Learner Characteristics and Learners' Inclination towards Particular Learning Environments

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Abstract: In addition to a face-to-face classroom learning environment, today's learners in higher education are likely to have also experienced a blended learning or an online learning environment. These learning environments not only differ in their delivery modes, but also learning activities, class interactions, assessment approaches, etc. Learners tend to have differing perceptions about the effectiveness of different learning environments. This study therefore investigates whether the reasons learners like or dislike a learning environment reveal learner characteristics that may explain why some learners are more inclined towards a particular learning environment. This study also examines whether learner demographics influence learner characteristics and their preference for a particular learning environment. Using an exploratory sequential mixed methods research design, this study first conducted several focus group discussions and then administered an online questionnaire survey to collect input from students at a local university. Analyses derived four learner characteristics (i.e. desire for direct support, digital readiness, learning independence, and online hesitancy) based on the reasons why the students liked or disliked face-to-face classroom learning, blended learning, or online learning environments. A cluster analysis further distinguished the students into three groups (i.e. classroom learners, insecure learners, and online learners) based on the four learner characteristics. Analyses also found that learners' demographics largely had no effect on learners' characteristics and their preference for a particular learning environment. The findings suggest that learner characteristics may provide a clue to why certain learners have a preference for a face-to-face classroom learning, a blended learning, or an online learning environment. A better understanding of the relationship between learner characteristics and learners' inclination towards a particular learning environment can be helpful to educational institutions and academics to design a range of engaging learning activities for learners with different characteristics.

Keywords: Learner characteristics, Learner demographics, Learning activities, Learning environments, Learning needs

1. Introduction

Teaching and learning in today's higher education can occur through various delivery modes. Besides the conventional face-to-face classroom learning mode, blended learning and online learning have become two increasingly popular alternatives for learners and educational institutions. However, teaching and learning in a blended learning or an online learning environment is different from that of a face-to-face classroom learning environment (Nortvig, Petersen and Balle, 2018; Thai, De Wever and Valcke, 2020). Some learners may be more comfortable with face-to-face classroom learning, while others may prefer online learning (Kauffman, 2015).

Different learners learn differently (Jamiah, Mahmud and Muhayyang, 2016), and learner characteristics affect how they learn (Kauffman, 2015). Past studies have attempted to distinguish learner characteristics in different ways. For example, competences, culture, personality traits, learning goals (Abyaa, Idrissi and Bennani, 2019); ethnic background, intellectual capital, cognitive relevance of prior knowledge (Maringe and Sing, 2014); and educational experience, learning approaches, self-esteem, motivation, flexibility, social background (Thomas and May, 2010). As learner characteristics differ, their learning strategies may vary (Abyaa, Idrissi and Bennani, 2019). Because of their individual differences, learners may also display different behaviours and have different expectations in their learning (Barker, 2012).

The current trend towards blended learning and online learning in higher education makes it increasingly crucial for higher education to explore learner characteristics at greater depth. Even though a vast number of learner characteristic variables have been proposed, Drachsler and Kirschner (2012) assert that defining and measuring learner characteristics is still an intricate endeavour. Furthermore, many past studies in this context mainly focused on online learning. Only a few were about blended learning or flipped classrooms (e.g. Balaban, Gilleskie and Tran, 2016; Kintu, Zhu and Kagambe, 2017; Roehling et al., 2017), or a comparison between face-to-face classroom learning and online learning (e.g. Fendler, Ruff and Shrikhande, 2016; Zacharis, 2011). There has not been much investigation of all three learning environments in the same study.

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To increase student engagement, it is important for lecturers to have an understanding of and adapt to the learning needs of learners (Bengtsen and Barnett, 2017). A learning environment that recognises individual student learning needs and interests would more effectively engage the students (Hockings, 2011). However, as student diversity is multidimensional, designing a learning environment to meet the diverse learning needs of all students from different backgrounds can be challenging (Hockings, Brett and Terentjevs, 2012).

In view of the research gaps in the relationship between learner characteristics and learning environments in past studies, it is timely now to re-examine the learner characteristics that are more current and relevant to today's face-to-face classroom learning, blended learning, and online learning environments. Academics would be able to better deliver positive learning experiences for individual students by first understanding the characteristics and motivation of the students (Vanslambrouck et al., 2018).

