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Predicting VARK Learning Styles from Five-Factor Personality of Computing Majors Studying Online

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Abstract. Students nowadays can effortlessly study without needing to physically attend classrooms via online learning. The COVID-19 pandemic has made online learning an inseparable part of the current education system. In online learning, teachers and students communicate through Learning Management Systems (LMS) and conduct classes, exams, quizzes, and share learning resources online. Recognizing students' individual learning style preferences is crucial in tailoring e-learning to match their needs. Previous studies have proven that personality traits impact the learning process and have interesting correlations with learning styles. The Visual, Auditory, Reader/Writer, Kinesthetic (VARK) is one of the most well-known theories amongst all other learning styles. In this study, multiple supervised machine learning algorithms were used and later compared to predict students' learning styles. The respondents of this study were students from Multimedia University- a Malaysian higher education institution; belonging to the faculty of computation and informatics, but from different education levels, i.e. foundation, diploma, bachelor's, and master's. Data was collected through online questionnaires utilizing google forms. A total of 381 respondents took part in this study. Results showed that most of the respondents belonged to the kinesthetic learning style, which was in alignment with studies done before in traditional education settings. It also demonstrates that the prediction of learning styles from personality scores is possible but with the highest accuracy of 54% when using binary classification. The outcomes of this study would assist educators in better adjusting their teaching methods and allow enhanced personalization for e-learning environments.

Keywords: E-learning, Five-Factor Personality traits, Learning Style Prediction, Machine Learning, VARK

1. Introduction

Humans are always curious to know more about themselves. Understanding one's abilities better, allows an individual to make efficient decisions. Each individual is distinct, with their own set of characteristics, intriguing factors, thought processes, and reactions. The way people see and absorb information is referred to as their learning style (Ackerman & Heggestad, 1997). Felder and Silverman (Lim, n.d) define it as a natural inclination and attributional power that is chosen by learners when it comes to information comprehension. It is an individual's favored method of recognizing and dealing with a collection of facts inclusive of psychological as well as emotional components (Atashrouz et al., 2008). The effectiveness of the learning process is dependent on the learner's learning style (Bokhari & Zafar, 2019). Numerous studies have been published and are still being conducted on the subject, and researchers have used them to identify the learning preferences of individuals. There is no clear evidence that one style of learning is superior to another, they are different and should be considered by academics when coming up with a learning method.

E-learning lets students study without having to physically attend classes during this pandemic. Learning Management Systems (LMS) connected students and teachers for class discussions, quizzes, and exams; learning resources were all available online. The quantity of knowledge a student acquires in a class is governed by several factors, including the student's innate ability and preparedness, as well as how perfectly the student's learning style matches that of the instructor. By providing students with individualized content, adaptive E-learning systems can aid in the facilitation of learning (Carter et al., 2002). Detecting a learner's learning style preference is an important first step in customizing e-learning to meet their educational needs. Students' learning styles are increasingly being defined based on their behavior and method of acquiring knowledge (Durling et al., 1996). A variety of learning style theories, with the VARK learning theory model being one of the simplest and most renowned. Information is learned via auditory, visual, kinesthetic, and reading/writing techniques. Another factor contributing to learning style theory is personality theory. Because online learning differs from traditional classrooms, the quality of the program, learners' personalities, and learning styles all have a substantial effect on their academic performance (Atashrouz et al., 2008). In a number of studies, personality traits and learning styles have been known to be correlated, which could help e-learners improve their learning and, as a result, their fulfillment and self-satisfaction with the learning process (Cattell, 1957).

The aims of this study are to firstly, discover if students majoring in IT have a particular learning style belonging to the VARK LS framework and does it change while learning online. Secondly, to see if students majoring in IT have a particular personality type belonging to the Big 5 personality framework and does it change while learning online, and finally to find out how accurately can their VARK LS be predicted from their Big 5 personality results.

