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Latent Class Analysis of Postgraduate Students' Behavioural Characteristics Towards ICT Use: What are their Job Creation Differences?

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Abstract
This study analysed the behavioural characteristics of ICT users among postgraduate students leveraging the Latent Class Analysis (LCA). The study, anchored on the Planned Behaviour Theory, followed the exploratory research design. It adopted the cluster random sampling technique in selecting 1,023 respondents from a population of 2,923 postgraduate students in four federal universities in South-South Nigeria. "Behavioural Characteristics and Job Creation Questionnaire (BCJCQ)", developed by the researchers, was used for data collection. Upon data collection and LCA analysis, the five-class solution was accepted as the best fitting model, based on statistical fit indicators (such as AIC, BIC, entropy, Gsq, and Chsq) and theoretical grounds. Consequently, five classes of behavioural ICT users were identified and named based on their item-response probability, conditional on class. The five classes were named Trendy, Outmoded, Pragmatic, Disciplined and Social users of ICT, with their unique characteristics discussed. The study tested for job creation differences among the classes using a one-way ANOVA and found a significant difference. On average, pragmatic users of ICT created more jobs than social, disciplined, and outmoded users. Trendy users were, on average, the minor job-creating class of ICT users. The study compared the bivariate differences in job creation among the classes using the Tukey HSD test of multiple pairwise comparisons. Based on the results obtained, discussions were made with implications for further research in the evolving area of LCA.

Keywords: ICT, Item-response probability, job creation, latent class analysis, LCA, mixture models.

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Introduction

Currently, the focus in Nigeria and other emerging nations is on how to get the population of people involved in creating new jobs for the growing economy. As a result of the enormous number of postgraduates entering the labour market and the lack of work possibilities to meet their demands, this need developed. To help the Nigerian economy reorient itself, several vocational skills acquisition programmes have been implemented in both the official and informal sectors to cultivate self-reliance in citizens to create jobs. In the informal sector, such programmes as National Open Apprenticeship Scheme (NOAS) and School-On-Wheel

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Scheme (SOW) were designed by the National Directorate of Employment (NDE) to boost the employment creation potential of the informal sector of the economy (National Directorate of Employment [NDE], 2019). Similarly, the establishment of Entrepreneurship Development Centres (EDC) and infusions of Information and Communication Technology (ICT) was also meant to equip postgraduates with adequate twenty-first-century skills for self-reliance, self-employment and career stability (NDE 2019).

Unfortunately, this expectation appears not to be maximally attained given the high level of postgraduate unemployment and the extent to which graduates are without functional skills for self-employment in Nigerian society. There have been repeated and strident complaints that Nigerian university graduates are not of employable quality and, in fact, half-baked, with an excessive amount of theory and little practical content (Ameh & Okpa, 2018; Odigwe et al., 2018). They are of questionable and sub-standard quality, lacking in knowledge, skills, attitude and ability to meet labour market requirements (Mbagwu et al., 2020; Okwu, 2006; Robinson, 2022). Many experts have also noticed that graduates of Nigerian universities in the twenty-first century seem to be lacking in skills and qualifications needed to support themselves and others (Uchendu, 2019; Undiyaundeye & Otu, 2015). This unfortunate situation seems to buttress the fact that the objectives of entrepreneurship education (meant to inculcate job creation potential in students) have not been maximised in Nigeria.

Job creation potential is the capacity to identify economic opportunities, promote self-employment as a career option, and foster creativity, risk-taking, and commitment (Magaji, 2019; Maina, 2013). Possessing such technical and business skills is necessary to launch a new enterprise (Brown, 2019; Owan, Agurokpon, et al., 2021; Verma et al., 2019). Recently, job creation has been defined as "the average quotient of the total number of Small and Medium Enterprises (NSMEs) owned by persons plus the total number of individuals employed (NIE) by such initiatives, as a per cent of the total number of persons studied" (Owan, Udida, et al. 2021; p.4). This is expressed mathematically by the cited authors as:

$$JC_I = \left(\frac{\frac{NSMEs}{n} + \frac{NIE}{n}}{2}\right) \text{x} \frac{100}{1} \quad (1)$$

Where:
JC_I = Job creation index
NSMEs = indicator of the total number of SMEs
NIE = Indicator of the total number of individuals employed
n = is the number of individuals studied
But:

$$NSME_I = \frac{Total\ number\ of\ SMEs\ owned}{Total\ number\ of\ respondents} \text{x} \frac{100}{1} \quad (2)$$

and

$$NIE = \frac{Total\ number\ of\ individuals\ employed}{total\ number\ of\ respondents} \text{x} \frac{100}{1} \quad (3)$$

From the above, it implies that the job creation index of individuals is a function of the total number of jobs established and the number of employees engaged. This is because job creation is viewed from three critical perspectives – self-employment, business initiatives and unemployment reduction (Owan, Agurokpon, et al., 2021). However, with the emerging changes in work demands occasioned using Information and Communication Technology (ICT), it is not surprising that job creation can be highly affected by ICT usage. In their empirical investigation, (Pichler & Stehrer, 2021) discovered that people with good ICT skills have more possibilities and are less likely to be unemployed. In general, their findings supported the notion that ICT skills are less helpful in predicting future employment in medium-level digital jobs; thus, skills in information and communications technology (ICT) tend to boost employment chances significantly.

