Innovations

Modelling the Learning Style of Students: A Discriminant Analysis

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Abstract

As the educational landscape continues to evolve, it's crucial to understand the unique needs and learning styles of students to effectively facilitate their academic success. This study generally aimed to build a model to classify the first-year teacher education students into their dominant learning styles. It made use of exploratory research design with the aid of an adapted questionnaire. Mean and percentage were utilized to group the students into their VARK learning style and discriminant analysis was used to derived discriminant model in classifying the students into different groups and identifying the variables with high discriminating power that could be used in separating the students into distinct groups. Results showed that visual group was the most dominant learning style of the students. Additionally, the derived discriminant models from the 4 clusters are accurate with high discriminatory power in separating the students into distinct groups based on their grades. The variables that have high discriminating power are The Child and Adolescent Learner and Learning Principles (Prof Ed 101), Physical Education 1 (PE 1n), Purposive Communication (Engl 100), and Readings in Philippine History (Hist 100). It's worth noting that the highest mean scores of the different subjects didn't show a significant difference from the mean scores of the other clusters. Overall, the study highlights the importance of identifying the dominant learning styles of students, which can aid in effectively facilitating their academic success.

Keywords: *1. VARK, 2. learning style, 3. discriminatory analysis, 4. academic success,5. teacher education*

Introduction

Learning is a lifelong process that has been extensively studied, and it is now well established that individuals have different learning styles based on cognitive, affective, and physiological factors. Felder and Silverman (1988) defined learning style as an individual's characteristic approach to learning. To improve learning outcomes, it is important for educators to understand and cater to these different learning styles. In the classroom, teachers can capture students' attention by using various techniques that cater to the different learning styles. By considering different learning styles, teachers can create effective teaching strategies tailored to the unique needs of each student. Modelling the learning style of students can help develop predictive models that accurately identify learning styles, which can further improve teaching strategies and resources, leading to better academic performance. Hence, educators must have a comprehensive understanding of how students learn and their individual learning styles to provide effective teaching strategies and improve learning outcomes.

Identifying students' learning styles helps their study habits, allowing them to attain good understanding and grades in various lessons, activities, and disciplines. According to Celce-Murcia (2001), a learning style is a generic approach—for example, global or analytic, auditory, or visual—that students utilize while learning a new language or any other topic. The typical cognitive, emotional, social, and physiological behaviors serve as generally consistent indications of how learners perceive, interact with, and respond to the learning environment, as defined by some researchers. Due to this, the teachers must first understand how to approach their students' learning styles to properly convey information. Teachers' understanding of such learning styles will play a significant role in students' learning. Students learn best when they understand the significance and value of the knowledge offered in the classroom. As a result, if pupils are uninterested in the presentation of knowledge, their learning style may suffer.

Furthermore, Baykan and Nacar (2007) stated that every person has a unique learning style, learning styles influence students' performance in a variety of ways. It determines how information is absorbed, processed, and stored in the brain, as well as how well children pay attention and concentrate. In line with the undergraduate students, the first-year university students encounter a difficult time during their first academic year since the learning methods utilized at the university differ from those employed in the school. As a result, students find it difficult to adapt to this new learning environment, which has an impact on their academic performance (Cora, 2007). Due to this, the primary goal of this study was to investigate the undergraduates' dominant learning style for making teaching and learning more successful, to assess, the VARK instrument will be used to collect data, which classified learning preferences as visual (V), auditory (A), reading-writing (R), or kinesthetic (K).

The main goal of this study is to identify the dominant learning style of first-year teacher education students and its implications for both learners and educators. By identifying the dominant learning style, students will be able to understand their preferences and use appropriate learning strategies, while teachers can adjust their teaching methods to meet their students' diverse learning styles. This research is also beneficial for future educators, as it provides them with valuable information on effective teaching tactics and different learning styles.

At the core of educational practices are the nature and needs of learners, and learning styles play a critical role in shaping 21st-century students into lifelong learners. Thus, this study is significant for school administrators, teachers, professors, researchers, and future researchers. The findings can guide school administrators in supervising teachers, while professors can gain a better understanding of their students' learning styles to foster meaningful learning. Students will benefit from the study's results by being exposed to familiar concepts that match their interests and needs, leading to a deeper appreciation and motivation for learning. Moreover, the researcher can utilize this study as a fundamental foundation for her career as an educator, given her knowledge of the learning styles applied by learners. Finally, this study serves as a reference for future researchers, providing necessary information for formulating new ideas and strategies for employing different learning styles.