2. Literature Review

2.1. Learning styles in education

Learning styles have been a topic of interest for researchers and educators alike for decades. Students' learning preferences can serve as a guide for curriculum development and a predictor of future academic success, according to research. Numerous studies have also established a strong link between learning style and academic success (Kolb, 2014). However, a study by Griggs indicates that Learning styles, Intellectual ability, and mental capacity have no correlation. He also believes that there is “no one-size-fits-all” approach to learning. Individual differences in problem-solving, learning processes, and decision-making have been found in psychological studies. Learning styles refer to individual variances in the learning process, such as differences in interpreting, assessing, and processing information (De Raad & Schouwenburg, 1996; Willcoxson & Prosser, 1996; Logan & Thomas, 2002). Similar formulations exist, such as Keefe's learning style definition, which states “Learning style includes cognitive, emotional, and physiological features, which are used to recognize how the learner understands the concepts and interacts with the learning environment” (De Raad & Schouwenburg, 1996). Individual preferences and priorities in the learning process are reflected in learning styles (De Young et al., 2011). Individuals with a strong visual memory but a weak verbal aptitude, for example, prefer to learn stuff visually rather than audibly. As a result, educators must take these disparities into account when presenting learning materials to students. According to some academics, if learners are presented with learning materials without taking into account their learning style preferences, their process of learning would be interrupted (Dewar & Whittington, 2000; Li & Zhou, 2007). Thus, in order to attain optimal educational outcomes, it is critical to consider learning styles during the learning process.

2.2. Different learning style frameworks

There are a variety of tools that may be used to categorize people depending on their learning styles. Kolb's learning style inventory is grounded on his learning cycle theory that comprises “Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation” (Dewar, & Whittington, 2000). Learning occurs when learners complete a cycle. Based on Kolb's Cycle hypothesis, Honey and Mumford (1986) created a questionnaire. Their survey comprises 80 questions and divides people into four categories: Activists, Theorists, Pragmatists, and Reflectors. Each category corresponds to a stage in Kolb's cycle (De Raad &

Schouwenburg, 1996). The Felder–Silverman Learning Style Index and Model was developed based on four learning style dimensions: “active/reflective, visual/verbal, sensing/intuitive, and sequential/global” (Fleming & Baume, 2006). The VARK learning style model, which has been modified from the VAK model, was introduced by Neil Fleming (Furnham et al., 2003). The VARK learning type model divides students into four categories: visual (V), auditory (A), reading (R), and kinesthetic (K). VARK is one of the earliest and most popular tools of learner style developed by Neil Fleming and Coleen Mills. The success of the model stems from its usability, authenticity, and the array of learning resources accessible to complement it.

2.3. Personality traits in education

Individual differences in cognitive and non-cognitive growth of knowledge have been proven to play a significant impact on knowledge development (Cattell, 1957; Abrahamian et al., 2004). Personality traits are generally inborn characteristics of a person and are frequently taken as unchangeable (Furnham et al., 1999). Extroversion and introversion have a significant influence on increasing e-learners' academic achievement in an e-learning environment. Because there are no teachers or other students present in an E-learning environment, it can be advantageous for students who prefer to be alone. It may be beneficial for these students because they rely on nonverbal communication rather than verbal communication (Cattell, 1957; Hernandez et al., 2020). Personality qualities account for a significant portion of the variation in learners' achievement (Karagiannis & Satratzemi, 2017; Furnham et al., 2003; Poropat, 2014). Some studies have looked at different academic domains separately (e.g. languages and mathematics) (De Raad & Schouwenburg, 1996; Laidra et al., 2007) and others have looked at different achievement measures (e.g., grades and standardized test scores (Lüdtke et al., 2004). The distinction between personality and intellect as well as the conceptual overlap between the two constructs have been heavily disputed in the literature. Ictenbas and Eryilmaz (2011), Idrizi and Filiposka (2018), and Spengler et al. (2016), among others, postulate that intelligence and personality dispositions have significant overlap, resulting in significant connections between personality and academic achievement. Even if personality and intelligence are considered separate categories (Spengler et al., 2013), it can be argued that people with different cognitive abilities employ intellectual resources differently in connection to personality qualities. As a result, achievement differences linked to personality would emerge (Johnson et al., 2004). These reasons imply that personality, intelligence, and academic accomplishment are intertwined and must be taken into account at the same time (İlçin et al., 2018).