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According to (Holmes & Tholen, 2013), the need for people with very rudimentary ICT abilities will wane. According to this prediction, those who are ICT illiterates or lack basic ICT abilities will have difficulties finding work in today's market and an unpredictable career path. In addition, some researchers have emphasised that since structural and technological development would likely enhance the demand for skills in executing ICT-related jobs, historically underrepresented groups may find it more difficult to find work in the future due to the digital divide (Falck et al., 2016; Hanushek et al., 2015; Vasilescu et al., 2020). Therefore, those without ICT skills are more likely to lack job stability (Aubert-Tarby et al., 2018; Fossen & Sorgner, 2022; Hite & McDonald, 2020).

It was shown by (Falck et al., 2016) that the magnitude of the ICT skills premium varied substantially across various professions. The researchers discovered that jobs that substantially depended on ICT abilities had greater returns on such skills than those that needed rudimentary computer skills. This helps explain why the ICT revolution's advantages are not shared equitably throughout the various job categories. According to (Piroșcă et al., 2021), more significant levels of ICT literacy were linked to higher rates of labour market involvement and better salaries. A study (Hampf et al., 2017) found that ICT abilities positively correlated with other human factors, such as education, age, and gender. As a result, the characteristics of ICT users affected their ability to create new jobs.

An ICT user refers to an individual with the capacity to use information and communication technologies such as the Internet, computers, smartphones, social media and specific applications to meet his/her needs. Postgraduate students capable of using the computer or other devices to source information on the web, send emails, chat with colleagues, collect research data and perform other functions are ICT users. Generally, ICT users do not necessarily need to be skilled or knowledgeable about ICT. It includes those who only visit bookmarked websites in their browsers to carry out a task, even without the ability to search and retrieve information from the Internet. It also includes those with high-level competence in using ICT for advanced computing.

Many studies on ICT users' characteristics have focused on personal and professional variables such as gender, age, experience, educational level, rank and location (Donkor & Nwagwu, 2019; Guillén-Gámez & Mayorga-Fernández, 2020; Karatsoli & Nathanail, 2020; Sánchez Prieto et al., 2020; Wu & Hong, 2022). For instance, a study (Vroman et al., 2015) found that educated adult users (65 to 70 years) are more likely to use ICT than those above the age range. Furthermore, age, attitudes, education, and socio-personal characteristics were found to be major contributing factors to ICT use. Another research (Odigwe & Owan, 2020) provided a disparity in results by proving that ICT utilisation is a decreasing function of age, with younger individuals being more competent in using ICT than older users. The cited study also showed, on average, that males were better ICT users than their female counterparts. On the contrary, (Owan, Asuquo, et al., 2021) found that age and gender significantly influenced the preparedness of academic staff to use internet-based outlets for research dissemination. However, the cited study research documented that female, and older academic staff demonstrated a higher intention to use than their male and younger counterparts.

In another development, the research of (Reisdorf et al., 2021) revealed that the major determinants of being an ICT proxy user are personal and economic variables as well as operational internet skills. Professional variables such as educational qualification, rank, experience and areas of research interest were validated by a Kruskal-Wallis test (Owan, Akah, et al., 2021) as significant factors affecting staff propensity to use electronic channels for research distribution (Owan, Akah, et al. 2021). However, the current study took a different perspective to adopt a statistical approach known as Latent Class Analysis (LCA after this) to classify the characteristics of ICT users based on their use cases. LCA "is a statistical procedure used to identify qualitatively different subgroups within populations who often share certain outward characteristics" (Weller et al., 2020; p.287). LCA is similar to cluster analysis in that it recovers hidden groups from observable data, but it is more adaptable since it is based on an explicit model of the data (Oberski, 2016). LCA is a kind of mixture model with a wide range of applications (Hancock & Samuelsen, 2008; Masyn, 2013; Sterba, 2013). All mixture models have the same goal: to offer a probabilistic categorisation of people into latent classes using a statistical model, with each class being one of the K categories of a discrete latent variable C (Bauer, 2021).

Using latent class analysis, or LCA, researchers may identify latent subgroups within a population by looking at various data points. LCA is implemented on categorical data (nominal and ordinal), while a related approach known as Latent Profile Analysis (LPA) is often used with continuous data. Work and organisational scientists are paying more attention to person-centred methods such as LCA (Morin et al., 2018; Woo et al., 2018). As a result, the LCA has widely been implemented in different empirical studies (Barbieri et al., 2021; Petersen et al., 2019; Sinha et al., 2018; M. Zhou et al., 2018). Researchers have used the LCA approach in education to identify four classes of painful childhood experiences (Merians et al., 2019).

