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ANTECEDENTS OF PHARMACY STUDENTS' PERFORMANCE IN NIGERIAN UNIVERSITIES: A CLUSTER ANALYSIS STUDY

Summary: Most student performance metrics are based on quantitative assessment from traditional test and examination scores. However, there is an apparent scarcity of exploratory qualitative studies to examine the characterization of traits, attitudes, and behaviors that may influence students' performance outcomes. Moreso because such characterization will contribute to informing and supporting appropriate corrective interventional strategies from educators. The study aimed to evaluate the antecedents of the academic performance of undergraduate pharmacy students using a cluster analysis framework. We examined the antecedents of interest as clusters depicting measures of relative strength of study behaviors, group study behavior, perceived lecturer support, perceived program difficulty, and a single demographic variable-age, evaluated in the context of self-reported academic performance. Using a structured questionnaire, cross-sectional survey data was obtained from 352 undergraduate pharmacy students in their third, fourth, and fifth year from three Nigerian pharmacy schools from April to May 2024 and analyzed using Two-step cluster analysis. Four distinct clusters emerged with perceived program difficulty and study behaviors as the highest predictors of cluster membership. Cluster 3 was the most dominant predictor based on the highest performance scores, followed by Cluster 2. Clusters 1 and 4 were identified by characteristically low (below average) study behaviors compared to the dominant clusters. The clustering method characterized the dominant proclivities, attitudes, and behavior of students which can potentially inform targeted interventional strategies from educators. The study findings provide more insight into prioritizing students' characteristics that enhance performance. Students should be encouraged to strive for an optimal mix of appropriate attitudes and behaviors to increase the likelihood of success in their academics. The study advocates periodic evaluation of students' perceptions of key performance antecedents to support adequate and informed remedial interventions. Implications of the study to educators and researchers are discussed.

Keywords: cluster analysis, students' behaviors, academic performance, pharmacy education

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Introduction

The evaluation of students' academic performance is an ongoing concern that is dependent on the information available to education administrators and managers. More often than not, educators base their decisions and interventional strategies on the quantitative assessment tools available to them (exams, assignments, continuous assessment tests, term papers). But there is less information based on the perspectives of students which may be more informative and useful for objective assessment by educators. Based on this apparent limitation, there is a gap in the objective assessment of personality traits, attitudes, and behaviors of students that influence their academic performance from the student's perspective. It is established from the literature that study behavior, group study behavior, perceived lecturer support, perceived program difficulty, and age (demographic factor) amongst other factors, impact the eventual performance of students (Jegede, Adepiti & Erhun, 2020; Burgess, Roberts, Ayton, & Mellis, 2018; Jegede, Adepiti, & Erhun, 2020; Kaufman, 2003; Petersen, Craig, Campbell, & Tafliovich, 2016; Ubaka, Sansgiry, & Ukwe, 2015).

The study behaviors of students are a critical measure of how well knowledge is obtained, processed, and used for required academic output (Sansgiry, Bhosle, & Sail, 2006; Sariem, Fwangshak, Shalkur, & Adeniyi, 2014). Study behaviors include attributes such as listening skills, reading skills, class attendance, reading time, and reading ability. A study by Chinn, Sheard, Carbone, & Laakso (2010), and Petersen, Craig, Campbell, & Tafliovich (2016), showed that students with better study behaviors are associated with better learning and academic performance. Hence, students who adopt the right study skills are poised to outperform those with poor study skills (Petersen, Craig, Campbell, & Tafliovich, 2016).

Furthermore, group study behavior is an extension of study behavior which involves the use of knowledge sharing and enlightenment derived from colleagues and peers on specific academic interests (Burgess, Roberts, Ayton, & Mellis, 2018). Group study entails the team-centered and problem-solving approach (Burgess, Roberts, Ayton, & Mellis, 2018; Kaufman, 2003) to learning which is useful for students to enhance performance. A study by Gloe (1999) revealed that students with good interactive and group study skills tend to perform better. A key attribute of group study is that students aggregate in small groups to brainstorm, share knowledge, and solve problems in an interactive and collaborative environment (Gloe, 1999). Therefore, we propose that students who engage in group study should perform better in their academic outcomes. Ubaka, Sansgiry, & Ukwe (2015) surmised that pharmacy students considered group study (that is, discussion of course materials with colleagues) as a major determinant of performance among pharmacy students in Nigerian Universities.

