International Review of Research in Open and Distributed Learning

Analysis of Success Indicators in Online Learning

Ermira Idrizi, Sonja Filiposka and Vladimir Trajkovijk

Volume 22, Number 2, May 2021

URI: https://id.erudit.org/iderudit/1078407ar
DOI: https://doi.org/10.19173/irrodl.v22i2.5243

See table of contents

Publisher(s)

Athabasca University Press (AU Press)

ISSN

1492-3831 (digital)

Explore this journal

Cite this article

Idrizi, E., Filiposka, S. & Trajkovijk, V. (2021). Analysis of Success Indicators in Online Learning. *International Review of Research in Open and Distributed Learning*, *22*(2), 205–223. https://doi.org/10.19173/irrodl.v22i2.5243

Article abstract

This article examines the impact of personality traits, learning styles, gender, and online course factors (course difficulty, group affiliation, provided materials, etc.) in the academic success of students taking online courses and their overall success rate through traditional classes. Students' performance in the online learning environment is still a new perception, and a fair numbers of details are still unknown, in stark contrast to the details known in regard to traditional learning methods. Different types of learners respond differently to online and traditional courses. A case study was performed in which students were asked to attend two online courses, with different difficulty levels, during one semester. One-way analysis of variance was used to determine which factors are significant for the academic performance of students taking online courses, as well as for their overall academic success. Findings from the case study indicate that female students score slightly better, course difficulty has impact on test results, emotional students are more susceptible to online environments, and learning styles are more difficult to identify in online classes.

International **R**eview of **R**esearch in **O**pen and **D**istributed **L**earning
Volume 22, Number 2

May – 2021

Analysis of Success Indicators in Online Learning

Ermira Idrizi, Sonja Filiposka, and Vladimir Trajkovik
Faculty of Computer Science and Engineering, Ss. Cyril and Methodius University, Skopje, Republic of North Macedonia

Abstract

This article examines the impact of personality traits, learning styles, gender, and online course factors (course difficulty, group affiliation, provided materials, etc.) in the academic success of students taking online courses and their overall success rate through traditional classes. Students' performance in the online learning environment is still a new perception, and a fair numbers of details are still unknown, in stark contrast to the details known in regard to traditional learning methods. Different types of learners respond differently to online and traditional courses. A case study was performed in which students were asked to attend two online courses, with different difficulty levels, during one semester. One-way analysis of variance was used to determine which factors are significant for the academic performance of students taking online courses, as well as for their overall academic success. Findings from the case study indicate that female students score slightly better, course difficulty has impact on test results, emotional students are more susceptible to online environments, and learning styles are more difficult to identify in online classes.

Keywords: online education, character traits, learning styles, academic success, gender

Introduction

Online learning is compelling as it demonstrates individuals' and organizations' commitment to improving education and to exchanging knowledge and skills on a larger scale. The online learning trend continues to expand, mostly driven by technology and increased demand for enrolment in higher education institutions. Educational gains are elevated by e-learning, but one cannot overlook its social benefits, bearing in mind its use during the COVID-19 pandemic.

Since the outbreak of the COVID-19 pandemic, distance learning has become the new cornerstone of education. Educational institutions across the world have been forced to halt physical classes, which only accelerated the development of online learning environments to hinder any further interruptions to the learning process. The shift to online learning can trigger the development of a modern, more successful way of educating students. What has been made clear by this pandemic is the relevance of transferring information across borders, companies, and all segments of society. With this sudden shift away from the traditional classroom, the growth of online learning will continue to increase in the post–COVID-19 world and affect the global education sector as a whole.

Based on these additions to teaching and learning, numerous studies have been done, where researchers compare conventional forms of learning with online learning for student outcomes. It is of note that these studies seem to have difficulties in drawing accurate conclusions. While demand for online learning remains high (Allen & Seaman, 2017), higher education professionals need to discover new methods of creating an environment that promotes efficient learning by taking into account student preferences (Bonk et al., 2015). Furthermore, in this shift to online education, additional disciplines will be added and curricula modification will be needed to provide a workforce capable of meeting the ever-growing technological needs of society. Additionally, students gain invaluable practical skills through their respective distance education courses, such as problem solving, quick information analysis, and conclusion forming; additionally, overall creativity and innovation are stimulated (Simonson et al., 2019). More importantly, students learn how to work together by participating in group learning sessions and develop habits that prepare them for the collaborative workplace of the future (Essien, 2015). The evolution of online learning has mirrored changes in technology and society in recent history, and it will presumably continue to do so in the foreseeable future (Rice et al., 2020).

In our previous work, we studied the implications of students' character traits and learning styles separately; we also analyzed students' satisfaction with quality of service (Idrizi & Filiposka, 2018). This study offers students a unique environment; they attend courses fully online, choose types of materials, and are not influenced or obliged to participate until the end, which creates for them a better environment to study.