A casual conversation with some university students about their individual preferences for a learning environment inspired this study. The students basically gave different reasons why they liked or disliked a particular learning environment. This study is based on the premise that the reasons learners like or dislike a learning environment provide insights into the role of learner characteristics in explaining why learners have a preference for a particular learning environment over others. This study therefore aims to answer two research questions: (1) whether the reasons learners like or dislike a learning environment reveal learner characteristics that may help explain why some learners are more inclined towards a particular learning environment; and (2) whether learner demographics influence learner characteristics and their preference for a particular learning environment. However, this study does not imply that placing learners in their preferred learning environment is a prerequisite for them to perform well in learning.

The following sections review learner characteristics and the research gaps that exist in past studies, introduce the research methods, present the data analyses and findings, and conclude the paper with a discussion of implications for practice, research limitations, and future research directions.

2. Literature review

2.1 Learner Characteristics

Considering that students are more diverse in large classes (Maringe and Sing, 2014), Abyaa, Idrissi and Bennani (2019) stress that the one-size-fits-all style of teaching and learning may have a deterrent effect on student learning effectiveness. When designing an inclusive pedagogy, Hockings (2010) suggests considering a range of individual differences; e.g. social classes, ethnic backgrounds, full-time or part-time students, work and life experiences, learning approaches, and the effect of these differences on learning. Knowing about such learner characteristics can help academics adjust their teaching strategies and activities for more effective learning, and provide better support for their students (Ghorbani and Montazer, 2015; Law, Geng and Li, 2019).

Past studies have not shown a clear consensus over the characteristics that can be used to best describe the diverse learners. Some researchers have attempted to categorise the wide-ranging characteristics of learners. For example, Thomas and May (2010) propose four dimensions: educational (e.g. skills, educational experience, learning approaches); dispositional (e.g. self-esteem, motivation, attitudes); circumstantial (e.g. age, flexibility, disability); and cultural (e.g. values, ethnicity, social background). Abyaa, Idrissi and Bennani (2019) highlight six categories of learners' characteristics: learner profile (e.g. age, gender); knowledge characteristics (e.g. knowledge level, competences); cognitive characteristics (e.g. learning styles, working memory capacity); social characteristics (e.g. social interactions, culture); personality traits; and motivation characteristics (e.g. interests, learning goals).

Although past studies were generally in agreement that learner characteristics are multi-dimensional, some studies considered only the socio-demographic variables. Some examples of such studies include Balaban, Gilleskie and Tran's (2016) study of the impact of flipped classrooms on student performance; Firmin et al.'s (2014) study of student success in massive open online courses (MOOCs); and Wang, Shannon and Ross's (2013) study of the levels of self-regulated learning and self-efficacy of students in online learning. However, a consideration of only the socio-demographic variables provides a far too simplistic view of the interactions between learner characteristics and learning environments.

Some studies have attempted to add a few other variables besides socio-demographics. Examples of these other variables include enrolment goals and motivations for MOOCs (Kizilcec, Sanagustín and Maldonado, 2017); student motivation and patterns of orientation (Mertens, Stöter and Zawacki-Richter, 2014); and willingness to work in groups, to seek new production information, and to try new products (Karamanos and Gibbs, 2012). However, it remains uncertain the extent to which these additional variables are able to account for learners' preference for face-to-face classroom learning, blended learning, or online learning environments.

To measure learner characteristics, some studies attempted to adapt existing scales that were initially developed for a different research context. Examples of these existing scales include learning goal orientation and proactive personality (Kickul and Kickul, 2006); computer-mediated communication anxiety (Wombacher et al., 2017); motivation and self-regulation (List and Nadasen, 2017); and intrinsic motivation, computer attitude, computer anxiety (Stiller and Bachmaier, 2017). Although it is a good attempt to use existing scales that have been validated, exactly how specific and relevant these scales are to expounding how learners perform in different learning environments may require further investigation.

In addition, some variables of learner characteristics in past studies may be considered outdated in view of current trends in technology use. For example, average hours spent using a computer or the Internet (Simmering, Posey and Piccoli, 2009); computer facilities, Internet usage (Yang and Tsai, 2008); and Internet use, prior use of web applications (Karamanos and Gibbs, 2012). Increased accessibility to and greater familiarity with the Web and digital technology may have already made technology a non-issue for students in their consideration of a learning environment.