Literature Review

Learning style is defined as “characteristic cognitive, affective, and psychosocial behaviors that serve as relatively stable indicators of how learners perceive, interact with and respond to the learning environment” (Curry, 1981). Basically, it is the learner’s preferred learning approach for all learning situations (Ph’ng, 2018); therefore, consider learning styles as one factor of success in higher education (Romanelli, Bird, & Ryan, 2009). Also, Dunn and Dunn (1993) define learning style as how each learner begins to concentrate on, process, absorb, and retain new and complex information. Further, Romanelli, Bird, and Ryan (2009) concluded that “a better knowledge and understanding of learning styles may become increasingly critical as classroom sizes increase and as technological advances continue to mold the types of students entering higher education.”

Several models and measures of learning styles can be used in this study, including the VARK Learning Style Inventory (Fleming & Baume, 2006; Fleming & Mills, 1992). This model categorizes students into four groups based on their preferred way of receiving and imparting knowledge: visual, audio, read/write, and kinesthetic (Lang, Wong, & Fraser, 2005). Students who can use more than one learning mode effectively are classified as multi-modal learners (Fleming & Mills, 1992). The VARK questionnaire has 16 questions, and the highest score in each area determines a student's learning style (Nilson, 2010). Created by Fleming and Mills, the VARK model represents learners' preferred physical sense during knowledge absorption and dissemination. It extends the VAK paradigm by distinguishing the visual category further into graphical/textual and visual/read/write learners (Murphy, Gray, Straja, & Bogert, 2004). The VARK model was the first to systematically apply a series of questions with assistance sheets for students, instructors, and employers to identify people's preferred methods of receiving or disseminating information (Fleming & Baume, 2006).

Further, Fleming and Mills (1992) proposed a categorization of learning patterns based on the preference in four modalities, known as the VARK model or VARK learning style. The visual (V) learners tend to grasp concepts better through visual representations such as charts, graphs, and diagrams. Aural or auditory (A) learners prefer to learn through lectures, group discussions, and listening to audio content. Read/write (R) learners tend to learn best through reading and writing activities and rely heavily on resources like the internet, lists, and manuals. Lastly, kinesthetic (K) learners prefer hands-on activities, practice, and simulations to learn better. This modality is associated with the use of experience and practice, whether real or simulated. Understanding the VARK model can be beneficial in creating teaching strategies that cater to different learning styles.

Additionally, there are seldom instances where learners prefer more than one mode. In this case, learners who do not have a standout model with one preference score well above other scores are called multimodal (Fleming & Mills, 1992). Many works use VARK learning styles because it could easily be modified the lesson’s contents to suit the VARK learners to keep their interest until the end of the class (Hasibuan, Nugroho, Santosa, & Kusimawardani, 2016). Hasibuan et al. (2016) mentioned that the VARK learning style uses an approach to teaching and learning materials that integrates all previous learning styles: Kolb’s, Honey and Mumford’s, and Felder Silverman’s models. In addition to that, the VARK model is one of the most influential and flexible models (Alghamdi, Lamb, AI-Jumeily & Hussain, 2014). For this reason, this research chose the VARK model to categorize the learners.

Addressing learning styles in education has been a topic of interest among educators and researchers globally. In a study by Kolb (2015), he emphasizes the importance of using a variety of teaching styles that cater to the different learning styles of students. He identified four different learning styles, namely: concrete experience, reflective observation, abstract conceptualization, and active experimentation. By utilizing a combination of these styles, teachers can create a diverse and dynamic learning environment that caters to different student needs. Additionally, researchers have also found that addressing learning styles can lead to better academic performance, as well as increased student engagement and satisfaction with their education (Felder & Brent, 2005).

In the Philippines, the Department of Education (DepEd) has recognized the importance of addressing learning styles in education. Through the K-12 curriculum, the DepEd has implemented differentiated instruction to cater to different learning styles and abilities of students. This approach provides a personalized learning experiences that considers the strengths and weaknesses of each student. According to the DepEd (2017), this approach has resulted in improved academic performance, increased student engagement, and a more positive learning experience overall. De Dios (2013) investigated learning styles in line with the K-12 Basic Curriculum Program and found that children developed their own pace of learning style, were empowered to make choices, and became accountable for their learning in the classroom and beyond. Similarly, Lumanog's research (2016) demonstrated that students' learning is more effective when it matches the instructor's teaching style, and that learning styles should be a guide for diversified teaching methods that cater to students' needs. Therefore, further studies about learning styles should be conducted among colleges and universities to cater to the learners' needs.