This article focuses on how different input variables—character traits, learning styles, gender, course difficulty level, and delivered materials and how they vary between online and traditional classes—influence students' academic achievements. Its scope is the provision of a deeper understanding of how different types of learners react to online courses. This can prove useful in better designing, evaluating, and marketing online courses. The article starts with an introduction of the importance of online learning and the differences between online and traditional learning. Then it reviews the related work that has been researched until the time of writing, regarding how personality, learning styles, and gender are related to students' academic success and other factors of significance in students' success rates in online courses contrary to traditional learning ("Related Work"). Next, it describes the methodology of the case study used and how participants were chosen and separated into groups for courses with different levels of difficulty and materials delivered (“Methodology”). The section titled “ANOVA Analysis” displays the analyses, which are executed on the given variables to gain insight into which of said variables have positive or negative impacts in academic results. The different roles such variables play in online courses in contrast to traditional learning are reviewed. Finally, discussions and conclusions are outlined in the final two sections via a showcase of how different variables impact the results of online and traditional classes. The article concludes with insights regarding advancing the conception of online courses in a more individualized manner.

Related Work

A recognized advantage of online and blended courses is that they provide both the teacher and the student greater convenience and accessibility. These are valuable assets for courses to effectively facilitate learning materials to students. Several meta-analyses have addressed this matter, generally concluding that well-structured online courses make learning easier for students (Siemens et al., 2015).

Discussions on the advantages and disadvantages of online learning opposed to traditional education have been based on a variety of parameters. Talebian et al. (2014) indicate that face-to-face education depends on time and place. Coincidentally, enrolment in online courses has been growing more rapidly in recent years (Seaman et al., 2018) due to an expanded environment that enables individual users to retain control over time, speed, location, and interactions with teachers and other participants. According to Kara et al., (2019), there are still factors challenging students to participate in distance education properly. Simonson et al. (2019) discuss the equivalency theory, which helps instructors provide learners with materials equivalent to, instead of identical to, materials handed out in traditional classrooms. Tseng and Chu (2010) have analyzed the relationship between the methods of learning and the outcomes of economics courses. They found that the online platform is vital for better learning and, therefore, preferable to the conventional way of learning. Also, McCarty et al. (2013) have examined the performance of students in microeconomics introductory classes. They found that students in online classes had an average final grade slightly higher than the average class grades. Clark (2020) states that in the near future, use of portable devices will expand learning using virtual and augmented reality, which will offer a more robust studying environment.

Nevertheless, there are also conflicting findings, with some research reports indicating that academic achievements are higher in traditional classrooms (e.g., Figlio et al., 2010; Page et al., 2017). Some other studies report no significant difference in student performance between online and traditional classes (e.g., Davies & West, 2018).

Results for a variety of methodological limitations must be evaluated with heightened attention. Students who choose online classes willingly may have different traits and purposes than students who choose conventional, in-person classes. For instance, students who opt for online classes may be older, have children, and be employed full-time (Ilgaz & Gulbahar, 2017). During the COVID-19 pandemic, while shifting all courses online, educational organizations were confronted with significant problems in their methods of planning, execution, and evaluation. On a minor note, however, the global pandemic uncovered possibilities for the nation to update its provision of education and to turn its focus to new technology.

The research looking at this abrupt transition to online learning is very narrow, and time is needed to evaluate the possible outcomes of this unexcepted shift to distance learning. Nevertheless, higher education organizations must improve their evidence-based policies, offer affordable mental health care, and adapt to the demands of evolving times (Toquero, 2020). According to Bao (2020), five standards of high-impact instructional practice for the successful implementation of large-scale online education have been observed: (a) sufficient significance—the quality, complexity, and duration of the instructional material must be adapted to electronic learning behavior; (b) efficient distribution—the pace of teaching has to be slower due to the low concentration of students in online learning; (c) adequate assistance—faculty and teaching assistants need to offer rapid support; (d) high-quality engagement—this is needed to boost the degree and scope of student engagement; and (e) a backup plan in consideration of the incredibly broad size of online education—preparation measures must be developed in advance to tackle future concerns such as the network traffic congestion problem. Moreover, while this online learning migration has been applied rapidly due to the COVID-19 pandemic, students' anxieties must be resolved in a number of ways to ensure that they can successfully and efficiently participate in electronic learning.

Another study (Crawford et al., 2020) highlights the response of a series of universities across 20 countries, where almost all universities switched to online education. Some were partly equipped for this initiative, providing several blended or entirely online offerings. Others had more issues offering all courses online, which depended also on the status of the country as having developed or developing economies. Although several higher education institutions initially concentrated on the shift to the online environment, the emphasis is now on online pedagogy (Crawford et al., 2020).