2.4. Different personality frameworks

The term "personality" has been defined in a variety of ways. Personality is defined by Schultz and Schultz (2009) as the internal and external characteristics of an individual's character that influence human behavior in various states. Eysenck (1994) argues that every person's personality is made up of their thoughts, feelings, wants, and behavioral patterns. There are many personality frameworks available; four popular and widely used frameworks are the Myers-Briggs Type Indicator, Five-Factor Model, Clifton Strengths, and Rational Experiential Inventory (Laidra et al., 2007). Based on Jung's personality theory, Isabel Briggs Myers and Kathrin Briggs devised the MBTI (Myers–Briggs Type Indicator) questionnaire (Jackson et al., 1996). MBTI was originally developed for corporate goals, but it is now also utilized for educational purposes (Allik & Realo, 1997). Openness or how adaptable a person is to new ideas/experiences; conscientiousness or how goal-oriented and tenacious an individual is; extraversion-introversion or to what extent is an individual energized by their environment; the agreeableness or to what extent an individual puts others' preferences above their own; neuroticism or sensitivity to stress or how much an individual prioritizes others' interests above their own are the 5 main attributes of personality which make up the Five-Factor model (Laidra et al., 2007). The Five-Factor model has established itself as an essential and useful taxonomy for classifying human personality structure (Barrick & Mount, 1991; Bakker et al., 2006; Hartmann & Klimmt, 2006; Schultz & Schultz, 2016; İlçin et al., 2018)

2.5. Relationship between learning style and personality traits

The definition of personality and learning style are inextricably linked. Indeed, it is thought that a learner's learning style is determined by his or her personality, therefore people with different personalities have distinct learning styles. Furnham discovered a link between Kolb's learning styles and Eysenck's personality theory in 1996 (Logan & Thomas, 2002). Furthermore, Eysenck demonstrated a link between personality traits and learning methods (Roberts et al., 2007). Learning styles are linked to cognitive characteristics, according to Drummond and Stoddard. In addition, according to Jackson and Jones (1996), there is a link between at least one of the personality qualities and learning style dimensions. Furthermore, Furnham and Jackson stated that a person's learning style is a subset of his or her personality (El Aissaoui et al., 2019). As a result, many researchers utilize personality models and learning styles in learning settings interchangeably.

2.6. The impact of learning style and personality traits on online education

Understanding how humans learn is critical for improving the accuracy of learning material customization (Soldz & Vaillant, 1999). When it comes to online education, the quality of the online program, the student's personality, and learning styles all have a noteworthy effect on academic performance, as online learning methods differ from those used in traditional classrooms (Atashrouz et al., 2008). Personality characteristics and learning styles are related, which may help e-learners improve their learning and, as a result, may increase the fulfillment and self-satisfaction with the learning process (Cattell, 1957). Zhang (2001) discovered several significant associations between the 5-personality traits, learning styles, and academic achievement. Additionally, the results indicated that there are significant gender differences in three personality traits: agreeableness, conscientiousness, and neuroticism. The strong relationships between personality traits and learning styles, as well as their combined impact on academic achievement, are elaborated on later.

3. Methodology

3.1. Sample selection

The sample selected for the study belonged to Multimedia University, a private higher education and research institution in Malaysia. The respondents were all students of the faculty of computation and informatics, but from different education levels, i.e., Foundation, Diploma, Bachelor's, Master's and Ph.D.

3.2. Data collection

Data was collected through online questionnaires utilizing google forms. A total of 381 respondents took part in this study, of which 268 respondents were male and 113 were female. All of the classes and academic activities were being held online due to COVID-19 restrictions.

For identifying learning styles under the VARK framework, the VARK Questionnaire (Version 8.01) was used and for identifying the personality under the Five-Factor framework, the Big 5 Inventory (BFI) was used. Both of the questionnaires were distributed to the respondents through WhatsApp and posted on Google Classroom for the students to take part in, with no time constraints. The data was collected while adhering to standard privacy guidelines where the respondents were aware of the purpose and usage of the data collected.