2.2 Learning Styles

Some past studies posit that learners differ in their learning styles. The concept of learning styles suggests that learners can be categorised into certain learning styles based on their preferred approach to information processing and understanding, and that when learning delivery is purposefully designed to match one's learning style, better learning performance can be expected (Drachsler and Krischner, 2012; Riener and Willingham, 2010). However, education researchers have refuted this concept as fundamentally flawed (Drachsler and Krischner, 2012; Newton and Miah, 2017; Riener and Willingham, 2010). Besides the fact that human cognitive activities entail not just one but multiple senses such as sight, hearing, or touch, there is no evidence to suggest that learners can learn better with a learning design which matches their learning style (Newton, 2015). It is also questionable to categorise learners into just one of a few learning styles when the validity of the instruments has not been established (Kirschner and van Merriënboer, 2013). Without taking the learning context and content into consideration, to mainly classify learners based on their learning styles may misinform learners that they can only learn effectively when a learning activity matches their learning style (Newton, 2015; Newton and Miah, 2017).

3. Research Methods

An exploratory sequential mixed methods research design was adopted for this study (Creswell and Creswell, 2018). First, this study collected qualitative data through focus group discussions to identify the variables for the development of a survey instrument. This instrument was then deployed in an online questionnaire survey to collect quantitative data for subsequent statistical analysis.

3.1 Focus Group Discussions

Several focus group discussions were conducted to collect input from university students on their reasons for liking or disliking face-to-face classroom learning, blended learning, or online learning environments. Students at a local university voluntarily participated in a total of five focus group discussions. Each discussion involved five randomly recruited participants from the diploma, bachelor's, or master's level. Their responses were coded and analysed using a qualitative software to reveal 26 common reasons, ranging across such themes as learning motivation, peer interaction, self-learning initiative, and learning attitude.

3.2 Online Questionnaire Survey

An online questionnaire survey was administered to collect data in preparation for a cluster analysis. A section of the survey instrument asked one question for each of the 26 reasons that were identified from the focus group discussions. All items were measured using a five-point Likert-type scale, 5 being "strongly agree" and 1 being "strongly disagree." Another section asked several demographic questions regarding gender, age, programme, education level, semester currently in, student status, and prior work experience.

Multiple announcements on the university's learning management systems (LMS) invited students to voluntarily participate in the survey. The data collection lasted about two weeks and received a total of 125 responses. A check was performed for multivariate outliers. Following the rule that a response is considered an outlier if the probability of its squared Mahalanobis distance is equal or less than 0.001 (Tabachnick and Fidell, 2019), 8 of the 125 responses were removed. Thus, 117 valid responses were used for later data analysis.

Of the 117 respondents, whose average age was 21.25 (SD=3.16), 52 (44.4.%) were female and 65 (55.6%) male. 94 of them (80.3%) were doing business-related studies and 23 (19.7%) computer-related studies. All of the respondents were full-time students. However, 28 (23.9%) of them were working part-time. A high percentage of them (76.1%) had prior work experience, while the remaining 23.9% did not. Table 2 provides a summary of the respondents' demographics.

4. Data analysis and Findings

4.1 Factor Analysis

In preparation for a cluster analysis, which aims to separate the respondents into groups based on their responses to the items which measure the 26 reasons why learners like or dislike the different learning environments, a factor analysis was first performed to reduce these items into a smaller number of factors (DiStefano, Zhu and Mîndrilă, 2009). Steinbach, Ertöz and Kumar (2004) highlight the need to reduce the number of variables for a cluster analysis as a large number may unwantedly produce marginal groups.

Both the KMO (>0.5) and Barlett's tests (p<0.05) were satisfactory for the factor analysis. To decide the deletion of items, two criteria were used: (1) items loaded <0.5 on any one of the factors, or (2) items cross-loaded >0.5 on two or more factors (Hair et al., 2014).

The first iteration extracted five factors, but one item had a low factor loading. After removing the item, there existed a simple structure of five factors. A following reliability analysis showed that all the factors had good Cronbach α (>0.8), except the fifth factor (.575). The fifth factor comprised two items. Because of the low factor reliability, both items were removed in the second iteration. A further third and fourth interaction removed two additional items that had a low factor loading. The final factor structure consisted of 21 items loaded on four factors. These factors were labelled *desire for direct support*, *digital readiness*, *learning independence*, and *online hesitancy,* respectively. The scores of these factors were saved for the subsequent cluster analysis.

Parallel analysis and Velicer's Minimum Average Partial (MAP) tests were conducted to further confirm the number of factors. Although the parallel analysis test suggested two factors, the revised MAP test (Velicer, Eaton and Fava, 2000) suggested four factors. Having considered the possibility that parallel analysis may under-estimate the number of factors when the first factor has a large eigenvalue (Beauducel, 2001) and taking into consideration the unidimensionality of the factors, it was decided to adopt a 4-factor model as suggested by the revised MAP test. Table 1 provides a summary of these factors.