It is essential for educational institutions to adapt a pedagogy system that encapsulates the different aspects of online learning, which differ greatly from aspects of traditional, in-person education. Traditional learning theories such as behaviorism, cognitivism, and constructivism (Tawfik et al., 2017) have influenced traditional learning and teaching methodology heavily. *Behaviorism* assumes that learning is tangible and real, as merely a computational mechanism of accumulated practice. In contrast to behaviorism, *cognitivism* emphasizes internal learning mechanisms. It suggests that learners use knowledge to understand and that knowledge can be processed and retrieved as appropriate. *Constructivism* puts emphasis on learning as a reaction to behaviorism and cognitivism, arguing that learners create awareness from their own interactions. The digital age requires new concepts about how learning happens. The theory of *connectivism* argues that knowledge is spread through a network of connections; thus, learning consists of the ability to construct and navigate those networks (Downes, 2020). Although connectivism focuses on where information is obtained and how learners communicate on the Internet, rhizomatic learning focuses on how learners access the network and seek knowledge as an innovative search for understanding.

Rhizomatic learning (Cronje, 2018) is based on the premise that knowledge is robust, nonlinear, and unpredictable and extends these concepts to the learning process. From a theoretical viewpoint, it is found that online learning is of an interdisciplinary type and is subject to continuous transition. Therefore, rather than sticking to a predetermined theoretical framework, we can take advantage of various theoretical approaches to broaden our perspectives and improve our educational environment. In this regard, we have been motivated by a theory of diversity in many respects (Bozkurt, 2019; Geng et al., 2019).

There has never been a greater need for a concerted, inclusive, and mutual global approach to best practice guidelines for online education. This article focuses on different indicators in online and traditional learning. Where according to Wu and Cheng (2019), gender has no significance in online classes, other studies come to the conclusion that success in online classes is more individual, with results demonstrating that students' average performance differs based on the particular mixture of course modalities and demographic variables (e.g., Glazier et al., 2020). Other indicators such as personality traits have been positively linked with student engagement (Zhang et al., 2020), and learning styles are likely not linked with students' performance (Mirza & Khurshid, 2020). In a time of global uncertainty, there is a collective need for mutual assets and knowledge to ensure that the schooling of our students will succeed in the face of COVID-19. Nevertheless, more research is necessary to understand fully why these differences exist and if they are due to course design, curriculum content, faculty involvement, or other factors that need to be considered.

Personality, Learning Styles, and Gender in Online Learning

Educational researchers have concentrated intensively on many variables that contribute to learners' academic achievement. Efforts are focused on identifying how personality traits and teaching styles contribute to academic accomplishments during distance learning. Another factor that was found important was gender—how male and female students differ in character traits and preferred learning styles, and how they succeed in online classes (Allen & Seaman, 2011). Traits are defined as coherent patterns of ideas, emotions, motives, and behaviors that an individual displays across circumstances (Komarraju et al., 2011). Character traits in our case have been explained using the model generated by Costa and McCrae (1992)—the so called Big Five, which consists of a range of five different personality traits:

- *Conscientiousness*—characterized by being disciplined, organized, and achievement-oriented.
- *Agreeableness*—refers to being helpful, cooperative, and sympathetic towards others.
- *Neuroticism*—refers to a degree of Neuroticism instability, impulse control, and anxiety.
- *Openness*—reflected in an intense intellectual curiosity and a preference for novelty and variety.
- *Extraversion*—shown through a higher degree of sociability, assertiveness, and talkativeness.

The Big Five framework has become a worldwide reliable method used to investigate the relationship between personality and different academic activities (Poropat, 2009). Personality is as important as, if not more than, intelligence in educational contexts. Different educational results have been effectively predicted by the related variations of the Big Five personality traits. Research has revealed that conscientiousness is the most reliable predictor of a person's online course experiences, and conscientiousness and openness both continue to be reliable predictors of academic success (Sandu, 2019). Opposing the positive influence of conscientiousness and openness, the Neuroticism trait appears to work as an inhibitor (Keller & Karau, 2013). Overall, outcomes from studies on personality and education have indicated that personality can play an important part in learning and academic success. It is also notable that the outcomes are similar for traditional learning and online learning (Köseoglu, 2016).

Learning styles make up another dimension of how a person learns and adapts to their educational environment (Diseth, 2013). One model commonly used to identify learning styles is Neil Fleming's VARK model, created in 1987 (Fleming, 1987). Fleming's model identifies four primary types of learning styles—visual, auditory, read/write, and kinesthetics—the initials of which are used to name the VARK model (Fleming & Baume, 2006):

- *Visual* learners like to be provided with demonstrations and can learn through descriptions.
- *Aural* learners learn by listening. They like to be provided with aural instructions appreciate aural discussions.
- *Read/write* learners take notes. They often draw things to remember them.
- *Kinaesthetic* learners learn best by doing. Their preference is for hands-on experiences. They prefer not to watch or listen and generally do not do well in the classroom. (Gašević et al., 2015)

Students are able to use all these sensory learning methods; however, each student has a distinct preference or set of preferences in which one mode is often dominant. Learners with a single learning style preference are referred to as unimodal, while others who prefer a range of styles are referred to as multimodal (Nakayama et al., 2017). We suppose that in an online course, the set of teaching styles is distributed differently than in a face-to-face course. Online learning systems typically include fewer auditory or verbal sections than traditional face-to-face lessons. They have a more exceptional ability to read and write parts of a task. Students with visual learning styles and read/write learning styles may do better in online courses than their complements in face-to-face courses (Howie, 2011).