4. Data Analysis

4.1. Gender

According to the bar chart in Fig 1, most of the respondents of the study were male and were more than twice the number of female respondents.

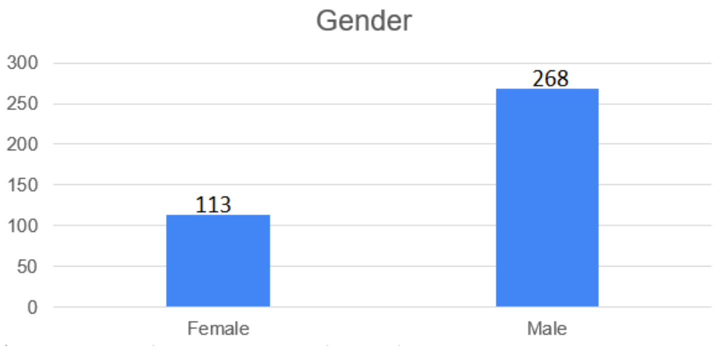

Fig. 1: Bar chart representing female to male ratio

4.2. VARK learning style

According to the bar chart in Fig 2, some of the respondents displayed a multimodal learning style preference on the VARK spectrum while a small number of respondents were unimodal. Most of the respondents scored high on kinesthetic, which was almost 70% of the whole population.

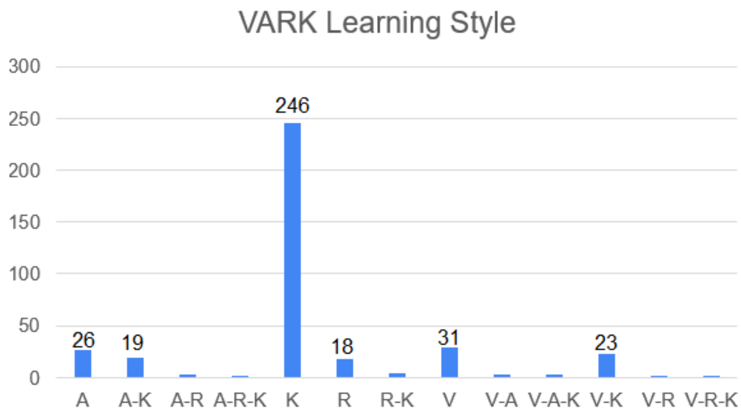

Fig. 2: Bar chart representing responses for VARK LS

4.3. Five-factor personality traits

According to the bar chart in Fig 3, two of the most popular traits in the respondent group were openness and agreeableness respectively. Openness covered 42% of the population whereas agreeableness covered roughly 41%. The third highest category, although far off, was the amalgamation of agreeableness and openness.

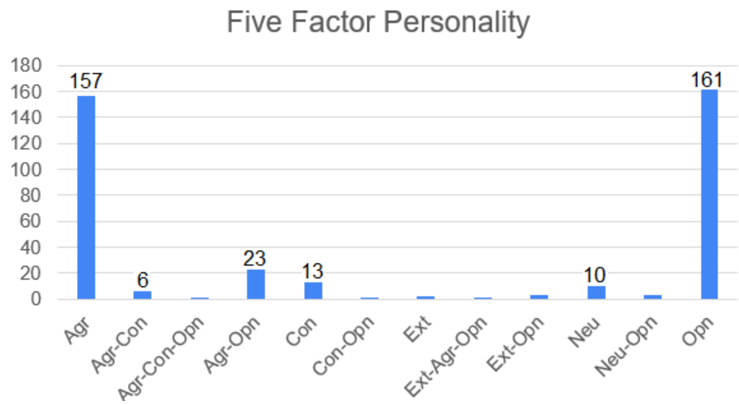

Fig. 3: Bar chart representing responses for Five-Factor personality trait

4.4. Correlations between VARK and Five-factor traits

The Pearson correlation coefficient, often known as Pearson's r, is a measure of the correlation between two variables. This was applied to evaluate the relationship between the variables in this study. Furthermore, a number between -1 and +1, determines how linearly linked the varying factors are.