The research of (Hutchesson et al., 2021) used the LCA to investigate various health-risk behaviours associated with psychological distress among Australian university students. Furthermore, studies have implemented the LCA in the field of education to classify principals' leadership types (Agasisti et al., 2019), students' alcohol use, drug use and risky behaviours (Afrashteh et al., 2017; Assanangkornchai et al., 2018; Pilatti et al., 2020), parental involvement in students' education (Zhou and Bowers 2020), students' expectations towards school analytic services (Whitelock-Wainwright et al., 2021) and so on. Many simulation studies (Nylund et al., 2007; Sijbrandij et al., 2019; Swanson et al., 2012; Wang et al., 2017) also abound in the literature, testing for new possibilities and experimenting with new ideas to help us better understand/improve the application of LCA for quality measurement. However, in the current study, the LCA approach is used to classify postgraduate students (participants of this study) into various classes based on their use characteristics of ICT. After revealing the latent classes, the researchers further compared the job creation differences across the various classes. The aim was to determine respondents' behavioural attributes and how job creation activities discriminate across these classes. The behavioural characteristics of the ICT users refer to the attitude portrayed by different ICT users.

Previously, related studies tended to have focused on classifying the attributes of ICT users based on the roles performed with these resources. For example, (Pichler & Stehrer, 2021) classified ICT users based on their job roles, such as high-level government officials and legislators, firm directors, commercial and administrative leaders, production supervisors, etc. Similarly, other studies have discovered that the adoption of ICT equipment such as computers, the Internet (including social media), mobile phones, closed circuit television (CCTV), security cameras, information extraction, spy satellites and Internet protocol gadgets help in crime reduction (Arisukwu et al., 2020; Laufs & Borrion, 2022; Nagrath et al., 2022; Owan & Ekpenyong, 2022). Software development with systems administration analysis was the focus of the unique user characteristics in this case. In analysing ICT users' characteristics, it was discovered that software engineers, computer programmers, systems analysts and computer support were highly in demand across the economy and industries identified in different countries (Hiranrat & Harncharnchai, 2018; Lovaglio et al., 2018; Russo & Stol, 2022; Siddoo et al., 2019).

However, in Nigeria, many researchers have established that word processing, software design, computer hardware management, networking security and systems administration are common ICT skills that characterised most of the population (Akah et al., 2022; Owan & Asuquo, 2021; Oyediran et al., 2020). It is pretty revealing that the classification of ICT users in the cited studies was rather casual and informed by the experiences of the scholars. Limited studies have adopted statistical and machine learning approaches such as the LPA, LCA, K means clustering, random forest regression and so on in classifying ICT users. Using such approaches can help us to understand sub-groups in a population better. Based on the extent of the review conducted, the researchers did not find any previous study that had classified ICT users based on their use/behavioural characteristics. None of the cited studies on LCA had also focused on job creation nor ICT users in the school context. The studies on the ICT have rarely used the LCA approach to classify ICT users based on their use characteristics.

The current study is grounded on the Theory of Planned Behaviour (TPB). The theory of planned behaviour (TPB) was covered in the chapter "From Intentions to Actions: A Theory of Planned Behaviour" (Ajzen, 1985). However, in 1991, Ajzen broadened the TPB to incorporate the notion of reasoned action's predictive potential (Ajzen, 1991). The theory of planned behaviour (TPB) ties people's thinking with their behaviour. According to this theory, people's behavioural intentions are affected by attitudes, subjective norms, and beliefs that they have some level of behavioural control. Following TPB, behavioural intention is the most significant proximal predictor of human social behaviour. The implication of the TPB to the current study is that users may likely utilise ICT differently based on their perceptions, actions, and experiences. The TPB is valid for the LCA analysis for naming and descriptive purposes. Whilst the LCA revealed the statistical groupings, the TPB helps understand the behavioural attributes of the group members using their response probability conditional on class. Since the LCA is quantitative but yields qualitative groups (Kawai et al., 2018; Xiangdong et al., 2005), we utilised a data-driven approach in the current study to statistically classify the behavioural characteristics of ICT users based on their perception and perspective. This enabled us to understand when, where, how, and why they utilise ICT resources for different purposes. The study used the LCA approach because ordinal data were obtained from the respondents. This study was designed to identify the classes of ICT users among postgraduate students based on their behavioural characteristics. The study was also designed to estimate the job creation variations among postgraduate students belonging to the different classes of ICT users identified.

Research questions

i. What are the classes of ICT users among postgraduate students based on their behavioural characteristics?
ii. What are the mean differences in job creation among postgraduate students belonging to different latent classes of ICT users?