Regarding gender differences in online learning, scarce empirical evidence calls for the pretense that personality traits and learning styles differ by gender or that they impact general academic achievement. Results are conflicting on how male and female students interact in online learning environments. A prior study by Beer et al. (2010) indicates that male students perform better in online learning. In contrast, Harvey et al. (2017) indicate higher grades for female students in online classes. Cuadrado-García et al.'s (2010) study shows little differences in how male and female students interact in online environments. Overall, the results generally indicate that no significant differences exist on average between male and female students in online class participation, grades, motivation, or satisfaction (Henderikx et al., 2019).

Research Questions

We looked at different indicators for academic achievements in traditional and online learning, with a main focus on character traits, learning styles, and gender. Therefore, we put forward following research questions:

R1: Which character trait is most significant in traditional and/or online learning?

R2: Does gender impact test results and academic achievements?

R3: Which learning style is noteworthy for traditional and/or online learning?

R4: How does course difficulty and group affiliation affect achievements?

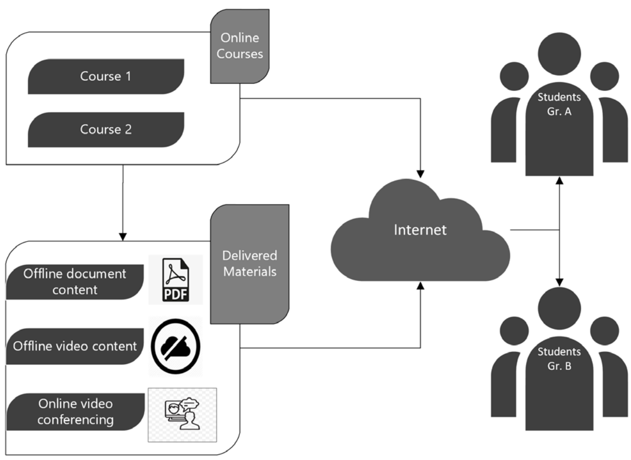
Methodology

Data were evaluated based on a case study, where participants were students who were part of two separate online courses that had different levels of difficulty. All participants were assessed using the revised NEO personality inventory (NEO PI-R; Uliaszek et al., 2019) and the VARK online questionnaire. Questioners were briefed on how they experienced the two online courses. This case study was conducted at the Faculty of Computer Science and Engineering, Ss. Cyril and Methodius University in Skopje, North Macedonia. The Moodle interactive interface was used for the management of student content during the experiment, as well as for the teachers' interaction with the content.

All participants attended two online courses during one semester: (a) Search Engines (C1 course), with a lower level of difficulty, and (b) Dynamic Websites (C2 course), with a higher level of difficulty (Idrizi & Filiposka, 2018). The initial number of students who started in the case study was 155, with 61 female and 94 male participating students. Of all participating students, 97 students filled out the VARK questionnaire, and 96 performed the Big Five questionnaire. The number of students who did not finish the case study was 101 in total: 74 male and 27 female students. Altogether, 54 students completed the case study and took the final test (34 female and 20 male students). Different presentation types were used for delivering the educational content of each course: offline document content (PDF documents), offline video content (recorded video presentations), and online videoconferencing (live videoconferences; Idrizi et. al, 2018). Students were split into two groups, A and B, with an equal number of participants—27 students each (see Figure 1). Group A students attending the C1 course were asked to pick their preferred type of learning materials; meanwhile, the C1 course instructor assigned the type of delivered materials to group B. For the C2 course, the opposite practice was implemented—that is, group B students picked their learning materials, and group A students were assigned the delivered materials by the instructor.

Figure 1

Case Scenarios for the Online Courses



One-way analysis of variance (ANOVA) is used to compare means of two or more samples. We thus could determine which of the variables had any significance in test results for the online courses and the overall grade point average (GPA) calculated from traditional classes taken by students who attended the two online courses. ANOVA was chosen due to the nature of the variables, having more than two levels in the cases of type of material delivered, VARK, and Big Five. Other methods for statistical analysis can deal with only continuous variables and/or two-level variables.

ANOVA Analysis

The one-way ANOVA method was used to determine whether any statistically significant differences existed between our variables for test results and GPA. ANOVA gives an approximation of how much variance in the dependent variable can be interpreted by the independent variable. It divides the results into inputs from various sources and then decides whether substantial variations exist between the sources of variance and provides a measure that represents the amount of the variability (see Tables 1 and 2).