Understanding the learning style of students that suits their skills, limitations, and preferences can improve their academic performance. The beginning of the tertiary education introduces students to different ways of learning and underpins the entire undergraduate curriculum. Therefore, investigating the learning styles of tertiary students is of interest to many researchers. In a study by Hassan et al. (2012), student's sex, age, years of study, stream, and grades were tested as possible predictors of learning style among undergraduate students. The findings indicated that grades are one of the factors affecting the learning styles of undergraduate students. Although, various variables predict how students perceive and process information, investigating the learning style of students based on their academic performance is also crucial. To help students understand their learning preferences, the researcher employed discriminant analysis to segregate the students according to their learning styles, using their grades during the first trimester of the school year.

The core intention of this study was to identify the best model for the dominant learning style of first year teacher education students on the basis of their grades. Specifically, it sought to answer the following questions:

- What are the classifications of the students as to their learning styles?
- What are the characteristics of the derived discriminant model in classifying the students into different groups?
- What are the variables with high discriminating power that could be used in separating the students into distinct groups?
- What is the mean comparison of the different subject averages among the clusters?

Method

Research Design

This research is quantitative in nature as it explains a particular phenomenon by gathering numerical data that is analyzed mathematically using computational techniques, as defined by Creswell (2013). Specifically, it is exploratory in nature as discriminant analysis was used to explore the possibility of classifying first-year teacher education students based on their learning style, as indicated by their grades.

Population and Locale of the Study

The respondents of the study were first-year teacher education students from the University of the Cordilleras. The sample consisted of 86 students, selected from the total population of 109, using Cochran's formula at a 0.05 margin of error and 0.05 level of significance. Only first-time enrollees were included in the sample to eliminate any familiarity bias that might affect the determination of dominant learning styles. Furthermore, irregular, returning, and students with incomplete grades were excluded from the sample.

Data Collection Instruments

This study utilized secondary data from the first trimester grades of selected first-year teacher education students. The data used included grades in Engl 100 (Purposive Communication), Fil 100 (Filipino sa Tanging Gamit), Hist 100 (Readings in Philippine History), Soc Sci 102n (Philippine Culture, Heritage and Indigenous Communities), Science 100 (Science, Technology and Society), Prof Ed 100 (The Child and Adolescent Learner and Learning Principles), Prof Ed 101 (The Teaching Profession), and PE 1n (Physical Education 1), which were obtained from the records of the college through the dean.

The study also made use of an adapted questionnaire, the VARK Learning Style Survey Questionnaire (VARK Questionnaire version 8.01) containing twenty (20) items. The questionnaire is composed of 4 parts according to the VARK learning style: Visual, Auditory, Read/Write, and Kinesthetic. Each part had 5 items each. In each item, the students were tasked to rank each item to how well they think each one fits with how they will go about learning something. A four-point rating scale with one (1) as the lowest to describe the least way the students learn and four (4) as the highest to describe the best way the students learn was used. The learning style with the highest mean was taken into account in determining the dominant learning style of the students. The dominant learning style of the students were used to obtain the initial grouping of the students.

Data Collection Procedure

Verbal and written permission was obtained from the Dean of the College of Teacher Education to conduct the study. After receiving approval, the grades of the students were copied and encoded in an excel format. Data on the students' dominant learning styles were gathered online using Google Forms, and some were collected in person. The survey form was accompanied by a letter of request that included the study's objectives, significance, potential risks and benefits to the respondents, and their freedom to refuse participation. To maintain the confidentiality of the results, the names of the students were replaced with numbers.

Treatment of Data

The data gathered were tabulated and analyzed using appropriate statistical tools based on the specific problems of the study. The discriminant analysis was done using Statistical Package for Social Sciences (trial version).

To classify the students as to their learning style, mean and percentage were used. Mean was first used to determine the dominant learning style of the students. Percentage was used to find out the distribution of the students according to their learning style. Univariate ANOVA was also used to determine the mean comparison of the different subject averages among the clusters.