Methods

This study draws from the epistemological philosophy of positivism and interpretivism, with a deductive approach (Ryan, 2018; Saunders et al., 2015). The research is mainly quantitative following the exploratory survey research design (Anderson & Lightfoot, 2022). This design was chosen because exploratory research is not meant to produce definitive proof but to help us get a deeper knowledge of the issue. If new data or ideas emerge during the exploration, the researcher(s) must be open to changing course. The population of this study comprised 2,923 postgraduate students from four Federal public universities with approved postgraduate programmes in South-South Nigeria. For security and confidentiality reasons, the names of the four participating universities are masked. However, the population of the study is distributed as follows – University A (N = 691), University B (N = 902), University C (N= 827) and University D (N = 503). The cluster random sampling technique was adopted in selecting a sample of 1,023 postgraduate students as respondents for the study. This sample represents 33.77% of the study's population and it is distributed as follows – University A (n

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= 242), University B (n = 316), University C (n= 289) and University D (n = 176). State Universities were not considered because most have yet to run postgraduate programmes.

An instrument entitled “Behavioural Characteristics and Job Creation Questionnaire (BCJCQ) was used for data collection. The BCJCQ was designed by the researchers and structured into three sections – A, B, and C. Section A was designed to collect the biodata such as gender, institution, age, and programme of study. Section B was designed with ten items to collect information on the behavioural characteristics of the respondents. Section C was designed with six items to collect information on the job creation activities of respondents. All the items in sections B and C of the questionnaire were organised on the four points Likert scale. Response options in sections B and C of the instrument ranged from strongly agree to strongly disagree. The instrument was validated by three experts (two psychologists and one psychometrist) in one of the participating institutions. The instrument's reliability was established using the Cronbach alpha approach after a trial test had been conducted on 30 postgraduate students from two participating institutions. The respondents in the trial test were not part of the sample but were drawn from the study's population.

The researchers obtained ethical clearance to research from the University of Calabar Research Ethics Committee after declaring it as not involving any human participation risk. A date was scheduled for each participating institution for data collection. Before the administration, we explained the objectives of the study and the role expectation of the respondents. Participants were told that participating in the study was voluntary and that the data solicited would be used only for research and publication purposes. Respondents were assured that the provision of their biodata was optional and where they are provided, they shall be anonymised in line with the Safe Harbour rules. The respondents were also assured that their responses to sections B and C of the survey would be aggregated and the statistical analysis results published in a peer-reviewed journal. After these explanations, the researchers administered copies of the instrument to 996 participants who consented to participate through the support of five research assistants. However, the researchers recovered 987 copies of the instrument administered. This indicated a return rate of 99.1% of the instrument's copies administered and a shortage of 3.52% from the original sample.

The collected data were sorted, scored and coded accordingly. The researchers transformed the data by adding all responses indicating disagreement across all the items in section B of the instrument to group 1 and all responses indicating an agreement to group 2. In LCA, when indicator variables have fewer levels, it is simpler to evaluate the class solution when several answer alternatives are collapsed into two or three options (Weller et al., 2020). However, the items in section C of the questionnaire were scored in a polytomous manner (“Strongly Agree” = 4, “Agree” = 3, “Disagree” = 2; “Strongly Disagree” = 1), with reverse scoring implemented on negatively worded items. The Snow Rasch Mixture Model (SnowRMM) module was used in performing the Latent Class Analysis (LCA) with the aid of Jamovi version 1.8.1 software.

Results

Latent Class Analysis

When conducting LCA, a few issues relating to the assumptions of the statistical procedure must be met to ensure that the results obtained are valid and valuable. First, the researchers considered the sample of this study large enough for LCA since it is well above the 300 cases often advocated by previous studies. Although small sample sizes are acceptable with simpler models (having fewer indicators and classes) and "well-separated" classes (Weller et al., 2020), it has been recommended that having at least 300 cases is ideal (Nylund-Gibson & Choi, 2018; Spurk et al., 2020). Secondly, the items used in the instrument design are theoretically underpinned and derived extensively from the works of a previous study (Birkland, 2019).

Even though the number of indicator variables in a model is up for debate, it seems that the more indicators in a model, the better the results will be (Weller et al., 2020; Wurpts & Geiser, 2014). The number of indicators included in previous research has ranged from four to as many as 20 (Rosato & Baer, 2012; Travis & Combs-Orme, 2007). According to previous research, ten indicator variables were used in the present study to measure the characteristics of ICT users. The SnowRMM module in Jamovi software was used for data analysis, and the LCA was performed in sequence, beginning from the 2-class model (the default) to the 8-class model (see Table 1). The models were compared using statistical and substantive theoretical criteria to determine the best model. We found that the 5-class model provided the best solution to our data based on the indicators of a combination of fit statistics such as Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), Entropy and so on.