In Tables 1 and 2, the first columns list the independent variable along with the residual model (e.g., the model error). The *df* columns illustrate the degrees of freedom for the independent variable (calculated by subtracting 1 from the number of levels within the variable) and for the residuals. The Sum Sq. *M* columns show the sum of squares (i.e., complete variation) between the group mean and the cumulative mean defined by that variable. The Mean Sq. *F* columns show the mean of the sum of squares, which is determined by dividing the sum of squares by the degree of freedom. The *F* value columns show the statistic of the *F* test: the mean square of each independent variable divided by the mean square of the residuals. The higher the *F* value, the more probable it is that the variance correlated with the independent variable is true and not attributed to chance. The columns Pr ($> F$) display the *p* value of the *F* statistic. This indicates how possible it is that the *F* value determined by the test would have been the same if the null hypothesis of no variation between the group means were accurate.

It must be noted that the results shown in Table 1 are related to student test success based on the two online courses only, whereas the results in Table 2 are related to the cumulative success—GPA—of students during their studies in traditional courses. The following variables have been taken into account: course difficulty, group affiliation, provided and preferred materials, Big Five traits, and VARK learning styles. We consider only those indicators in which the *p* value is equal to a significant code, which indicates how certain we can be the indicator has an impact on the dependent variable.

Significant codes vary between the two tables, showing a distinction between online and traditional courses. The following is an overview of each variable:

- *Course difficulty* proved to be essential for students' test results in online courses, whereas this variable shows no indication in overall academic success.
- *Group affiliation*, whether students belonged to group A or group B, also subsequently proved to be significant for students' test results based on groups they acquired the delivered materials.
- *Gender*'s impact cannot be assessed as significant for the test results in online courses but has significance related to overall academic success in traditional classes.

- From the *Big Five traits*, the Neuroticism trait is noteworthy for test results and also for overall academic achievement, whereas for the online courses, the significance is noticeably reduced.

- *VARK learning styles* are far more significant for students' achievements in traditional courses than in online courses. Also note that students taking online classes preferred the visual learning styles, but in traditional courses, the read/write style was more significant.

- *Provided/preferred materials* are indicated as significant only for overall academic success.

Table 1

ANOVA Analysis for Test Results in Online Courses

Test	*df*	Sum Sq. *M*	Mean Sq. *F*	*F* value	Pr (> *F*)
Course difficulty	1	21.33	21.333	22.887	.000*
Group affiliation	1	3.70	3.704	3.973	.050***
Gender	1	1.55	1.550	1.663	.201
Provided materials	2	0.15	0.076	0.081	.922
Preferred materials	2	1.67	0.834	0.894	.413
Neuroticism	1	2.91	2.911	3.123	.081†
Extraversion	1	0.41	0.411	0.441	.508
Conscientiousness	1	1.37	1.371	1.471	.229
Agreeableness	1	1.26	1.260	1.352	.248
Openness	1	0.80	0.803	0.861	.356
VARK	11	17.97	1.634	1.753	.077†
Visual	1	5.47	5.470	5.868	.018***
Aural	1	0.00	0.002	0.002	.968
Read/write	1	0.00	0.001	0.001	.977
Kinesthetic	1	0.23	0.228	0.245	.622
Residuals	80	74.57	0.932		

Note. Test is normalized using a scale 0 to 5.

* $p < .001$. ** $p < .01$. *** $p < .05$. †< .1.

Table 2

ANOVA Analysis for Overall Academic Success

Grade point average	*df*	Sum Sq. *M*	Mean Sq. *F*	*F* value	Pr (> *F*)
Course difficulty	1	0.000	0.000	0.000	1.000
Group affiliation	1	0.000	0.000	0.000	1.000
Gender	1	1.206	1.206	4.092	.046***
Provided materials	1	2.221	2.221	7.539	.007**
Preferred materials	1	1.206	1.206	4.094	.046***
Neuroticism	1	3.829	3.829	12.995	.001*
Extraversion	1	0.369	0.369	1.253	.266
Conscientiousness	1	0.338	0.338	1.148	.287
Agreeableness	1	0.211	0.211	0.715	.400
Openness	1	0.049	0.049	0.167	.684
VARK	11	10.944	0.995	3.377	.001*

Visual	1	0.005	0.005	0.018	.894
Aural	1	0.600	0.600	2.037	.157
Read/write	1	1.197	1.197	4.063	.047***
Kinesthetic	1	0.434	0.434	1.472	.229
Residuals	80	23.569	0.295		

Note. * $p < .001$. ** $p < .01$. *** $p < .05$. †< .1.

Next, a correlation analysis of these significant variables was generated to determine which variables were positively or negatively correlated with online test results and, subsequently, overall GPA.

Figure 2 indicates that of the variables, course difficulty is the main factor in students' success when taking online courses. Positively correlated are also VARK and the visual learning style, which can be explained due to the majority of delivered materials being in visual format. Group affiliation is also positively correlated to test results: students in group A scored better test results. A negative correlation with the Neuroticism trait was observed, implying that students who scored higher within the range of this trait have difficulties gaining good test results.