To derive the discriminant model in classifying the students as to their learning style, on the basis of their grades, discriminant analysis was employed. Specifically, Stepwise canonical discriminant analysis using Wilk's Lambda as the criterion for inclusion/exclusion of variables was used to determine the variables with high discriminating power that could be used in separating the students into distinct groups. Likewise, this was used to derive the canonical or linear combinations of the variables that summarize between-class variations. Furthermore, the resulting discriminant functions was assessed for validity and predictive accuracy using Proportional chance criterion (CPRO) and Press' Q statistic.

Results and Discussion

Classification of Students as to their Learning Style

Classification of Students as to their Dominant Learning Style using the VARK Questionnaire

The mean and percentage were first employed to classify the sample first year teacher education students at the University of the Cordilleras using the data gathered on their dominant learning styles. The classification of students as to their VARK learning style is presented in Table 1. As reflected in Table 1, 36 students were identified under Visual, 22 under Auditory, 15 under Read/Write, and 13 under Kinesthetic. Results revealed that the most common dominant learning style of the students was Visual and the least preferred learning style was Kinesthetic, this accounted for 41.86% and 15.12%, respectively.

Table 1. Dominant learning style of the students

Cluster	Frequency	Percent
Visual	36	41.86%
Auditory	22	25.58%
Read/Write	15	17.44%
Kinesthetic	13	15.12%

Cluster Performance Profile

The profile of the four groups based on the eight performance variables of the first-year teacher education students is presented in Table 2. Result shows that the visual group has the highest mean in most of the subjects measured except PE 1n and Soc Sci 102n. Auditory group, has the lowest mean in most of the subject except Hist 100. The read/write and kinesthetic group do not give distinct average in most of the subjects measured. Kinesthetic group has the highest mean in PE 1n and read/write group has the highest mean in Soc Sci 102n.

Table 2. Classification of cases using fisher linear discriminant function

Cluster	Variables	Mean	STD. Deviation
Visual	Engl 100	90.53	1.812
	Fil 100	88.50	2.444
	Hist 100	91.53	3.598
	PE 1n	90.58	2.951
	Prof Ed 100	85.67	3.207
	Prof Ed 101	89.36	2.344
	Science 100	88.44	2.699
	Soc Sci 102n	85.69	3.396
Auditory	Engl 100	84.55	2.721
	Fil 100	83.05	3.415
	Hist 100	85.95	4.971
	PE 1n	86.05	3.373
	Prof Ed 100	80.77	2.689
	Prof Ed 101	82.36	3.374
	Science 100	81.77	3.351
	Soc Sci 102n	80.64	3.215
Read/Write	Engl 100	88.53	1.922
	Fil 100	87.33	3.155
	Hist 100	85.07	4.992
	PE 1n	88.73	3.218
	Prof Ed 100	84.33	2.193
	Prof Ed 101	87.27	2.120
	Science 100	83.60	3.795
	Soc Sci 102n	86.27	4.250
Kinesthetic	Engl 100	86.69	3.966
	Fil 100	86.38	3.429
	Hist 100	89.15	3.555
	PE 1n	91.62	4.194
	Prof Ed 100	83.69	4.231
	Prof Ed 101	86.15	3.738
	Science 100	85.77	4.419
	Soc Sci 102n	83.77	4.419

Characteristics of the Derived Discriminant Model

Assessment of the Validity and Predictive Accuracy of the Discriminant Model Derived

The derived Discriminant Models for the four clusters are as follows:

$$Visual = -1136.681 + 11.486X_1 + 2.309X_2 + 6.503X_3 + 4.871X_4$$
$$Auditory = -1006.088 + 10.975X_1 + 2.152X_2 + 6.277X_3 + 4.259X_4$$
$$Read/Write = -1087.475 + 11.390X_1 + 1.979X_2 + 6.411X_3 + 4.825X_4$$
$$Kinesthetic = -1094.912 + 10.810X_1 + 2.276X_2 + 6.884X_3 + 4.702X_4$$

Using these derived models in classifying cases, the classification summary table presented in Table 3 shows the number and percent of students classified correctly and incorrectly. It reveals that 76.8% of the total cases were correctly classified. The model obtained from analysis may only be applicable to the sample used. To produce a nearly unbiased estimate of the proportion misclassified, a leave-one-out classification as cross-validation check was performed whereby each subject was excluded and then classified using the discriminant function based on the remaining subjects (Afifi, May, & Clark, 2003). The leave-one-out cross validation gives a 69.6 % accuracy which may still be good. The over-all estimate of the error in classification is 23.2% which is considered negligible.