Table 1: Fit indicators and criteria for determining the class model to be selected

No. of Classes	AIC	BIC	Entropy	Gsq	Chisq
2	12415	12518	6.27	4325	10992
3	12078	12235	6.09	3966	8707
4	11560	11770	5.81	3426	7602
5	10864	11129	5.45	2709	9870
6	11145	11463	5.6	2968	5102
7	11074	11446	5.59	2874	4781
8	10724	11150	5.36	2503	6709

As shown in Table 1, the 5-Class model was chosen because when taken as a combination, it has the lowest AIC, BIC, Entropy and Gsq. Although the 6, 7, and 8 class models all have lower AICs than the chosen model, the 5-class model was chosen because it maintained consistency across other fit indices (such as the BIC) and aligned with theoretical knowledge. Besides, when it comes to fit statistics, the Bayesian information criterion (BIC) is gradually being credited as the most trustworthy (Nylund et al., 2007; Patterson et al., 2002; Weller et al., 2020) and the most widely reported in LCA studies (Killian et al., 2019).

The Latent Class Plot (in Figure 1) was further used to illustrate the posterior probability of the manifest variables (Items) conditional on the class. After determining the number of classes that best suit the data, the next thing was to name these classes using theoretical and practical knowledge based on the class response probability response pattern (See Table 2). As shown in Table 2, the classes were considered large because none had less than 11% of the sample. Previous studies recommend that having 5% of the sample or higher in all the classes is large (Nylund-Gibson & Choi, 2018). We named the classes of behavioural ICT users as trendy, outmoded, pragmatic, disciplined and social (More on this in the result section).

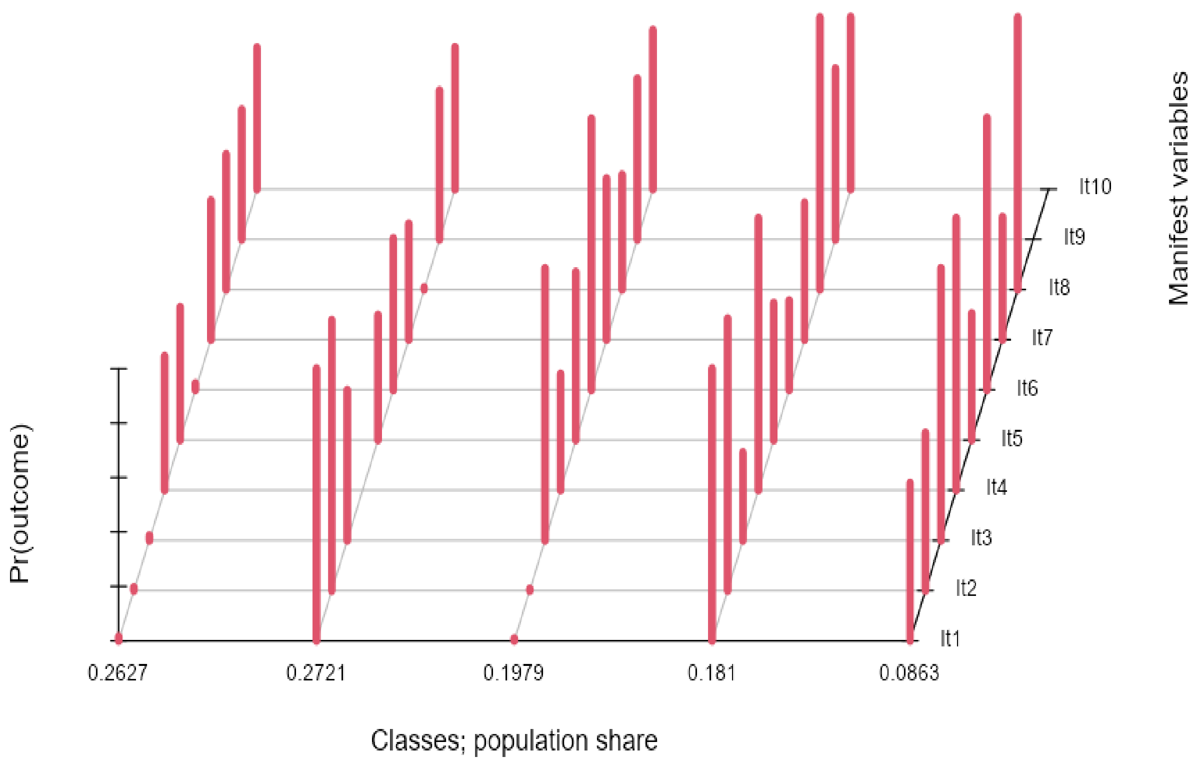

Figure 1: Latent Class Analysis Plot showing the probabilities (Pr) of manifest variables (Items) conditional on class membership

Research question 1

What are the classes of ICT users among postgraduate students based on their behavioural characteristics? Based on the result presented in Table 2, five classes of ICT users were identified. These classes include the trendy, outmoded, pragmatic, disciplined and social ICT users, as discussed below.

1. Trendy users

Following the class membership, conditional on the response probability, it was discovered that the trendy users of ICT are those that keep up with the latest developments in ICT. They constitute 39.6% of the participants of this study. They are more likely to own many state-of-the-art ICTs and can demonstrate an eagerness to try new ICT innovations because, for them, ICTs are more like fun toys. This class of ICT users often seek new ways of using ICT in every facet of their lives. Although they tend to place a high value on technologies that promote socialisation to build bonds with their network, trendy users are less likely to communicate with an extensive network of contacts in social spaces and are less likely to use ICT gadgets in completing business-related tasks.