Table 1: Factor analysis results

Items	Mean	SD	Desire for direct support	Digital readiness	Learning indepen-dence	Online hesitancy
I can learn better under direct supervision of lecturers.	3.87	.896	.853			
I like to get immediate response from lecturers.	4.20	.833	.783			
I like to meet others face-to-face in class.	4.00	.861	.783			
I prefer to ask lecturers directly whenever I have a doubt.	3.82	.943	.761			
I need regular guidance of lecturers in my learning.	3.68	.918	.758			
I like to use the physical facilities provided by the university.	3.63	.867	.671			
I like to have face-to-face interaction with others.	3.86	.870	.595			
I find it more attentive listening to lecturers in class.	3.69	1.078	.560			

Items	Mean	SD	Desire for direct support	Digital readiness	Learning indepen-dence	Online hesitancy
I am comfortable with using digital technologies.	3.75	.899		.902		
I feel comfortable interacting with others online.	3.45	1.087		.862		
I like the flexibility of where I want to learn.	3.76	.906		.612		
I like to seek new information.	4.02	.743		.558		
I like to review learning materials at my own pace.	3.58	.958		.506		
I am disciplined enough to learn on my own.	3.52	1.022			.895	
I am clear about my learning goals.	3.74	.853			.735	
I am keen to learn on my own.	3.49	1.014			.723	
I am motivated to learn on my own.	3.44	1.021			.620	
I find it tedious to download learning materials online.	3.21	1.055				.938
I feel lonely learning alone.	2.99	1.148				.629
I am easily distracted by activities that are not related to my learning.	3.36	1.062				.624
I find online learning materials not as interactive as face-to-face lectures.	3.53	1.022				.553
% of variance explained			29.202	25.647	6.263	5.189
Eigenvalue			6.132	5.386	1.315	1.090
Cronbach α			.890	.835	.876	.799
Note: KMO (.835); Bartlett's test (<.001); extraction method: Principal Components Analysis; rotation method: Promax						

4.2 Cluster Analysis

To identify the clusters that are discrete, Oberski (2016) differentiates two types of model-based clustering approaches, i.e. latent profile analysis (or Gaussian finite mixture model) for continuous variables and latent class analysis (or binomial finite mixture model) for categorical variables. As this study used the factor scores from the factor analysis, a latent profile analysis was performed using R and the mclust package.

To determine the best data-fitting model and the number of clusters, the model-based clustering approach compares different models of parameterisations and number of clusters. The best model is the one with the highest Bayesian Information Criterion (BIC) value among the models (Boehmke and Greenwell, 2019; Fraley and Raftery, 2007). Besides the BIC value, the integrated complete-data likelihood (ICL) value is also a useful criterion (Scrucca et al., 2016).

Figure 1 depicts the fitted models and their BIC values from the mclust analysis. The three-cluster VVI model had the highest BIC value (-1271.545). The best ICL criterion (-1289.299) also provided the support for a VVI model of three clusters. A VVI model indicates that the three clusters contain different number of cases and each has a different shape. In addition, the clusters have a diagonal distribution with an orientation parallel to the axes (Boehmke and Greenwell, 2019).

The three clusters comprised 81 (71%), 6 (5%), and 30 (24%) of the total 117 respondents, respectively. Considering the learner characteristics (and their relative means) that each of the three clusters is particularly associated with, the clusters are labelled classroom learners, insecure learners, and online learners, respectively. Figure 2 depicts the means of desire for direct support, digital readiness, learning independence, and online hesitancy of each group. The classroom learners show relatively higher means than the insecure learners and online learners in desire for direct support and online hesitancy, but lower means than the online learners in digital readiness and learning independence. The insecure learners show relatively lower means than the classroom learners and online learners in desire for direct support, digital readiness, and learning independence, but a higher mean than the online learners in online hesitancy. A direct opposite to the classroom learners, the online learners show relatively higher means than the classroom learners and insecure learners in digital readiness and learning independence, but lower means than the classroom learners in desire for direct support and online hesitancy.