Table 3. Classification matrix of the discriminant function

		Learning Style	Predicted Group Membership				Total
			1	2	3	4	
Original	Count	1	30	1	0	0	31
		2	2	13	1	0	16
		3	5	0	6	1	12
		4	5	1	0	4	10
	%	1	96.8	3.2	0	0	100.0
		2	12.5	81.3	6.3	0	100.0
		3	41.7	0	50.0	8.3	100.0
		4	50.0	10.0	0	40.0	100.0
Cross-validated	Count	1	28	1	2	0	31
		2	2	11	2	1	16
		3	4	0	6	2	12
		4	5	2	0	3	10
	%	1	90.3	3.2	6.5	0	100.0
		2	12.5	68.8	12.5	6.3	100.0
		3	33.3	0	50.0	16.7	100.0
		4	50.0	20.0	0	30.0	100.0

Proportional chance criterion (C_{PRO}) and Press' Q statistic were employed to assess the validity of the discriminatory power against a chance criterion. The computed value of the C_{PRO} of 30.7% clearly suggests that the classification matrix's hit ratio of 76.8% is better than a chance model, indicating that it is valid against a chance model. The values in Table 4 also indicates that the hit ratio of 70.6% for the holdout sample exceeded both the maximum and proportional chance values by chance accuracy criteria of 44.9% and 30.7%, respectively. The computed Press' Q statistic of 98.79 exceed the classification accuracy of 6.63 expected by chance at a statistically significant model. This further suggests that the model was an adequate predictor for group separation. Hence, the model investigated has a good predictive power as suggested by proportional chance criterion and Press' Q statistic. However, Chan stated that: "One must be careful as Press's Q is adversely affected by sample size." Thus, it is possible that discriminatory power of the classification is not statistically better than chance and the derived model does not fit the data.

Table 4. Comparison of the goodness of the classification results

Model Measures	Original Sample	Holdout Sample
Hit Ratio	76.8%	70.6%
Maximum Chance	44.9%	70.6%
Proportional Chance	30.7%	70.6%
Comparison with Hair et al. (2010) 1.25 times higher than chance	38.4%	
Press Q table value	6.63	
Press Q computed value	98.79**	

** - significant at 1% level of significance

Variables with High Discriminating Power Used in Separating Students into Distinct Groups

Using the VARK learning style of the students to classify the students, the discriminant models were derived using stepwise canonical discriminant analysis with Wilk's Lambda as the criterion for inclusion/exclusion of variables. Table 5 shows the prior tests for the validity of the groupings which is the test of equality of group means. As reflected in Table 5, the averages in Engl 100, Fil 100, Hist 100, PE 1n, Prof Ed 100, Prof Ed 101, Science 100, and Soc Sci 102n are not significantly equal across groups as shown by the Wilk's Lambda statistics with significant F-values. This means that there is a highly significant difference between the groups' centroids. Thus, the VARK learning style of the students were distinct and valid for further modelling purposes.

Table 5. Test of equality of group means

Subject	Wilk's Lambda	F	DF1	DF2	Sig
Engl 100	0.519	20.081	3	65	0.000
Fil 100	0.694	9.551	3	65	0.000
Hist 100	0.682	10.125	3	65	0.000
PE 1n	0.641	12.135	3	65	0.000
Prof Ed 100	0.706	9.038	3	65	0.000
Prof Ed 101	0.488	22.733	3	65	0.000
Science 100	0.623	13.104	3	65	0.000
Soc Sci 102n	0.713	8.736	3	65	0.000

The selection of the most significant variables used for the analysis were selected through the Stepwise Wilk's Lambda procedure, where variables are selected for entry based on their discriminatory power to be included in the linear discriminant function. According to Chan (2005), the Wilk's Lambda shows the proportion of the total variance in the discriminant scores not explained by differences among groups which gives an indication on how discriminating the derived model. At each step, a variable that minimizes the overall Wilk's Lambda is entered or retained. On the other hand, a variable is removed if the F-value is lower than 2.71, the default value set in the software used.