2. Outmoded users

The next class of ICT users identified in this study are the Outmoded users, which according to Table 2, constitute 11.5% of the study's respondents. A look at the response pattern indicates that postgraduate students tend to be nostalgic about previous technologies and are less likely to follow modern ICT trends. The outmoded users are more likely to surround themselves with outdated technology because they believe that older technologies are better and can prominently display traditional ICT gadgets while putting newer technologies in obscure places. They are also less likely to express excitement in current ICTs than in the past.

Unlike the trendy users, outmoded users are not interested in trying new ICT innovations and do not seek new ways to use ICT in every facet of their lives. Although they are less likely to communicate with an extensive network of friends in the social space and are less likely to use ICT gadgets to complete tasks related to daily business, they tend to maintain ICT-free spaces to enjoy real-life relationships with family/friends.

3. Pragmatic users

This study's third class of postgraduate students are pragmatic ICT users. About 14.8% of the respondents of this study are in this category. They represent those that are (interested in) making practical use of ICT for business-related purposes. They may be regarded as relatively objective in using ICT to fulfil a specific need at a time. Table 2 also shows that pragmatic ICT users are less likely to use ICT for fun, besides helping them perform specific business-related functions. Pragmatic users are more likely to often communicate with an extensive network of friends in the social media space, for perhaps business connections, customer outreach and communications. Pragmatic users of ICT share some outmoded attributes because they are less likely to switch from device to device as new technologies and are less interested in seeking new ways to use ICTs. Despite the similarity, pragmatic users are almost unlikely to feature outdated ICT devices at prominent locations and are somewhat excited about current technology. Furthermore, pragmatic users have a 50 per cent chance to place little or no high value on technologies that promote socialisation within their network. We can say that pragmatic users bridge the gap between trendy and outmoded users.

4. Social users

Constituting 13.1% of the postgraduate students who participated in the study, the social users of ICT tend to use ICT in building social connections. This class of ICT users are more likely to often communicate with an extensive network of friends in the social media space and are 64% more likely to place a high value on technologies that promote socialisation to build bonds with their network. This study also revealed that social users are 100% not eager to try innovations and are 99% unlikely to seek often new ways to use in other facets of life. It was also revealed that social users of ICT are 100% unlikely to formulate strict, self-imposed guidelines on how often/much to use ICTs and maintain ICT-free spaces to enjoy real-life relationships with family/friends. There is a 50:50 chance for social users to deploy ICT gadgets in completing tasks related to daily businesses. Social users are 96% unlikely to display traditional forms of ICT gadgets while obscuring newer technologies. However, they are 94% certain to be excited about current ICTs than the ones in the past.

5. Disciplined users

The LCA of this study shows that 20.9% of the respondents of this study are disciplined users. According to the result in Table 2, disciplined users are 100% likely to formulate strict, self-imposed guidelines on how often/much to use ICTs; 100% very proud to maintain ICT-free spaces to enjoy real-life relationships with family/friends; and 100% not likely to be excited in current ICTs as the ones of the past. Disciplined users were 99% likely to prominently feature traditional forms of ICT gadgets while obscuring newer ones. Although they are less likely to display eagerness to try new ICT innovations nor seek new ways of using ICT daily, they are pretty more likely to use ICT gadgets in completing tasks related to daily businesses. Discipline users are more likely only to use ICT to fulfil specific business needs. Perhaps because disciplined are likely to develop a high value for technologies that promote socialisation, they often communicate with an extensive network of friends in the social media space.

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Table 2: Estimated class-conditional response probability

Manifest Items	Response categories	5 Latent Class Model				
		Trendy 39.6%	Outmoded 11.5%	Pragmatic 14.8%	Social 13.1%	Disciplined 20.9%
Eagerness to often try new ICT innovations	Agree	.99	.02	.00	.00	.46
	Disagree	.01	.98	1.00	1.00	.54
Often seeking new ways to use ICTs in every facet of life.	Agree	1.00	.02	.01	.01	.46
	Disagree	.00	.98	.99	.99	.54
Formulation of strict, self-imposed guidelines on how often/much to use ICTs	Agree	.64	.99	.02	.00	1.00
	Disagree	.36	.01	.98	1.00	.00
Often communicating with an extensive network of friends in the social media space	Agree	.48	.48	.62	.51	.54
	Disagree	.52	.52	.38	.49	.46
Using ICT gadgets to complete tasks related to daily businesses	Agree	.46	.49	.58	.50	.51
	Disagree	.54	.51	.42	.50	.49
Always maintaining ICT-free spaces to enjoy real-life relationships with family/friends	Agree	.64	1.00	.01	.00	1.00
	Disagree	.36	.00	.99	1.00	.00
Using ICTs only to fulfil a specific need at a time	Agree	.45	.47	.55	.58	.53
	Disagree	.55	.53	.45	.42	.47
High value for technologies that promote socialization	Agree	.55	.48	.50	.61	.48
	Disagree	.45	.52	.50	.39	.52
Displaying traditional forms of ICT gadgets more prominently while obscuring newer ones	Agree	.39	1.00	.07	.04	.99
	Disagree	.61	.00	.93	.96	.01
No excitement in current ICTs as the ones of the past	Agree	.37	1.00	.10	.06	1.00
	Disagree	.63	.00	.90	.94	.00