According to table 1, it can be found that there are no significant relationships (positive or negative) between the variables. A negative relationship is visible between Visual scores and Openness personality; Auditory scores and Neurotic personality; Reader writer scores and Agreeable and extrovert personality. But none of the relationship strengths are noteworthy (>0.5).

Table 1: Correlation between VARK Learning style and Five-Factor personality trait scores

Attribut...	A	Agr	Con	Ext	K	Neu	Opn	R	V
A	1	0.172	0.035	0.366	0.403	-0.205	0.139	0.177	0.182
Agr	0.172	1	0.409	0.120	0.125	-0.147	0.047	-0.115	0.137
Con	0.035	0.409	1	0.283	0.015	-0.311	0.281	0.030	0.085
Ext	0.366	0.120	0.283	1	0.049	-0.392	0.385	-0.049	-0.063
K	0.403	0.125	0.015	0.049	1	0.073	0.040	0.127	0.439
Neu	-0.205	-0.147	-0.311	-0.392	0.073	1	-0.159	0.089	0.062
Opn	0.139	0.047	0.281	0.385	0.040	-0.159	1	0.055	-0.039
R	0.177	-0.115	0.030	-0.049	0.127	0.089	0.055	1	0.329
V	0.182	0.137	0.085	-0.063	0.439	0.062	-0.039	0.329	1

4.5. Applied Machine learning algorithms

Multiple supervised machine learning algorithms were used to predict VARK learning style from Five-Factor personality scores. As most of the respondents belonged to the Kinesthetic learning style, the prediction was made to see which algorithms performed best at predicting Kinesthetic learners from non-Kinesthetic learners. The RapidMiner (version 9.10.0) was used to carry out this stage of the study. The outcomes of the three best-performing algorithms are displayed in table 2.

Table 2: The performance overview of applied machine learning algorithms

	Generalized Linear Model		Decision Tree		Random Forest	
Criterion	Value	Standard Deviation	Value	Standard Deviation	Value	Standard Deviation
Accuracy	54.0%	± 5.5%	50.0%	± 10.0%	54.0%	± 11.4%
Classification Error	46.0%	± 5.5%	50.0%	± 10.0%	46.0%	± 11.4%
AUC	41.4%	± 6.4%	48.8%	± 11.5%	61.2%	± 6.9%
Precision	49.6%	± 8.0%	41.4%	± 6.4%	70.0%	± 44.7%
Recall	64.7%	± 18.6%	0.0%	± 0.0%	16.7%	± 10.2%
F Measure	55.0%	± 10.1%	0.0%	± 0.0%	27%	± 10.2%
Sensitivity	64.7%	± 18.6%	0.0%	± 0.0%	16.7%	± 10.2%
Specificity	43.7%	± 18.4%	100.0%	± 0.0%	92.7%	± 10.1%

A brief explanation of the criteria in **table 2** is provided below-

SPECIFICITY: The fraction of true negatives (TN) that were projected as negatives is known as specificity**.**

Specificity = TN / (FP + TN)

SENSITIVITY: A statistic for assessing a model's capability to determine true positives (TP) in each of the given categories.

Sensitivity = TP / (TP + FN)

PRECISION: A parameter that measures how many true positive (TP) forecasts have been made.

Precision = TP / (TP + FP)

AUC: This is a rundown of the Receiver-Operating Characteristic curve that evaluates a classification model's ability to differentiate among multiple classes. AUC or the area between the curve depicts the distinguishment power between positive and negative classes for a particular model. The greater value of AUC indicates better performance.

ACCURACY: A metric for determining the model which is the most effective in detecting connections and trends between variables in a dataset based on the data, input as well as training.

Accuracy = (TP+TN)/(TP+FP+FN+TN)

CLASSIFICATION ERROR: There are two types of errors in statistics, false positives (FP) also known as Type 1 errors and Type 2 errors which is often referred to as false negatives (FN). It's common to be able to raise one while lowering the other through model selection and tuning. It often depends on the nature of the problem and/or the developer to decide which error type is to be accepted.