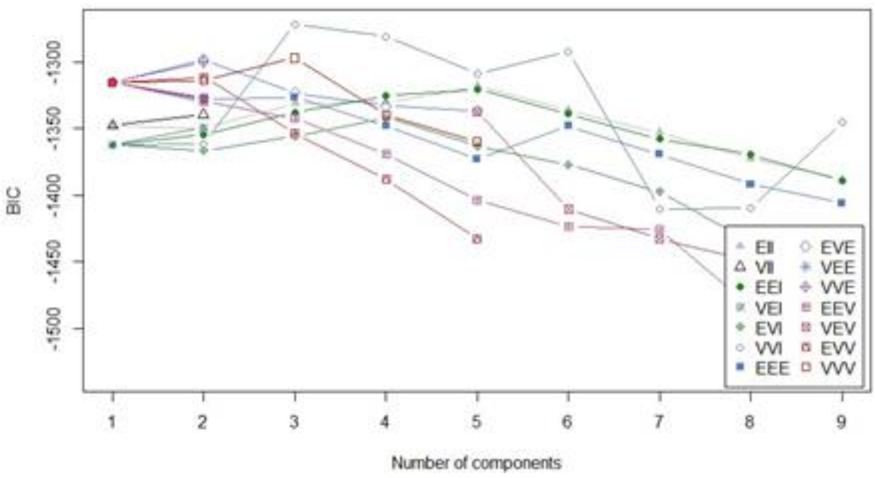

Figure 1: The BIC values and models

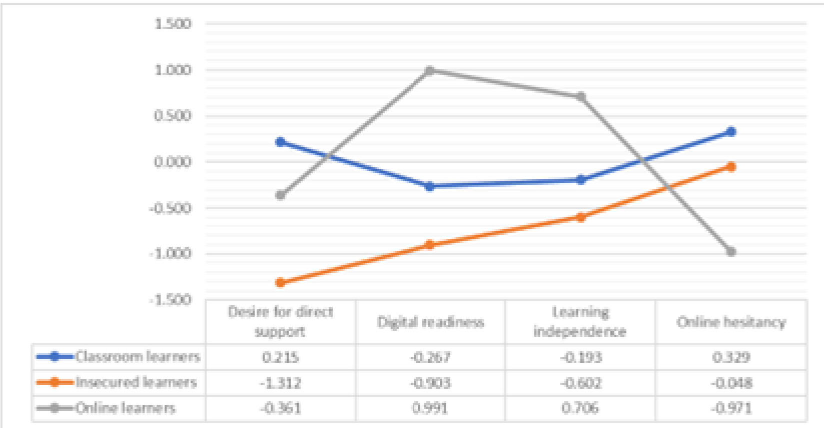

Figure 2: Means of learner characteristic

Figure 3 depicts the result of a classification analysis. The respondents were allocated to the individual groups at an uncertainty rate of less than 95%, providing the evidence of high membership probability of at least 95% for each respondent.

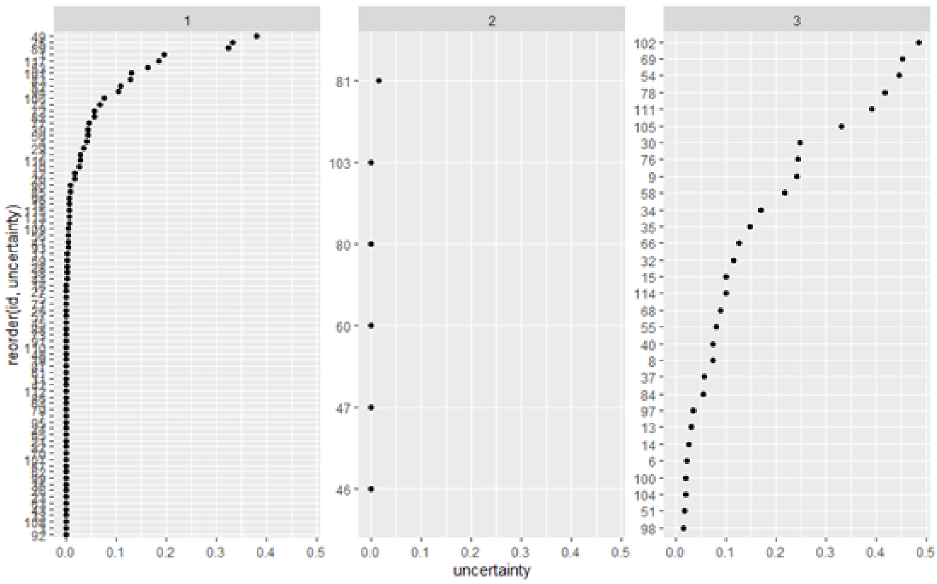

Figure 3: Classification analysis

Table 2 provides a summary of the respondents' demographics, categorised by classroom learners, insecure learners, and online learners. The respondents were spread across the three groups and their numbers differed in terms of gender, programme, education level, semester, student status, and work experience.