Research question 2

What are the mean differences in job creation among postgraduate students belonging to different latent classes of ICT users? In answering this question, the researchers used the nominal class membership variable generated during the LCA analysis to test for differences in job creation among members of the five latent classes. The dependent variable is job creation, characterised by continuous data derived from adding responses to the six items in section C of the questionnaire per person. A one-way analysis of variance was performed to compare the mean job creation among the classes. According to the descriptive result in Table 3, trendy ICT users (n = 148) have a job creation mean of 14.27±4.99. Outmoded users (n = 119), pragmatic users (n = 265), disciplined users (n = 228) and social users (n = 227) have a mean job creation of 15.19±5.81, 17.58±5.56, 15.71±5.37, and 17.03±5.00 respectively. This implies that, on average, pragmatic users of ICT create more jobs. Social, disciplined, outmoded and trendy users of ICT follow this. It was further proven by the ANOVA result that there is a significant mean difference in the job creation of postgraduate students based on their behavioural characteristics of ICT use ($F_{[4, 982]} = 12.18$, $p < .00$). Due to the significance of the result in Table 3, the Tukey HSD post-hoc test of multiple pairwise comparisons was performed (see Table 3).

The analysis in Table 4 shows no significant difference in job creation between outmoded versus trendy users of ICT and between disciplined versus trendy users. However, there is a significant difference in job creation between pragmatic versus trendy users and between social versus trendy users. The result also indicates that the difference in the job creation between pragmatic versus outmoded users and between social and outmoded users of ICT is statistically significant. However, there was no significant mean difference in job creation between disciplined and outmoded ICT users. Further comparisons revealed a significant mean difference in job creation between pragmatic and disciplined ICT users. On the contrary, no significant mean difference was found between pragmatic and social ICT users regarding job creation activities. At the .05 level of significance, no significant mean difference in job creation was found between disciplined and social users of ICT.

Table 3: Descriptive and Inferential Results of a one-way ANOVA showing the mean differences in job creation among different classes of ICT users

Classes	N	Mean	SD		SE
Trendy users	148	14.27	4.99		.41
Outmoded users	119	15.19	5.81		.53
Pragmatic users	265	17.58	5.56		.34
Disciplined users	228	15.71	5.37		.36
Social users	227	17.03	5.00		.33
Total	987	16.24	5.46		.17
Source	SS	df	Mean Square	F	P
Between Groups	1388.75	4	347.19	12.18	.00
Within Groups	27997.34	982	28.51		
Total	29386.09	986			

Table 4: Tukey posthoc test of multiple pairwise comparisons of the mean differences in job creation based on the classes of ICT users

(I) Class	(J) Class	MD	SE	p	95% CI
Trendy users	Outmoded users	0.92	0.66	.63	0.87, 2.72
	Pragmatic users	3.315*	0.55	.00	1.82, 4.81
	Disciplined users	1.45	0.56	.08	0.10, 2.98
	Social users	2.761*	0.56	.00	1.22, 4.30
Outmoded users	Pragmatic users	2.392*	0.59	.00	0.78, 4.00
	Disciplined users	0.52	0.60	.91	1.13, 2.17
	Social users	1.838*	0.60	.02	0.19, 3.49
Pragmatic users	Disciplined users	1.870*	0.48	.00	0.55, 3.19
	Social users	0.55	0.48	.78	0.77, 1.87
Disciplined users	Social users	1.32	0.50	.07	0.05, 2.68

* The mean difference is significant at the .05 level; MD = Mean difference

Discussion of findings

This study was designed to obtain qualitative classes of ICT users through the LCA approach based on their behavioural characteristics. The study was also designed to quantitatively discriminate the extent of job creation based on the qualitative classes of ICT users. Through the LCA, five latent classes of ICT users were discovered among postgraduate students in South-South Nigeria based on their behavioural characteristics. As carefully named, these classes of users include the trendy, outmoded, pragmatic, social and disciplined users. It was established that these categories of ICT users deploy technology in unique ways based on their perceptions, beliefs and orientation. This result was consistent with the theory of planned behaviour, which prescribes that three main components shape a person's behavioural intentions: attitude, subjective standards, and perceptions of their behavioural control (Ajzen, 1985, 1991). This explains why members of different classes of ICT users are obsessed with making use of ICTs in ways they consider convenient for themselves. The result of this study offers empirical grounds for the ICT user type discussed by (Birkland, 2019). For instance, the trendy users of ICT share similar ICT characteristics as the enthusiastic users (Birkland, 2019). Furthermore, the pragmatic and social users in the current study share similar attributes to the practicalists and socialisers in the cited study.