Perception of lecturer support by students is an important factor that influences good academic output. The more students receive adequate support, and enlightenment from their teachers the higher the likelihood to comprehend and perform better (Jegede, Adepiti, & Erhun, 2020; Xhomara, 2021). A study by Alrakaf, Sainsbury, Rose, & Smith (2014) revealed that pharmacy students placed a premium on the enthusiasm, expertise, and explicit presentation style of their lecturers in their learning environment. Moore, Armstrong, & Pearson (2008) stated that educators must improve their understanding of the teaching needs and motivations of their students.

Perceived program difficulty has been viewed as a factor that may stimulate more hard work from students, or may produce despair and low confidence in students (Choi et al., 2019; Erhun, Jegede, & Ojelabi, 2022; Jegede, Adepiti, & Erhun, 2020; Liu et al., 2021). Intuitively, students tend to deploy more effort or hard work when they perceive a course is inherently difficult, thereby triggering better performance (Choi et al., 2019).

Demographic attributes of students are a factor that may influence performance. Studies by Kleijn, Ploeg, & Topman (1994) and Sansgiry, Bhosle, & Sail (2006) suggested that newer, younger student

faculty tend to perform lower compared to more mature students due to an apparent deficit in experience. Conversely, Ubaka, Sansgiry, & Ukwe (2015) discovered that age was a significant factor when it comes to academic performance as younger students (below 25 years) performed significantly better than older students in the seven schools of pharmacy surveyed in Nigeria.

Cluster analysis characterizes items into subgroups or clusters based on common features they share within a group but with sufficient differences between clusters to adequately differentiate them (Kent, Jensen, & Kongsted, 2014; Rodriguez et al., 2019). Therefore, the use of a single attribute to explain the subgroup within a population is avoided (Leonard & Droege, 2008). Cluster analysis is a robust exploratory research method that enables a researcher or investigator to identify, and understand the distinct groups that may exist in the dataset (Crum, Nelson, de Borst, & Byrnes 2020), This technique has been proposed for use in a variety of settings; medical diagnostics (Bellazzi & Zupan, 2008), education (Abdullah, Herawan, Ahmad, & Deris, 2011), sciences (Leonard & Droege, 2008), marketing (Oamen & Omorenuwa, 2022), management research (Ketchen & Shook, 1996) among others. Education managers are expected to adopt clustering methodologies to obtain objective criteria to support quality decision-making. Two-step cluster analysis is a type of unsupervised classification statistical approach in which the groups or classes from a dataset are unknown to the researcher before analysis (Kent, Jensen, & Kongsted, 2014; Rodriguez et al., 2019: Witten & Frank, 2005). Therefore, the Two-step clustering method enables differentiation based on attributes inherent in the dataset.

This study is probably the first to aggregate or characterize students' attributes in the performance context using cluster analysis. The study findings will provide preliminary objective empirical evidence on the relative contribution of attitudes and behaviors that predict or influence academic performance among undergraduate pharmacy students.

The objectives of the study were to 1] illustrate the use of two-step cluster analysis to classify or characterize students' attributes into defined clusters, and 2] derive implications of classifying students' characteristics on education management for undergraduate pharmacy students

Methodology

Participants and study design

The study participants consisted of 195 (55.4%) females and 157 (44.6%) males with a mean age of 22.80 years (SD=2.37). Participants were randomly selected based on their year of study- third-year (*n*=118), fourth-year (*n*=115), and fifth-year (*n*=117) undergraduate pharmacy students respectively from three government-owned Universities situated in southwest Nigeria namely the University of Ibadan, Obafemi Awolowo University, and Olabisi Onabanjo University. A self-reported questionnaire-based cross-sectional study was used to obtain data from three hundred and fifty-two purposively selected undergraduate pharmacy students. Ethical approval was obtained from the Ogun State Research Ethics Directorate with approval number OGHREC/467/139.