The results of the stepwise process are summarized in Table 6. At step 1, Prof Ed 101 entered and had the highest degree of discrimination as indicated by the F-value of 22.733 with the lowest Wilk's Lambda value of 0.488. In discriminant analysis, the lower the value of the Wilk's Lambda, the better its discriminating power. A small Wilk's Lambda value (near 0) indicates that the group's mean scores differ (Chan, 2005). At step 2, PE 1n was entered with F-value of 13.768 and a Wilk's Lambda of 0.369. The succeeding steps indicated that Engl 100 was entered in the third step. This followed by Hist 100, having the lowest Wilk's Lambda to be included in the discriminant analysis. However, Fil 100, Prof Ed 100, Science 100, and Soc Sci 102n was not included in the analysis since they did not meet the set criterion and were found to have less discriminatory power. This means that Prof Ed 101 was the strongest predictor, followed by PE 1n, Engl 100, and Hist 100. Meanwhile, Fil 100, Prof Ed 100, Science 100, and Soc Sci 102n were less successful as predictors of learning style.

Table 6. Summary of stepwise selection procedure

Step	Course Entered	F Value	Wilk's Lambda
1	Prod Ed 101	22.733	0.488
2	PE 1n	13.768	0.369
3	Engl 100	10.999	0.298
4	Hist 100	9.480	0.249

The variables that emerged and were included in the derivation of the canonical discriminant function were the Prof Ed 101 raw score (X_1), PE 1n raw score (X_2), Engl 100 raw score (X_3), and Hist 100 raw score (X_4). However, the raw score of Fil 100, Prof Ed 100, Science 100, and Soc Sci 102n were found to be not significant in discriminating between groups formed by the Ward's method. Hence, were not included in the discriminant functions formed.

The resulting canonical discriminant function were standardized and raw canonical coefficients were normalized to give canonical variables with mean equal to zero and unit within-class variance. The canonical variates of the discriminant functions have the following standardized axes:

$$Can1 \ = 0.561X_1 + 0.223X_2 + 0.417X_3 + 0.212X_4$$
$$Can2 \ = -0.039X_1 + 0.776X_2 + (-0.657)X_3 + 0.362X_4$$
$$Can3 \ = -0.441X_1 + (-0.347)X_2 + 0.131X_3 + 0.924X_4$$

The coefficients of the discriminant functions represent the relative contribution of the associated variable to the canonical function. Discriminant scores can be computed by multiplying each coefficient by its corresponding discriminating variable and summing the products. The individual cases discriminate scores on the functions were used to plot the axes. Plotting the different cases unto the first and second canonical discriminant function axes is found in Figure 1.

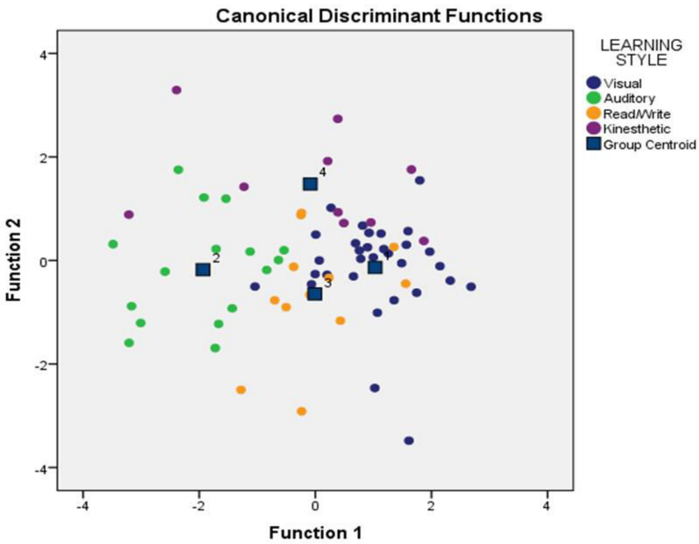

Figure 1. Plot of cases on the first and second canonical discriminant functions as axes

Table 7. Summary of eigenvalues, Wilk's Lambda, and Chi-square test of significant for the derived canonical functions

Function	Eigen Value	% of var.	Can. Corr.	Wilk's lambda	Chi-square	DF	Sig
Can1	1.427*	70.8	0.767	0.249	89.078	12	0.000
Can2	0.429*	21.3	0.548	0.603	32.331	6	0.000
Can3	0.159*	7.9	0.371	0.863	9.463	2	0.009