Figure 2

Correlation of Significance Codes for Test Results

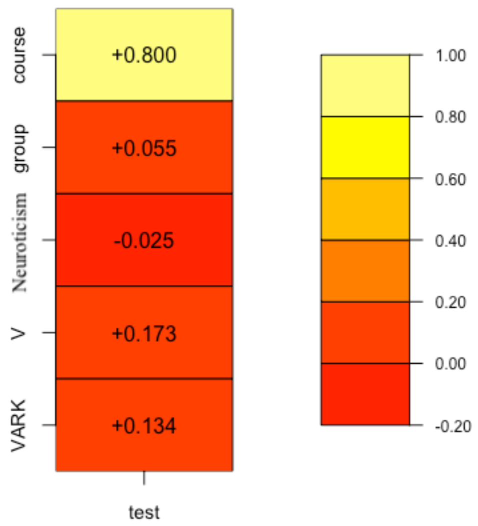
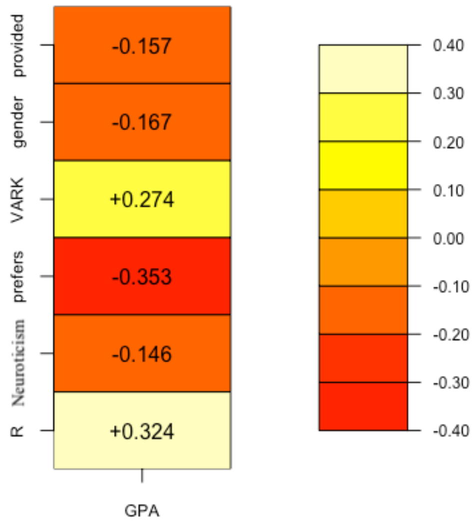


Figure 3 shows the correlation of the significant variables with GPA, highlighting that gender is negatively correlated with GPA. This indicates that male students have lower GPAs than female students taking traditional, in-person engineering classes. Additionally, for overall success rate, it is not important for students to choose their materials delivered since the variables of preferred and provided materials have a negative correlation with overall GPA. The Neuroticism trait is a constraint for students in achieving better academic results and in a more significant manner than in online courses. VARK has a more positive correlation with GPA than test results, since learning styles are more easily identified in traditional classes. The read/write style is enhanced because most materials provided for online classes are in read/write format.

Figure 3

Correlation of Significance Codes for Overall Academic Success



Discussion

Our research results, based on ANOVA analysis, point out some noteworthy connections between different variables that are significant in students' academic success in online classes. They further suggest that online and traditional learning techniques are distinct (Faulconer et al., 2018). Our research highlights the following discussion points (discussed in more detail below): (a) character traits' impact on test results, (b) the impact of students' gender on identifying learning styles and success in online classes, (c) the impact of learning styles on taking online courses compared with traditional courses, and (d) the impact of course difficulty on students' success.

Impact of Character Traits

Our first research question was to determine which character trait was more consistent during traditional and online learning, and whether character traits influenced students' test results. Our research indicates that the Neuroticism trait had the highest influence on students' success rates. The consciousness trait, on the other hand, is understood to be a stable indicator of high academic achievement (Icekson et al., 2020). However, consciousness was not as influential as the Neuroticism trait, which typically has a detrimental effect on the outcome of online course examination but with a higher significance on overall academic performance (Altanopoulou & Tselios, 2018). This suggests that students who rank higher on Neuroticism struggle in all educational settings but marginally less in online classes where they are able to manage their anxieties (Redecker et al., 2011; Wu & Lai, 2019).

Impact of Gender

The second research question focused on gender, that is, whether a student's gender is a factor in their academic success. It should be noted that the gender factor showed variety in its significance in our case study. Namely, gender is not a notable parameter in ANOVA Table 1, which exclusively reflects variables for online learning. This is compared to ANOVA Table 2, which summarizes the overall classes taken in the traditional manner, where gender is a significant variable. In accordance with a prior study

(Stojilović et al., 2012), the findings here indicate that female students outperform their male peers with better grades (Noroozi et al., 2018).

Impact of Learning Styles in Traditional and Online Learning

The third research question asked whether the impact of learning styles differs in traditional and online learning environments. VARK styles are less significant for online courses, whereas they are more important for traditional courses with students' and teachers' physical presence. This is particularly the case with the read/write learning style, since the learning materials used by students in traditional classes are mainly in read/write format. A practical example of this research finding is a male student participating in the case study who scored the highest test results of the class. His answers to the VARK questionnaire further indicate that students often are not aware of which learning style suits them best. In the online environment, identifying styles can be a challenge since instructors cannot directly observe students and assess the most suitable style for them. This once again illustrates the difficulty and unpredictability in assigning the learning materials tailored to students' learning styles in online classes compared with traditional classes (Husmann & O'Loughlin, 2019; Kirschner, 2017).