Measurement of Variables

The latent variables or constructs were measured on a Likert-type scale with indicators or items derived from extant literature. 1] Studying behavior (SSB) adapted from extant literature [Aboagye, Amponsah, & Johnson, 2020; Delphine, Sylvestre, Gabriel, & Wenceslas, 2020; Didarloo & Khalkhali, 2014; Jegede, Adepiti, & Erhun, 2020; Liao, Shah, Griswold, & Porter, 2021; University of Houston-Clear Lake. Study skills assessment questionnaire, 2023] measured by 13 items on a 5-point Likert scale of *never* to *always*; 2] Perceived program difficulty (PD) scale was adapted from studies (Choi et al., 2019; Erhun, Jegede, & Ojelabi, 2022; Jegede, Adepiti, & Erhun, 2020; Liu et al., 2021), measured by 10 items on a 4-point Likert scale (*strongly agree to strongly disagree*); 3] Group study

behavior (GSB) developed from studies (Jegede, Adepiti, & Erhun, 2020; Xhomara, 2021) with 7 items on a 4-point Likert scale (*not at all* to *To a great extent);* 4] Lecturer support (Jegede, Adepiti, & Erhun, 2020; Xhomara, 2021) measured by 7 items on a 4-point Likert scale (*not at all* to *To a great extent);* and 5] Academic performance was measured by 8 items on a 5-point Likert scale *(poor* to good). The academic performances of students were measured as self-reported measures based on the perception of students (Aluh, Abba, & Afosi 2020). See Appendix for details.

Analytical Procedure

The two-step cluster classification method in the Statistical Program for the Social Science (IBM SPSS) was applied to the dataset; the variables were selected as continuous constructs and standardized. The Two-step method was used because it is robust with all data forms (that is, metric and non-metric data). The approach involved the log-likelihood distance measure with Schwarz's Bayesian criterion (BIC) in which the number of clusters would be automatically determined by the software. The classification output was evaluated based on self-reported performance measures set in the evaluation field of the model. The normality of data was assessed by using skewness and kurtosis measures to ensure or ascertain if the dataset is normally distributed (Collier, 2020). The indicators for each construct were transformed into mean composite scores using the transform function in SPSS.

A simplified illustration of a Boxplot

The Boxplot is a graphical or visual representation of data distribution using median values and divisions. It is a useful method for explaining and comparing data. Typically, it shows a three-number summary of a set of data as follows-1] minimum, 2] median, and 3] maximum. The position of the median line in the box determines if it is normally distributed, a positive skew (to the left), and a negative skew (to the right).

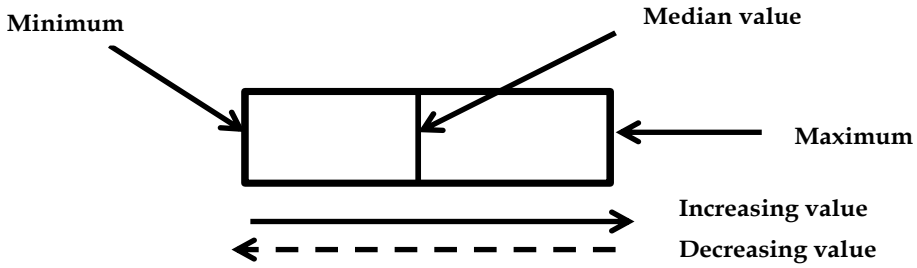

Figure 1. *Simplified description of a boxplot*

From Figure 1, lower mean values of an item or measured values tend towards the left-hand side of the middle line (referred to as the median value). This direction describes decreasing values (dashed line arrow); higher values of an item or measure tend in the direction of the right-hand side, which explains increased values of the item (solid line arrow). Generally, the values of items may extend beyond the boundaries of the minimum and maximum values, thereby depicting extreme values.

Results

Demographic attributes of respondents

352 valid responses were obtained out of 400 structured questionnaires distributed representing an 88% response rate. The sample consisted of (*n*=118, 33.5%) third-year, (*n*=115, 32.7%) fourth-year, and (*n*=117, 33.2%) fifth-year pharmacy students undergoing from the three schools of pharmacy in southwest Nigeria.