Classification Error = (FN + FP) / total number of a dataset

RECALL: A parameter that measures the amount of true positive (TP) predictions made from all possible positive predictions. Contra precision, which only considers the true positive (TP) predictions from all positive predictions, recall considers the positive predictions that were missed.

Recall = TP / (TP + FN)

F MEASURE/ F1 Score: The proportion of precision to recall.

F1 Score = 2*(Recall * Precision) / (Recall + Precision)

5. Results and Discussion

Personality and learning style both play a role in how well a student does in class. According to existing studies, personality and learning styles are correlated. There were three main goals for the study. The first one was to see if students who majored in IT had a certain way of learning or not. In our research, we have found that the learning styles of computer science students who took online classes, preferred kinesthetic as their favorite learning style which is similar to the result found in the study by Hermandez et al. (2019) who investigated the learning styles of computer science students in both scenarios of online learning and face to face classes. A study by Khaled et al. (2018) revealed that third-year students in electronics engineering preferred to learn through kinesthetic methods, where 87% of learners were single-mode learners on the VARK spectrum, 11.38% were bi-modal, and 1.62% were quad-modal. Kinesthetic was the most common way pupils learned, even if they are bi-modal.

The second goal was to determine whether individuals majoring in IT possessed a specific personality feature. Interestingly, most respondents in our study scored high on the Five-Factor personality spectrum in the categories of agreeableness and openness. According to previous research, inquisitiveness, strong analytical skills, drawing attention to details, being mathematically oriented with good problem-solving abilities, as well as strong communication skills, and being a significant contributor to a team effort, as a competent technical player, are all common characteristics of engineering students (Bokhari & Zafar, 2019).

The third goal of this paper was to see how well their Five-Factor personality scores could predict the students’ VARK LS. Multiple linear and non-linear classification models were looked into to tackle this part of the study. Due to the data having weak correlation in applying Pearson’s r, it was concluded that the problem was a non-linear binary classification problem. Most of the time, classifier models like Decision Tree outperformed the best prediction models: SVM and KNN. Because there was only one type of learning style (Kinesthetic) in the sample and the classification was non-linear. The Decision Tree and Random Forest model were used to predict the student's learning style (Kinesthetic=1, non-Kinesthetic=0) at the end. The accuracy of 50% and 54% was the peak output respectively by the Decision Tree and Random Forest model. This indicates that VARK learning styles can’t be predicted from Five-Factor scores alone and more independent variables need to be added in order to achieve a better performing model.

6. Limitations

Only the VARK framework for learning style and the Five-Factor framework for personality were investigated in this study; no other learning styles or personality frameworks were evaluated. Moreover, the current project was limited to IT majors who were studying online at a Malaysian private institution. Future research should reproduce the same study for different disciplines from the same institute or the same major from different institutes and examine the differences in the results. Besides that, the machine learning algorithms were only utilized to predict one type of learning style, which is the kinesthetic learner type, on a small sample size. A considerably bigger sample size should be sought in the follow-up study, which should include all four types of VARK learning styles as well as all five types of Five-Factor personality traits.

In terms of evaluating the performance of machine learning algorithms, due to the type of prediction, only binary classification algorithms were looked into. Follow-up research should explore beyond that with diverse datasets, using other multiclass algorithms for a further mature understanding of the topic.

7. Conclusion

This study contributes to bridging the gap in learning style prediction and pays attention to the students’ majors and utilizes personality scores to predict learning styles; as they have been found to be correlated in previous research. It also attempts to look into the difference in results between existing studies done in traditional classrooms versus post-pandemic online classrooms for IT majors. As previously stated, determining the students' learning styles was not given substantial weight in the conduct of IT courses online. Many studies looked at the impact of learning styles and personality on students’ engagement, performance, and motivation as well as explored auto-determination of learning styles using machine learning. Yet, most of these studies looked into traditional classroom settings in pre-pandemic times with just a handful looking into e-learning. The outcomes of this study can greatly benefit STEM-based faculties who can definitely utilize the research findings as input to improve their teaching practices and adapt their teaching approaches to meet the learning styles of their pupils, resulting in increased class performance and grades. Various LMS developers can also benefit from this study while designing and integrating personalized features into their systems.

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