Impact of Course Difficulty and Group Affiliation

Our fourth research question explored the influence of course complexity and group affiliation. ANOVA analyses reveal that the level of online course difficulty has a key influence on test result outcomes, whereas materials provided based on group affiliation on the basis of student interests have a larger influence on total academic performance than on individual test results.

Conclusion

In conclusion, the findings of this research contribute new information about essential differences in students' academic success between online courses and traditional courses. The online educational environment can be considered more neutral, since the impact of external factors on students is reduced and they can interact with the teaching/learning process as individuals. Course difficulty proved to be the main significant variable and factor in online courses, also influencing student test results. Gender had no major influence on online course test results, compared to traditional class results, where female students scored slightly better on the overall academic success.

Character traits, which define how individuals react in different circumstances, are important information in the teaching process, regardless of the environment. The Neuroticism trait seems to act as an inhibitor for student success. However, in online classes, students who scored higher in the Neuroticism trait did not feel social pressure and were more in control of their emotions, so its significance is clearly less trivial in online classes than in traditional classes. This finding may indicate that this trait is not as impactful in online courses as in traditional classes.

The learning styles indicator (VARK) shows a greater significance in traditional courses contrary to online courses. This is especially important for the read/write style since most materials are available in this format. Assigning the proper style to students in online classes is more challenging than in traditional ones.

These results may provide teachers and course developers with useful insights on how they can influence and reshape their online courses. They can also help define new learning possibilities best suited for students' strengths based on individual preferences. In summary, the analyses conducted and this study's findings provide new understandings of ways to achieve academic success (especially in the emerging sector of online education in North Macedonia) by showcasing both (a) links between personality traits, group affiliation, gender, and learning styles to academic achievements; and (b) the varying impacts of these variables in traditional and online education.

It must be noted that in order to prevent any bias in the results, students were not forced to continue the experiment throughout the semester. This led to students dropping out during different stages of the course. Thus, due to the large number of dropouts, additional research and case studies are needed to confirm that the findings presented in this article can be used in a general context. Future work is needed to enhance our understanding of the complex nature of academic achievement in online classes.

References

Allen, I. E., & Seaman, J. (2011). *Going the distance: Online education in the United States, 2011*. Sloan Consortium. https://files.eric.ed.gov/fulltext/ED529948.pdf

Allen, I. E., & Seaman, J. (2017). *Digital compass learning: Distance education enrollment report 2017*. Babson Survey Research Group. https://files.eric.ed.gov/fulltext/ED580868.pdf

Altanopoulou, P., & Tselios, N. (2018). Big Five personality traits and academic learning in wiki-mediated collaborative activities: Evidence from four case studies. *International Journal of Distance Education Technologies*, *16*(3), 81–92. https://doi.org/10.4018/ijdet.2018070105

Bao, W. (2020). COVID-19 and online teaching in higher education: A case study of Peking University. *Human Behavior and Emerging Technologies*, *2*(2), 113–115. https://doi.org/10.1002/hbe2.191

Beer, C., Clark, K., & Jones, D. (2010). Indicators of engagement. In C. H. Steel, M. Keppell, P. Gerbic, & S. Housego (Eds.), *Curriculum, technology and transformation for an unknown future: Proceedings ascilite Sydney 2010* (pp. 75–86). http://ascilite.org.au/conferences/sydney10/procs/Beer-full.pdf

Bonk, C. J., Lee, M. M., Reeves, T. C., & Reynolds, T. H. (Eds.). (2015). *MOOCs and open education around the world*. Routledge.

https://doi.org/10.4324/9781315751108

Bozkurt, A. (2019). From distance education to open and distance learning: A holistic evaluation of history, definitions, and theories. In *Handbook of research on learning in the age of transhumanism* (pp. 252–273). IGI Global. https://doi.org/10.4018/978-1-5225-8431-5.ch016

Clark, J. T. (2020). Distance education. In E. Iadanza (Ed.), *Clinical engineering handbook* (2nd ed., pp. 410–415). Academic Press. https://doi.org/10.1016/b978-0-12-813467-2.00063-8

Crawford, J., Butler-Henderson, K., Rudolph, J., Malkawi, B., Glowatz, M., Burton, R., Magni, P. A., & Lam, S. (2020). COVID-19: 20 countries' higher education intra-period digital pedagogy responses. *Journal of Applied Learning & Teaching*, *3*(1), 1–20. https://doi.org/10.37074/jalt.2020.3.1.7

Cronje, Johannes C. (2018) Learning 3.0: Rhizomatic implications for blended learning. In K. Persichitte, A. Suparman, & M. Spector (Eds.), *Educational technology to improve quality and access on a global scale* (pp. 9–20). Springer. https://doi.org/10.1007/978-3-319-66227-5_2

Cuadrado-García, M., Ruiz-Molina, M. E., & Montoro-Pons, J. D. (2010). Are there gender differences in e-learning use and assessment? Evidence from an interuniversity online project in Europe. *Procedia-Social and Behavioral Sciences*, *2*(2), 367–371. https://doi.org/10.1016/j.sbspro.2010.03.027