Table 1. *Descriptive statistics and Normality of data*

Constructs	Minimum	Maximum	Mean	SD	Skewness	Kurtosis
SSB	1.50	5.00	3.73	0.66	(0.26)	(0.22)
GSB	1.00	4.00	3.22	0.70	(1.06)	0.74
LS	1.29	4.00	3.11	0.55	(0.48)	(0.07)
AP	1.63	5.00	3.88	0.73	(0.36)	(0.50)
PD	1.00	4.00	3.17	0.53	(0.85)	1.77

Note. SD=standard deviation, SSB=study behavior, **PD**=perceived program difficulty, **LS**=lecturer support, **GSB**=group study behavior

From Table 1, the descriptive statistics of the constructs were presented. The table showed that the mean values ranged from 3.11 (lecturer support) to 3.88 (academic performance. The normality of the data was also examined by skewness and kurtosis measures; with optimal values expected to be between ±2 to 10 (Collier, 2020). It showed that the skewness range was -0.26 to -1.06 (considered acceptable). Also, the kurtosis value was -0.07 to 1.77, which is acceptable. Therefore, it is concluded that the data is normally distributed.

Evaluation of Cluster Quality and Validity

Cluster model quality was evaluated based on silhouette quality or index (which was within the 0.5 range, hence acceptable); cluster ratio was 2.00 which implies that the ratio of size of the smallest (cluster 4) to the largest (cluster 1) is less than one-third which is the benchmark for relative cluster sizes. All predictors were reasonable predictors of clusters, but study behavior, perceived program difficulty, and lecturer support were the most dominant predictors (with the largest predictor relevance).

Analysis and Interpretation of Clusters

A visual inspection of the boxplots (Figure 2) revealed four distinct clusters- Cluster 1; (n=104, size= 29.5%), cluster 2 (n=101, size=28.7%), cluster 3; (n=95, size= 27.0%), and cluster 4 (n=52, size=14.8%).

Cluster	1	2	3	4
Label	Students' Cluster 1	Students' Cluster 2	Students' Cluster 3	Students' Cluster 4
Description	Below Average SSB, Above Average PD, Very Low LS, Below Average GSB, and Average Age	Above Average SSB, High PD, Average LS, High GSB, and Above Average Age	High SSB, Below Average PD, Above Average LS, Average GSB, and Below Average Age	Below Average SSB, Very Low PD, High LS, High GSB, and Average Age
Size	29.5% (104)	28.7% (101)	27.0% (95)	14.8% (52)
Inputs	SSB 3.31	SSB 3.96	SSB 4.25	SSB 3.15
	PD 3.24	PD 3.52	PD 3.04	PD 2.56
	LS 2.65	LS 3.16	LS 3.38	LS 3.45
	GSB 2.70	GSB 3.59	GSB 3.23	GSB 3.55
	Age 22.61	Age 24.40	Age 21.16	Age 23.10
Evaluation Fields	AP 3.52	AP 4.02	AP 4.08	AP 3.98

Figure 2. *A diagram showing the comparative attributes of clusters*

SSB=study behavior, **PD**=perceived program difficulty, **LS**=lecturer support, **GSB**=group study behavior, **AP**=Academic performance