Table 2: Respondents' demographics

Respondents' demographics	Full sample (n=117)	Classroom learners (n=81)	Insecure learners (n=6)	Online learners (n=30)
Age (mean)	21.25 (SD=3.16)	21.14 (SD=3.07)	21.00 (SD=2.10)	21.60 (SD=3.61)
Gender				
Female	52 (44.4%)	39 (48.1%)	2 (48.1%)	11 (36.7%)
Male	65 (55.6%)	42 (51.9%)	4 (51.9%)	19 (63.3%)
Programme				
Accounting and Finance	18 (15.4%)	12 (14.8%)	1 (16.7%)	5 (16.7%)
Business Administration	19 (16.2%)	13 (16.0%)	2 (33.3%)	4 (13.3%)
Business Information Systems	9 (7.7%)	6 (7.4%)	--	3 (10.0%)
Computing	14 (12.0%)	10 (12.3%)	--	4 (13.3%)
Logistics Management	21 (17.9%)	15 (18.5%)	1 (16.7%)	5 (16.7%)
Management	16 (13.7%)	10 (12.3%)	1 (16.7%)	5 (16.7%)
Marketing	10 (8.6%)	8 (9.8%)	1 (16.7%)	1 (3.3%)
MBA	10 (8.5%)	7 (8.6%)	--	3 (10.0%)
Education level				
Diploma	44 (37.6%)	28 (34.6%)	3 (50.0%)	13 (43.3%)
Bachelor's degree	62 (53.0%)	46 (56.8%)	3 (50.0%)	13 (43.3%)
Master's degree	11 (9.4%)	7 (8.6%)	--	4 (13.3%)
Semester				
1st semester	28 (23.9%)	22 (27.2%)	2 (33.3%)	4 (13.3%)
2nd semester	27 (23.1%)	19 (23.5%)	2 (33.3%)	6 (20.0%)
3rd semester	38 (32.5%)	27 (33.3%)	2 (33.3%)	9 (30.0%)
4th semester	8 (6.8%)	5 (6.2%)	--	3 (10.0%)
5th semester	6 (5.1%)	4 (4.9%)	--	2 (6.7%)
6th semester or later	10 (8.5%)	4 (4.9%)	--	6 (20.0%)
Student status				
Full-time student and not working part-time	89 (76.1%)	66 (81.5%)	6 (100.0%)	17 (56.7%)
Full-time student and working part-time	28 (23.9%)	15 (18.5%)	--	13 (43.3%)
Work experience				
No	28 (23.9%)	21 (25.9%)	3 (50.0%)	4 (13.3%)
Yes	89 (76.1%)	60 (74.1%)	3 (50.0%)	26 (86.7%)

4.3 ANOVA and Independent Sample t-Ttsts

A One-way ANOVA test showed that learner characteristics were statistically significantly different for at least one of the groups. Three follow-up independent sample t-tests showed that there were significant statistical differences in the learner characteristics between any two groups. Table 3 summarises the results of the tests.

Table 3: ANOVA and independent sample t-tests

Learner characteristics	All groups	Classroom learners vs insecure learners	Classroom learners vs online learners	Insecure learners vs online learners
Desire for direct support	$F_{2,\ 114}$=9.688 P<.001***	$t_{80.044}$=13.740 P<.001***	t_{109}=2.561 P=.012*	$t_{29.009}$=-6.697 P<.001***
Digital readiness	$F_{2,\ 114}$=32.654 P<.001***	$t_{81.828}$=5.944 P<.001***	$t_{85.840}$=9.220 P<.001***	$t_{29.723}$=19.010 P<.001***
Learning independence	$F_{2,\ 114}$=14.468 P<.001***	$t_{61.898}$=2.989 P=004**	t_{109}=5.000 P<.001***	$t_{33.961}$=-9.730 P<.001***

Learner characteristics	All groups	Classroom learners vs insecure learners	Classroom learners vs online learners	Insecure learners vs online learners
Online hesitancy	$F_{2,\,114}$=32.114 P<.001***	$t_{80.627}$=4.136 P<.001***	$t_{99.119}$=10.401 P<.001***	$t_{29.339}$=11.281 P<.001***
*Note: ***significant at the 0.001 level; **significant at the 0.01 level, *significant at the 0.05 level*				

Subsequent one-way ANOVA tests showed that there were no significant statistical differences between learner characteristics and the respondents' demographic background, except for between desire for direct support and education as well as between digital readiness and student status. Table 4 summarises the results of the tests. A correlation analysis also showed that there were no significant correlations between age and learner characteristics at the 0.05 level.