*First 3 canonical discriminant functions were used in the analysis

Results of the discriminant analysis produced the eigen value, percent of variance, Wilk's Lambda, and significant tests of the derived canonical functions are summarized in Table 7. It shows that the three discriminant functions (Can1, Can2, Can3) were statistically significant in discriminating between groups as evidently supported by the Chi-square statistics with corresponding associated probabilities of 0.000, 0.000, and 0.009. The value of the Wilk's Lambda for the discriminant functions are 0.249, 0.603, and 0.863. This means that the first canonical discriminant function is considered with high discrimination, as supported by the rule that a Wilk's Lambda close to zero is an indicator of high separation between group centroids. Also, the canonical correlation suggests that the first function has a higher discriminating power between groups than the second and third function. Specifically, the first function with a canonical correlation of 0.767 suggests that the discriminant function and the predictor is highly correlated with each other. However, the Chi-square test for significance revealed that the three canonical discriminant functions were statistically significant, hence the other functions have high discrimination. These results were also shown graphically on the scatter plot of the individual cases on the first two canonical discriminant functions, where the distances between group centroids is prominent in the first canonical axes.

Table 8. Canonical structure matrix

VARIABLES	CAN1	CAN2	CAN3
Prof Ed 101	0.851*	-0.066	-0.299
Engl 100	0.762*	-0.469	0.138
Prof Ed 100[b]	0.626*	-0.196	0.030
Science 100[b]	0.544*	0.039	0.177
Fil 100[b]	0.421*	-0.138	0.019
Soc Sci 102n[b]	0.330*	-0.160	-0.208
PE 1n	0.467	0.742*	-0.278
Hist 100	0.473	0.314	0.815*

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions

*. Largest absolute correlation between each variable and any discriminant function

b. This variable is not used in the analysis.

Table 8 shows the discriminant variables which discriminate between groups on the three-discriminant function. These values are comparable to factor loadings and indicate the substantive nature of the variables. Looking at the structure matrix and bearing in mind that all the variables were significant in separating the groups, it shows that Prof Ed 101, Engl 100, Prof Ed 100, Science 100, Fil 100, and Soc Sci 102n load highly on the first canonical discriminant function (Can1), PE 1n loads highly on Can 2 and Hist 100 loads highly on Can 3.

Cross Validation of the Holdout Sample

To assess the reliability and generalizability of the findings, cross validation was utilized to validate the output derived from the discriminant function analysis. The discriminant functions which emerged from the analysis will be determined whether or not it will correctly classify the individuals in the holdout sample. In here, the discriminant weights mentioned in the previous sections, were multiplied by the values of the predictor variables in the holdout sample to generate the discriminant scores which are used in classifying the students into the different groups. A high percentage of correct classification indicates that the discriminant functions are reliable and can be utilized to classify cases into groups (Hair et al., 1995).

The actual group of the students determined using the VARK Learning Style Questionnaire, the group predicted by the discriminant functions derived from the analysis sample, and the discriminant scores of each case were summarized in Table 9. As reflected in Table 9, each case was classified by the functions derived from the analysis sample. Cross validation shows that 70.6% of the holdout sample were correctly classified. Five of the cases of 17 cases in the holdout sample were misclassified. The overall estimate of the error in misclassification in the holdout sample is 29.4% which is considered negligible. This indicates that the discriminant function can be utilized in classifying students as to their learning style. Hence, the output derived from the analysis sample was stable and has a good predictive power.

Table 9. Summary of actual group, predicted group, and discriminant scores of the holdout sample

Case Number	Actual Group	Predicted Group	Discriminant Scores		
			Function1	Function2	Function3
70	3	3	-1.289	-1.236	-1.277
71	2	2	-4.075	0.801	-1.563
72	1	1	2.526	0.641	0.061
73	4	2**	-1.425	1.428	0.614
74	3	3	-0.158	0.577	-2.420
75	1	4**	0.243	2.120	1.021
76	2	2	-2.377	1.580	1.535
77	1	1	1.758	-0.902	-0.608
78	2	1**	-0.654	0.672	0.625
79	4	2**	-1.270	-3.169	0.433
80	4	4	-0.382	1.192	-1.030
81	2	2	-1.281	0.610	0.986
82	1	1	1.600	-0.463	-1.006
83	2	2	-2.292	0.080	0.568
84	3	2**	-1.043	0.540	-0.944
85	2	2	-3.132	0.544	-2.609
86	1	1	1.078	0.428	-1.640