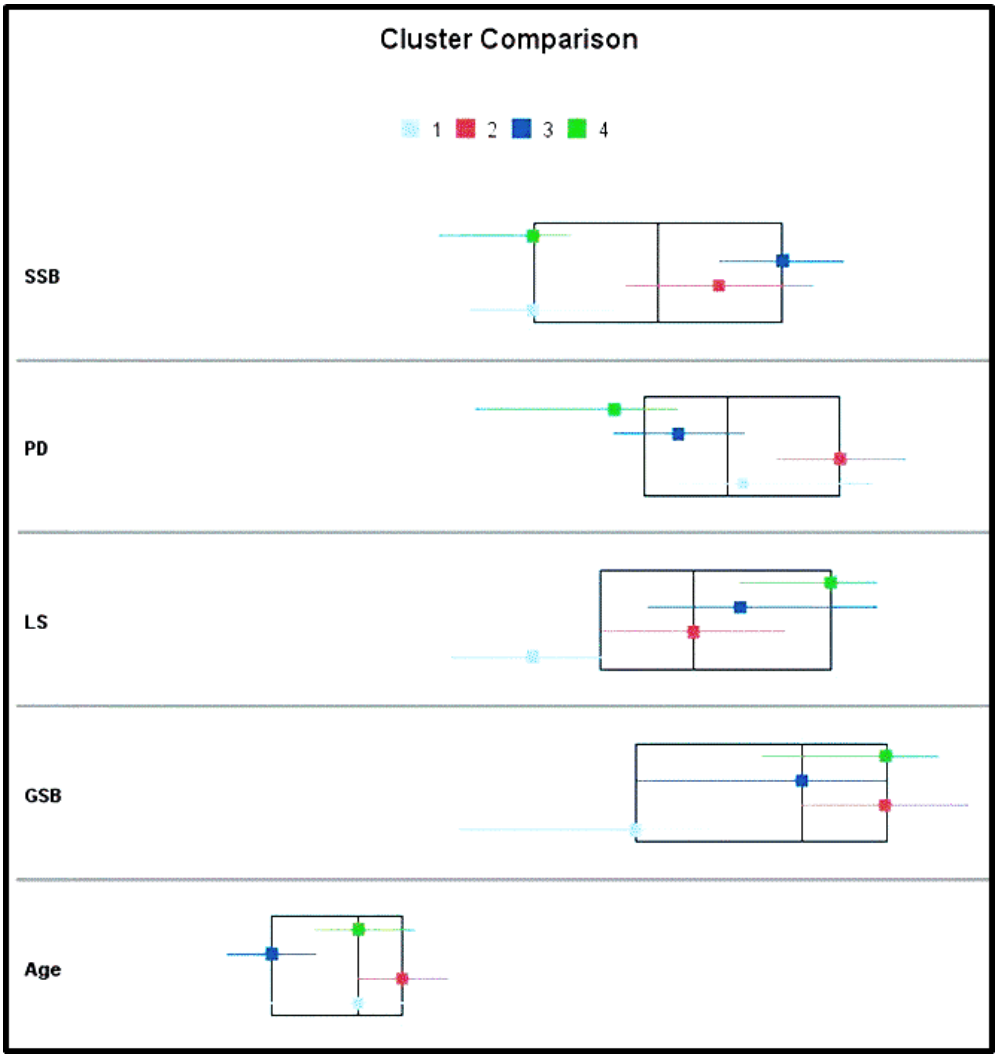

Figure 3. *A boxplot showing the distribution of constructs relative to each other*

Note. Cluster colors- cluster 1-□, cluster 2-□, cluster 3-□, and cluster 4-□
SSB=study behavior, **PD**=perceived program difficulty, **LS**=lecturer support, **GSB**=group study behavior

Figure 3 shows the comparative distribution of each cluster with score values displayed on the boxplot. Values above the **median point** were considered to be above average; values on **the maximum point** were considered to be high; above **the maximum point** were considered to be very high; values on **the minimum point** were considered to be low; and finally, values **below the minimum line** are considered to be very low.

Furthermore, from Figures 2 and 3, more details of the clusters based on the evaluation field of academic performance (AP) are presented as outlined below:

1. Study behaviors and perceived program difficulty were the dominant predictors of performance and cluster membership
2. The relative importance of constructs were study behavior-1.00, perceived program difficulty-0.73, lecturer support-0.67, group study behavior-0.57, and Age=0.52.

3. Clusters 2 and 3 had the highest performance scores of 4.02 and 4.08 respectively.
4. Clusters 1 and 4 had the lowest scores of 3.52 and 3.98 respectively
5. A closer look at clusters 2 and 3 revealed that study behavior scores were higher than clusters 1 and 4.
6. The highest performance cluster (3) had below-average perceived program difficulty compared to cluster 2 with high perceived difficulty.
7. Cluster 3 had a higher perception of lecturer support compared to the average value from Cluster 2
8. But cluster 3 had average group study behavior value compared to high values from cluster 2
9. Interestingly, the respondents in the high-performance cluster 3 were younger compared to other clusters.
10. A key difference between Cluster 1 and Cluster 4 is that Cluster 4 has a higher perception of lecturer support and higher group study skills compared to Cluster 1
11. There was no apparent difference in age between all clusters, although, the highest-performing cluster had the lowest age.
12. Finally, the lowest performance scoring clusters 1 (3.52) and 4 (3.98) had below-average study behaviors which is the dominant predictor of performance.