Although this study established a significant difference among the users, the trend was inconsistent regarding job creation differences. This finding implies that even though there is a significant difference among at least two of the bivariate pairings, some groups did not differ substantially from others. Nevertheless, it was discovered that, on average, pragmatic users of ICT create more jobs than social, disciplined, outmoded and trendy ICT users in descending order, respectively. Even though pragmatic users had the highest mean value for job creation, the study did not find any significant pairwise difference from social users of ICT. This means that both pragmatic and social users are more likely to create jobs at similar levels, with perhaps a negligible marginal difference in favour of the former. However, a wide gap exists in the job creation mean of pragmatic users from members of other classes such as outmoded, disciplined and trendy users. Pragmatic and social users of ICT may have edged other counterparts in the extent of job creation, perhaps because they tend to use ICTs more objectively than others. Although social ICT users tend to be addicted to building connections, these connections could translate into meaningful business links. The present study could not cover the aspects of the specific ICT activities of postgraduate students.

However, this study attributes any notable differences in job creation among the classes to chance (for non-significant bivariate differences) or individual, opportunity and environmental factors (for significant bivariate differences) such as family background, nature of jobs created, socio-economic status, external support and so on. This finding tallies with the result of another study (Dencker et al., 2009) which found that individual and opportunity factors significantly influence negatively and positively the job creation of new firms. Similarly, a study (Nallari et al., 2011) established that jobs in national economies and private companies are affected by variables such as the prevailing economic environment that has recently suffered from the global financial crisis. Thus, it would not be surprising if individuals in any ICT class of users can create jobs. This is because job creation may be independent of a person's behaviour, especially when other people manage their business initiatives.

Limitations and Implications for further research

This study faces the limitation of a small sample size obtained from four universities in a region in Nigeria; thus, the result of this study may not give a better reflection of things from a broader view of postgraduate students if the scope is increased. Consequently, it is recommended that future studies expand the scope of this study to the general population for a complete result. It was beyond the scope of this study to consider whether specific skills possessed by postgraduate students were an underlying factor in their ICT behavioural characteristics. Therefore, future studies should consider this aspect for further research. Future researchers should also consider linking specific behavioural characteristics of ICT users to specific jobs they are more likely to create. Even though statistical, practical and theoretical grounds were used in extracting and naming the classes of ICT users, it is often a limitation in almost all LCA studies that naming these classes may be misleading or fallacious. Furthermore, despite the strength of LCA in assigning people to classes based on the likelihood that they will be in that class, given their pattern of scores on indicator variables (Muthen & Muthen, 2000); appropriate class assignment is not always guaranteed (Weller et al., 2020). This implies that further researches are still necessary in this area to ensure that the characteristics of ICT are adequately explored from multiple contexts toward a theoretical understanding.

Conclusion

This study was designed to identify the behavioural characteristics of ICT users among postgraduate students and determine their job creation differences. An LCA was performed, and five groups of ICT users emerged based on their response probability conditional on class. The five groups are pragmatic, outmoded, trendy, social and disciplined ICT users. A significant job creation difference was recorded between at least two classes. The post-hoc test revealed at the .05 alpha level that there were five significant and five non-significant mean differences among all the multiple pairwise comparisons. This means that people's behaviour towards ICT use will likely influence how they can create jobs. Although it was beyond the scope of this study to reveal the type of jobs specific class of ICT users are likely to create, the current study has laid the groundwork for further research. Future research needs to use the behavioural characteristics described in this study to identify the types of jobs postgraduate students are likely to create. The current study will, however, create awareness by informing the public, particularly postgraduate students, that their behaviour towards ICT use has a bearing on their capacity to create jobs. The link between behavioural character and job creation is direct, depending on use, but can also be indirect through confounding variables such as time, opportunity cost, user type, finance and environmental factors. This means that the time spent using ICT resources based on users' character affects the degree to which they engage in other ventures, affecting their job creation. Since this study did not provide evidence of one group being better than another in using ICT, the implication is that their behaviours might affect how, where and when they use it, whom they use it with, and what they use it for.

Recommendations

Based on the conclusion of this study, the following recommendations were made:

1. Postgraduate students should use the characteristics of ICT users described in this study to identify their group membership and try to understand their disposition for job creation.
2. Members of each class of ICT should understand their core strengths and weaknesses likely to inhibit the degree of their job creation. Measures should be identified to reduce the effect of such weaknesses on job creation potential, such as reducing time spent using ICT resources, changing one's perception, or creating a balance between time spent using ICT for profitable and non-profitable purposes.
3. Several jobs can be created for self and others while using ICT resources in developing nations, such as Nigeria. Therefore, users should identify and leverage these opportunities regardless of behavioural class membership.
4. Regardless of character or behavioural class membership, postgraduate students should try to make positive use of ICT by tapping into the wealth they can be used to create. This is very important for developing countries like Nigeria.

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