	2.002	9.100	38.521	3.681
3	1.742	7.917	46.438	1.742	7.917	46.438	3.831
4	1.344	6.111	52.549	1.344	6.111	52.549	3.653
5	1.042	4.734	57.283	1.042	4.734	57.283	3.191
6	1.014	4.609	61.892	1.014	4.609	61.892	2.305

Subsequently, as the research data was extracted based on split case analysis, items with communalities extraction value below .5 are excluded from the factor loading. Thus, item numbers 8 and 13 are excluded in this case, as the values for these items in both sites (public universities in Sabah and Sarawak) were below the required value. For Sarawak sites, the extraction value is .407 and .475.

Different types of extractions were done, but it was finalised with Promax at the value of .4. This was because the items were perceived to be correlated. Its analysis indicated the cleanest segregation value across components. The findings are in the Pattern Matrix, shown in Table 3.

TABLE III. PATTERN MATRIX

Item	*Component* 1 BI	2 SI	3 EE	4 PE	5 HM	6 SA
18. I have skills in using digital media for learning purposes	.843					
19. I am confident in using digital media for learning purposes	.816					
20. I intend to use digital media for learning in the future	.807					
22. I want to use different digital media for different learning purposes	.674					
12. I have the knowledge necessary to use digital media for learning purposes	.572					
21. I will use my own digital media to personalise my learning.**	.438				.304	
7. My peers and lecturers think that I should use social media for learning purposes		.802				
9. I use social media for personal learning because my friends do it too		.796				
8. I use digital learning tools (e.g. socrative, padlet, Prezi) because my lecturer and peers use them.*		.697				
6. The use of personal learning tools/strategies/platforms is useful for my informal learning		.617				
10. My parents encourage me to use digital media for learning purposes**		.478		.376		

3. The use of university digital platform increases the quality of learning	.780			
4. The use of university learning platforms is easy	.772			
13. A specific person or group is available for assistance with any technical problem I may encounter.*	.629			
5. The use of personal learning tools/strategies/platforms is useful for my university studies**	.490			
1. The use of digital media for personalised learning enables me to accomplish my needs more quickly and efficiently.		.951		
2. The use of digital media for personalised learning enhances my learning motivation		.730		
14. I use digital media to play games			.890	
15. I use digital media to access social media			.745	
11. I have the resources necessary to use digital media for learning purposes**	.340		.399	
17. I prefer having control over my learning content				.851
16. I prefer having control over my learning pace				.799

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.a,b
a. Which State is your university in? = Sarawak
b. Rotation converged in 7 iterations.
a. *Between 2 components, the component with a higher value than .5 is included
b. ** items excluded due to factor loading <.5 OR communalities <.5.

The extraction method for factor analysis is through Principal Component Analysis, while the rotation method is based on Promax with Kaiser Normalisation of .4. The rotation converged in 7 iterations. Based on this analysis, several steps were taken to exclude specific items from the next step. Firstly, the outcome for items 8 and 13 was excluded due to the communalities' value of less than .5. Then, based on the factor loading, any items with a value of less than .5 will be excluded. In this case, four items, which are items 5, 10, 11 and 21, were excluded. Therefore, 6 items within the original constructs will be excluded in the multiple linear regression stage. Similar to the value noted based on the Eigenvalues above 1, the components were differentiated into 6, compared to 7 anticipated ones. These components or variables are the Behavioural Intention (BI), which is the dependent variable, and 6 dependent variables, which are Social Influence (SI), Effort Expectancy (EE), Performance Expectancy (PE), Hedonic Motivation (HM) and Student Agency (SA).

4.3 Multiple Linear Regression

The third and final stage of the analysis is the multiple linear analysis. It is a predictive tool for estimating the relationship between the six independent variables; social influence, effort expectancy, performance expectancy, hedonic motivation and student agency. These variables are set against the dependent variable, the behavioural intention of utilising digital technology to personalise learning, both formally and informally. The analysis results are provided in Tables 4, 5, and 6 to indicate model summary, ANOVA and Coefficients, respectively.