Discussion

Using the exploratory research approach in cluster analysis, the study highlighted the importance of classifying or characterizing students' attributes into defined clusters based on empirical data, and to derive implications of classifying students' characteristics on education management for undergraduate pharmacy students.

The clustering strategy or algorithm enables segmentation of students' perceptions based on similarities of traits within groups, and at the same time maintains distinctiveness between groups (Rodriguez et al., 2019). For instance, based on the relevance of the input parameters (study behavior, perceived program difficulty, and perceived lecturer support), the dominant cluster (3) has the highest score for study habits compared to the other clusters including below-average perceived difficulty and above average lecturer support. This implies that students tend to achieve better academic performance outcomes when they exhibit high study behaviors, a low sense of perceived difficulty in the undergraduate pharmacy degree program, and receive reasonable support from their lecturers. Conversely, the reverse is the case for the lowest performing group (cluster 1), characterized by below-average study behaviors, a higher sense of difficulty, and a very low perception of lecturer support. This finding corroborates the assertion of Jegede, Adepiti, & Erhun, (2020) that more institutional support especially from lecturers is required to support the academic performance of pharmacy students.

By extension, the above analysis comparing clusters 1 and 3 provides critical information that can support or guide intervention from educators. For instance, the high-performing group (cluster) may require more lecturer involvement to strengthen performance outcomes, while the lowest-performing group (cluster 1) would require more targeted guidance to develop the right study skills and more encouragement and support from lecturers. Younger students with a comparatively lowest mean age of 21.16 years were in the higher performing group (cluster 3); this corroborates the assertion of Ubaka, Sansgiry, & Ukwe (2015).

A critical assessment of the lowest-performing clusters (clusters 1 and 4) projects the role of students' perceptions of antecedents of academic performance. For instance, cluster 4 had higher performance scores compared to cluster 1 with lower scores of lecturer support and group study behavior. This finding further strengthens the important role of lecturer support and engagement in group study to support performance.

There are salient implications of the study that can help provide enhanced outcomes for students. The study outcomes obtained using cluster analyses reinforce the need for education managers and researchers to adopt holistic and robust analytical methods to evaluate students' attributes which could be behavioral and/or attitudinal. This is particularly relevant as it enables educators to identify segments or groupings that identify attitudinal and behavioral characteristics among students. Therefore, the manager or researcher does not place his interpretation or inference on just one criterion but on a set of criteria to support objective conclusions about the learning needs of students. Furthermore, this analytical approach when properly applied, improves the characterization of attributes, patient groups, and distinguishable groups in social and clinical research. In addition, obtained clusters can be used as a basis for group comparisons to explore differences between groups with a sample population.

There are some limitations to the study; first, although the use of Two-step clustering analysis is known to be robust and reliable (Kent, Jensen, & Kongsted, 2014), we used only the Two-step method for the study and findings were not cross-validated with other potentially better clustering algorithms. The cluster group output was not compared in the context of performance in terms of linear regression methods such as analysis of variance to identify the significance of group-specific differences. Future research is required to examine time-dependent changes in performance outcomes among undergraduate pharmacy students by using longitudinal study approaches.

Conclusion

The study applied cluster analysis techniques to explore the antecedents influencing students' academic performance and attempts to assess them as characteristics that can affect performance, as well as inform interventions from educational managers. The study highlights the relevance of holistic evaluation of the performance output of students' performance based on key parameters outlined in the study. The study concludes that better performance is obtained from pharmacy students when they adopt the right study behaviors, have a low perception of program difficulty, engage their lecturers' support, and are involved in group study. The groups or clusters derived can be used as a template for more comparative group analysis. The study recommends periodic evaluations of students' attitudes and behavior to support timely and targeted corrective interventions from educators.