Table 4: ANOVA tests

Learner characteristics	Gender	Programme	Education level	Semester	Student status	Work experience
Desire for direct support	$F_{1,\,115}$=2.491 P=.117	$F_{8,\,108}$=.870 P=.544	$F_{2,\,114}$=3.866 P=.024*	$F_{5,\,111}$=.823 P=.536	$F_{1,\,115}$=.068 P=.794	$F_{1,\,115}$=.310 P=.579
Digital readiness	$F_{1,\,115}$=.001 P=.978	$F_{8,\,108}$=1.763 P=.092	$F_{2,\,114}$=1.634 P=.200	$F_{5,\,111}$=.659 P=.655	$F_{1,\,115}$=5.044 P=.027*	$F_{1,\,115}$=1.327 P=.252
Learning independence	$F_{1,\,115}$=.139 P=.710	$F_{8,\,108}$=.925 P=.499	$F_{2,\,114}$=2.009 P=.139	$F_{5,\,111}$=.353 P=.879	$F_{1,\,115}$=1.023 P=.314	$F_{1,\,115}$=1.148 P=.286
Online hesitancy	$F_{1,\,115}$=.061 P=.806	$F_{8,\,108}$=.653 P=.731	$F_{2,\,114}$=1.146 P=.322	$F_{5,\,111}$=1.621 P=.160	$F_{1,\,115}$=.059 P=.808	$F_{1,\,115}$=1.610 P=.207
*Note: *significant at the 0.05 level*						

Fisher's exact tests showed that there was no statistical evidence to suggest an association between the respondents' demographic background and the groups, except student status (P=.013). Table 5 summarises the results of the Fisher's exact tests.

Table 5: Fisher's exact tests

Respondents' demographics	Groups	
	Value	P-value
Gender	1.464	.545
Programme	7.319	.987
Education level	2.388	.642
Semester	9.125	.448
Student status	8.297	.013*
Work experience	4.224	.117
*Note: *significant at the 0.05 level*		

5. Discussion

To better understand the characteristics that can help explain why some learners are more inclined towards a particular learning environment, this study proposes that a good starting point is to simply ask the learners the reasons they like or dislike a learning environment. The findings indicate that these reasons have indeed provided the basis for the derivation of four learner characteristics, lending support to the study's assertion that an understanding of learners' like or dislike of a learning environment is useful in uncovering learner characteristics.

The four learner characteristics help explain the principal differences in the respondents' preference of learning environments, and divide the respondents into three groups, i.e. classroom learners, online learners, and insecure learners. It appears that the classroom learners and online learners are the two major groups. The respondents in both these groups have rather distinct characteristics in their preference for a face-to-face classroom learning or an online learning environment. The insecure learners are a minority group, making up only about 5% of the total respondents.

The classroom learners have higher levels of desire for direct support and online hesitancy, as compared to the online learners. As the largest of the three groups, over 80% of the respondents in this group are full-time students who do not work part-time. It may be that these students do not need to juggle studying and working, and thus find the conventional university life more enjoyable, preferring to interact with their lecturers and peers face-to-face rather than online. The classroom learners appear to have less confidence about learning online. This finding is consistent with that of Stiller and Köster (2016), which found that students who dropped out from an online training course were more likely to have greater computer anxiety.

In contrast to the classroom learners, the online learners have higher levels of digital readiness and learning independence. About one-third the size of the classroom learners, close to 45% of the respondents in this group are full-time students who work part-time. It is reasonable to presume that these students value the flexibility of learning online. The online learners appear to be technologically savvy in such activities as searching for information or interacting with others online and have better preparedness for self-directed learning. This finding concurs with that of Tratnik, Urh and Jereb (2019), which reported that online students were more independent than classroom students.

Relative to the classroom learners and online learners, the insecure learners have the lowest levels of desire for direct support, digital readiness, and learning independence. Although the insecure learners have a low degree of learning independence, coupled with a low level of readiness to use technology, it seems that they do not have a strong desire for obtaining direct support from their lecturers or peers. Although this is a minority group, this finding is significant because it shows that there may be students who face challenges in their studies and are in need of additional academic assistance, but do not realise that they should be reaching out for such assistance.