** -Misclassifiedcase

Mean Comparison of the Cluster Means

The mean comparison of the four clusters for each course using univariate ANOVA is shown in Table 9. Results revealed that Visual group had the highest mean score of 90.53 in Engl 100 which was not found statistically different from Read/Write group with mean score of 88.53. In Fil 100, Visual group (88.50) had the highest mean score but not found to be statistically different from the mean scores of Read/Write (87.33) and Kinesthetic (86.38). Visual group had the highest mean in Hist 100 but not found to be substantially different from Kinesthetic group with mean score of 89.15. Kinesthetic group had the highest mean score of 91.62 in PE 1n which did not differ significantly to the mean scores of Visual (90.58) and Read/Write (88.73). In Prof Ed 100, Visual group obtained the highest mean score of 85.67 which was found not statistically different to the mean scores of Read/Write (84.33) and Kinesthetic (83.69). For Prof Ed 101, the highest scorer was Visual group (89.36) which did not differ significantly to Read/Write group (87.27). In Science 100, Visual obtained the highest mean score of 88.44 which was found not statistically different from Kinesthetic with mean score of 85.77. Read/Write (86.27) had the highest score in Soc Sci 102n which did not differ significantly to the mean score of Visual (85.69).

Although visual learners have the highest performance in most of the subjects, their performance did not differ significantly to the performance of the other learners. However, there are other areas where these learners performed least. This may suggest that adapting teaching strategies according to the characteristics of the learners could improve their academic performance in these areas. A study conducted by Mulalic, Shad, and Ahmad, (2009) mentioned that in order to provide students the best learning opportunity, educators must consider learning styles and accommodate these differences in the classroom. Previous studies found that students who were given appropriate education according to their learning style profile achieved higher academic performance (Shirazi & Heidari, 2019; Vizeshfar & Torabizadeh, 2018). The results imply that adapting teaching strategies like the use of visual aids such as graphics, color-coded materials could help visual learners perform better. Also, teaching methods that cater to auditory learners, such as the use of mnemonic devices, participative discussions, integrating music into lectures, etc., could aid in their improvement in all courses. Furthermore, encouraging students to take notes during discussions, providing charts, and many more strategies could assist them master the lessons and enhance their performance. Teachers may employ hands-on techniques to help kinesthetic learners perform better, such as conducting practical exercises, presenting case studies and learning via trial and error.

Table 10. Mean comparison of the four clusters using univariate ANOVA

Subjects	Visual	Auditory	Read/Write	Kinesthetic	F Value
Engl 100	90.53[a]	84.55[b]	88.53[a]	86.69[c]	27.746**
Fil 100	88.50[a]	83.05[b]	87.33[a]	86.38[a]	15.505**
Hist 100	91.53[a]	85.95[b]	85.07[bc]	89.15[a]	12.135**
PE 1n	90.58[a]	86.05[b]	88.73[ab]	91.62[a]	11.139**
Prof Ed 100	85.67[a]	80.77[b]	84.33[a]	83.69[a]	11.391**
Prof Ed 101	89.36[a]	82.36[b]	87.27[ac]	86.15[c]	27.963**
Science 100	88.44[a]	81.77[bc]	83.60[cd]	85.77[ad]	19.846**
Soc Sci 102n	85.69[a]	80.64[bc]	86.27[ad]	83.77[cd]	10.516**

** - significant at 1% level of significance
Mean with the same letter do not differ significantly

Conclusion

In conclusion, this study has revealed that the visual learning style is the most dominant among students. Additionally, the discriminant model developed in this study has been found to be an adequate predictor for classifying students according to their learning styles based on their grades. The academic variables with the highest discriminating power were found to be The Child and Adolescent Learner and Learning Principles (Prof Ed 101), Physical Education 1 (PE 1n), Purposive Communication (Engl 100), and Readings in Philippine History (Hist 100). However, there was no significant difference found among the highest scorers of different subjects.

Based on the results, it is recommended that educators acknowledge the preferred dominant learning style of their students to improve academic performance. However, it is suggested that further research should consider other learning styles aside from VARK in grouping students. The discriminant function model developed from this study can be used with caution to classify students into their dominant learning style, but it is important that the future sample comes from a similar population used in this study. Additionally, teachers are encouraged to use a variety of teaching methods to accommodate different learning styles and to foster students' success. Finally, future studies should be done by applying the discriminant model to other samples and re-estimating the discriminant function for a larger number of samples.

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