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Appendix
QUESTIONNAIRE

Biodata

Gender, Age, Present course Level,

Questionnaire Items

A. Program Difficulty

1. Overall, pharmacy courses are difficult to comprehend
2. Pharmacy training is physically demanding and stressful for me
3. My time studying pharmacy is entirely occupied
4. My program affords me little time for leisure/recreational activities
5. I expend a lot of my time on my studies
6. My course load is quite overwhelming
7. I have to read for long hours to grab the concepts taught
8. I think pharmacy is very stressful compared to other disciplines
9. If given a choice, I prefer a lighter workload than I currently have
10. Leisure time is not always available for me

Likert type- Strongly Agree, Agree, Undecided, Disagree, Strongly Disagree

B. Studying Skills

1. I am eager to ask questions when in doubt about things taught
2. I set up a daily schedule to study and complete assignments
3. I readily use the Internet and library resources to supplement my learning
4. I read when it is most suitable/convenient with minimal distractions
5. I set study goals and ensure I meet them
6. I take notes during class lectures
7. I make summaries of lecture notes in my own words
8. I anticipate questions to be asked in exams and ensure I know the answers
9. I follow course outlines to ensure I am up to date on requirements
10. I plan ahead of tests by using a to-do-list
11. I set up study goals for each course and devote time to attaining them
12. I recall easily the things I have studied
13. I study with the intent of remembering

Likert type- Always, often, sometimes, rarely, never

C. Group Support

1. I enjoy studying in a study group
2. I learn better when I discuss with colleagues
3. Difficult subjects are easier to learn in groups
4. Tutorials conducted by colleagues can be very helpful in facilitating learning
5. I learn better ways to study when I engage in group learning
6. We review and answer past questions a lot more easily in study groups
7. The sharing and exchange of ideas in study groups can be useful and positive

Likert type- To a great extent, somewhat, very little, not at all

D. Lecturer Support

1. My lecturers are accessible and available
2. My lecturers are always eager to help me
3. My lecturers give pep talks to encourage us
4. My lecturers organize extra classes to augment our learning
5. My lecturer encourages me when faced with academic challenges
6. My lecturers are friendly and supportive
7. My lecturers are timely and always available for classes

Likert type- To a great extent, somewhat, very little, not at all

E. Academic Performance

1. I am doing better in my courses now compared to before
2. My course scores are better now than before
3. I meet my set academic goals as planned
4. My present study habits have benefited my grades
5. Group study has improved my learning ability
6. My academic grades have significantly improved over time
7. My comprehension and retention ability have improved over time
8. My understanding of course concepts has improved appreciably
9. I have better performance compared to the previous semester

Likert type- very poor, below average, average, above average, good

Biographical notes

Theophilus Ehidiamen OAMEN had his Bachelor of Pharmacy Degree (BPharm) from the University of Benin, MPharm (Clinical) from the University of Ibadan, MBA (Operations Management), and MPhil (Pharmacy Administration) from Obafemi Awolowo University; FPCPharm (Public health) from West African Postgraduate College of Pharmacists., and PhD (Management) from University

of Central Nicaragua. He is one of the leading experts in the use of structural equation modeling techniques in Nigeria. He has reviewed, authored, and co-authored more than 34 publications in peer-reviewed local and international journals. His research interests include- Pharmacy Education, Pharmaceoeconomics, Pharmacy management, and Psychometrics.

Ayodapo Oluwadare JEGEDE had his Bachelor of Pharmacy degree (BPharm), M.Sc. (Pharmacy Administration), and PhD (Pharmacy Administration) from the prestigious Obafemi Awolowo University. He holds a Doctor of Pharmacy degree (PharmD) from the University of Benin and is a Fellow of the West African Postgraduate College of Pharmacists. He teaches and researches extensively in pharmacy education and human resource management with over 20 publications in local and international journals. He is the Head of the Department of Clinical Pharmacy and Pharmacy Administration, Faculty of Pharmacy, Obafemi Awolowo University.