TABLE IV. MODEL SUMMARY

Model	***R***	***R Square***	***Adjusted R Square***	***Std. Error of the Estimate***
1	.521[a]	0.272	0.253	0.53164

a. Which State is your university in? = Sarawak

TABLE V. ANOVA

Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Regression	20.687	5	4.137	14.639	.000[c]
Residual	55.397	196	0.283		
Total	76.084	201			

TABLE VI. COEFFICIENTS

Model	Unstandardised Coefficients		Standardised Coefficients	t	Sig.		
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	1.234	0.375		3.291	0.001	0.494	1.973
Social Influence	0.129	0.051	0.163	2.531	0.012	0.029	0.230
Effort Expectancy	0.134	0.058	0.158	2.321	0.021	0.020	0.248
Performance Expectancy	0.179	0.067	0.184	2.697	0.008	0.048	0.311
Hedonic Motivations	0.058	0.057	0.068	1.015	0.311	-0.055	0.171
Student Agency	0.227	0.055	0.272	4.101	0.000	0.118	0.336

a. Which State is your university in? = Sarawak
b. Dependent variable: behavioural intentions

c. Predictors: (constant) student agency, performance expectancy, social influence, hedonic motivations, effort expectancy

The findings indicated that the R-value is .521, while the R Square value is .272. While the R Square value may be deemed relatively low, for social research studies, the value is acceptable. This is supported by the arguments made by [21;22] that an R square value as low as 10 per cent is acceptable due to the difficult nature of predicting human behaviour accurately. Nonetheless, the researchers can only accept low values if some of the components in the coefficient's findings indicate a statistical significance of .05. Thus, based on the significant value in the coefficients table, four of the independent variables bear significant relationships towards the independent variables. These independent variables are student agency, at 0.00; performance expectancy, at 0.008; social influence, at 0.012; and effort expectancy, at 0.021.

5. Discussion

Various aspects of the respondents, including demographic profiling and their feedback towards the studied phenomenon, have been studied. First, it can be noted that most of the respondents were Sarawakian, even though almost one-fifth of them were Sabahan. Additionally, the majority of the respondents were undertaking non-STEM courses. Despite their area of origin being reasonably balanced, between rural and semi-rural, against urban, most of the respondents still belong to the B40 monthly household income group, categorised as the lowest group bracket in Malaysia [23].

As for facilities, the most common personal digital devices that the respondents owned are smartphones and laptops, with support through personal internet offered through a cellular network, which is known to have the disadvantage of providing limited data allowances compared to home Wi-Fi or the internet [24].

Interestingly, few respondents highlighted the availability of digital libraries as part of their digital amenities. For digital amenities that the respondents have access to in their respective universities, the usage is at an acceptable percentage. At the same time, a small number of them indicated that they need access to these facilities, as they currently study from home, which is an inevitable impact of Covid-19.

From the factor analysis, the researchers found that out of 22 items, only 16 were placed in their respective components. The factor loading for these items was clean, and all are above .5. Among the six expected independent variables, one was not included: facilitating conditions. This may explain the moderate percentage of universities' facilities' usage in the demographic profiling, as this indicates their belief in technical facilities and support available in their respective universities [25]

Finally, based on the multiple linear regression analysis, although the F value of 14.639 is deemed acceptable due to the unpredictability of human nature, it can be noted that 4 out of 5 dependent variables have indicated statistical significance at 0.5 value. These factors are student agency, at 0.00; performance expectancy, at 0.008; social influence, at 0.012; and effort expectancy, at 0.021. Through this analysis, it may be an exploratory aspect that may assist the researchers further in understanding the use of digital technology in their endeavour to personalise their learning, whether formally or informally.

6. Conclusion

As previously indicated, the findings in this report are part of a larger-scale project, and these are the initial analysis that needs to be done as a priori analysis. The initial results have allowed the researchers to consider a few issues further. Firstly, the lack of awareness of accessible digital facilities in the university may be an aspect that the researchers can explore, which may be revealed through in-depth interviews with some respondents. Secondly, it is worth noting that while most of the respondents belong to the B40 household income bracket, the ownership of smartphones and laptops was unanticipated by the researchers. There was also a higher percentage of respondents who were dependent on cellular internet compared to cable internet. Finally, while there were 5 dependent variables identified in factor analysis, only four of them rendered statistically significant. Hedonic motivation does not seem significant for the participants in this study, a point worth noting, considering the higher percentage of personal digital amenities accessible.

There are a few study limitations based on this report. Firstly, while the sampling was based on criteria, the distribution and acceptance were based on convenience sampling. Due to poor responses via online survey distribution, the survey had to be distributed on campus. Therefore, there could not be any control of equal distribution among respondents of different courses or areas of origin, which may contribute to additional findings. Still, on a larger scale, the research team aims to focus on digital equity among rural/semi-rural students, particularly in East Malaysia. The findings have given the researchers fundamental aspects that can be further investigated. The findings will be further consolidated with advanced statistical and qualitative analysis, which may contribute to understanding the studied phenomenon.

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