This finding also points to a plausible assumption that the respondents are in favour of either face-to-face classroom learning or online learning. A cohort made up of predominantly classroom learners and online learners may be well-served by a blended learning environment, a hybrid mode of learning delivery that brings together the best of face-to-face classroom learning and online learning environments. A blended learning environment can still fulfil the needs of classroom learners for direct face-to-face interactions with their lecturers and peers, and that of online learners for greater learning flexibility.

Past studies have reported no effect of demographic background on learner performance in different learning environments (Fendler, Ruff and Shrikhande, 2016; Kintu, Zhu and Kagambe, 2017; Roehling et al., 2017). This study finds that only student status, but not the other demographic factors, may influence learners' preference of learning environment. In addition, learners' demographics do not appear to have widely influenced the characteristics of learners either, with the exception of education level and the desire for direct support, as well as student status and the level of digital readiness. Although this study cannot conclusively infer a link between a specific education level with a greater or lesser desire for direct support, or a specific student status with a higher or lower degree of digital readiness, it still points to a prospective future research direction.

6. Conclusion

In conclusion, although different learner characteristics have made learners diverse, this study has succeeded in identifying the characteristics that help distinguish three learner groups. The findings reinforce the notion that, considering the diversity of students in terms of learner characteristics, learning design should begin with an understanding of such elements as student learning needs, learning capabilities, and learning gaps; and their effect on teaching pedagogy (Gordon, Reid and Petocz, 2010). A learning environment that takes into consideration the characteristics of learners would greatly support and engage learners to enhance their overall learning experience and performance (Ghorbani and Montazer, 2015; Kintu and Zhu, 2016).

6.1 Implications for Practice

Given the differences in such features as learning delivery, class interaction, and learning feedback between face-to-face classroom learning, blended learning, and online learning environments (Thai, de Wever and Valcke, 2020), educational institutions and academics must understand the issues and challenges that learners of various characteristics face in their learning in order to engage them more effectively. Academics and educational institutions should not assume that all learners in a given learning environment have the same level of prior experience or expectations (Simon et al., 2020), readiness (e.g., technology literacy and competency) (Robinson, 2019), or skill sets (e.g., time management, self-regulation) (Coman et al., 2020; Tseng, Yi and Yeh, 2019). Instead, it may be necessary to teach learners certain skills to better prepare them for a certain learning environment and to use different pedagogical approaches to design learning activities that are better suited to meet the varying learning needs of diverse learners.

To meet intended learning outcomes, Ramsden (2003) underscores the importance of designing learning within specific contexts. Previous education experiences, coupled with such elements as teaching, curriculum, and assessment designs, can affect one's orientation to studying, and subsequently one's perception of task requirements, learning approaches, and learning outcomes. Thus, to achieve intended learning outcomes, learning contexts need to be carefully created to foster learning. The findings support Ramsden's (2003) advice on learning contexts by adding insights about differences in learner characteristics. These insights can be useful for educational institutions and academics to better create learning contexts that help learners transit successfully from one learning environment to another.

It is vital to emphasise that although learners may have a preference for a particular learning environment, this does not necessarily mean that learners cannot perform well when studying in a less preferred learning environment. When studying in a learning environment that they do not initially like, some learners may gradually change their perception of that learning environment after having recognised its advantages, and eventually find ways to overcome its limitations. Lee et al. (2021) reported that, in a study of students' online course satisfaction during the Covid-19 pandemic, learners were able to adapt to cope well in a transition from face-to-face classroom learning to online learning.

Certain characteristics of learners may also change over time because of such factors as their stage in life, external environment, or skills development. For example, when a learner has graduated from university and started to work full-time, when a learner's daily schedule no longer allows much time or location flexibility, or when a learner has developed study skills and has become more adept at self-directed learning or has attained a higher level of digital literacy. These changes in learners' characteristics will eventually affect their perception and attitude towards different learning environments.

6.2 Research Limitations and Future Research Directions

Two research limitations and two future research directions should be highlighted. First, the participants in this study were from the same university. Therefore, the findings may not be generalisable to a wider context. Future research may conduct a similar study in different educational institutions for results comparison. Second, a majority of the participants in this study were full-time students who do not work part-time. Their perception of time, location, and learning flexibility may be different from that of learners who study part-time and work full-time. Future research may conduct a similar study in different higher education settings for a more a wide-ranging understanding of this topic.

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