Costa Jr, P. T., & McCrae, R. R. (1992). Four ways five factors are basic. *Personality and Individual Differences, 13*(6), 653-665. https://doi.org/10.1016/0191-8869(92)90236-i

Davies, R. S., & West, R. E. (2018). Technology integration in schools. In J. Spector, M. Merrill, J. Elen, & M. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 841–853). Springer. https://doi.org/10.1007/978-1-4614-3185-5_68

Diseth, Å. (2013). Personality as an indirect predictor of academic achievement via student course experience and approach to learning. *Social Behavior and Personality: An International Journal*, *41*(8), 1297–1308. https://doi.org/10.2224/sbp.2013.41.8.1297

Downes, S. (2020). Recent work in connectivism. *European Journal of Open, Distance and E-Learning*, *22*(2), 113–132. https://doi.org/10.2478/eurodl-2019-0014

Essien, A. M. (2015). Effectiveness of cooperative learning methodology in improving students' learning attitudes towards English language. *International Journal of Arts & Sciences*, *8*(2), 119–127. http://www.universitypublications.net/ijas/0802/html/DE4C352.xml

Faulconer, E. K., Griffith, J. C., Wood, B. L., Acharyya, S., & Roberts, D. L. (2018). A comparison of online and traditional chemistry lecture and lab. *Chemistry Education Research and Practice*, *19*(1), 392–397. https://doi.org/10.1039/c7rp00173h

Figlio, D. N., Rush, M., & Yin, L. (2010). Is it live or is it Internet? Experimental estimates of the effects of online instruction on student learning (Working Paper 16089). National Bureau of Economic Research. https://doi.org/10.3386/w16089

Fleming, N. D. (1987). VARK inventory. Retrieved January, 20, 2003 https://vark-learn.com/introduction-to-vark/the-vark-modalities/

Fleming, N., & Baume, D. (2006). Learning styles again: VARKing up the right tree! *Educational Developments*, *7*(4), 4–7. https://www.vark-learn.com/wp-content/uploads/2014/08/Educational-Developments.pdf

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. TechTrends, 59(1), 64-71. https://doi.org/10.1007/s11528-014-0822-x

Geng, S., Law, K. M., & Niu, B. (2019). Investigating self-directed learning and technology readiness in blending learning environment. *International Journal of Educational Technology in Higher Education*, *16*(1), Article 17. https://doi.org/10.1186/s41239-019-0147-0

Glazier, R. A., Hamann, K., Pollock, P. H., & Wilson, B. M. (2020). Age, gender, and student success: Mixing face-to-face and online courses in political science. *Journal of Political Science Education*, *16*(2), 142–157. https://doi.org/10.1080/15512169.2018.1515636

Harvey, H. L., Parahoo, S., & Santally, M. (2017). Should gender differences be considered when assessing student satisfaction in the online learning environment for millennials? *Higher Education Quarterly*, *71*(2), 141–158. https://doi.org/10.1111/hequ.12116

Henderikx, M., Kreijns, K., Castano Munoz, J., & Kalz, M. (2019). Factors influencing the pursuit of personal learning goals in MOOCs. *Distance Education*, *40*(2), 187–204. https://doi.org/10.1080/01587919.2019.1600364

Howie, D. (2011). *Teaching students thinking skills and strategies: A framework for cognitive education in inclusive settings*. Jessica Kingsley Publishers. https://www.ibs.it/teaching-students-thinking-skills-strategies-libro-inglese- dorothy-howie/e/9781843109501

Husmann, P. R., & O'Loughlin, V. D. (2019). Another nail in the coffin for learning styles? Disparities among undergraduate anatomy students' study strategies, class performance, and reported VARK learning styles. *Anatomical sciences education*, *12*(1), 6–19. https://doi.org/10.1002/ase.1777

Icekson, T., Kaplan, O., & Slobodin, O. (2020). Does optimism predict academic performance? Exploring the moderating roles of conscientiousness and gender. *Studies in Higher Education*, *45*(3), 635–647. https://doi.org/10.1080/03075079.2018.1564257

Idrizi, E., Filiposka, S., & Trajkovik, V. (2018, September). Character traits in online education: Case study. In S. Kalajdziski & N. Ackovska (Eds) *ICT 2018: ICT Innovations 2018. Engineering and Life Sciences* (pp. 247-258). Springer, Cham. https://doi.org/10.1007/978-3-030-00825-3_21

Idrizi, E., & Filiposka, S. (2018). VARK learning styles and online education: Case *Study*. *Learning*, 5-6. https://www.researchgate.net/publication/327869001_VARK_Learning_Styles_and_Online_Education_Case_Study

Ilgaz, H., & Gulbahar, Y. (2017). *Why do learners choose online learning: The learners' voices*. International Association for Development of the Information Society. https://eric.ed.gov/?id=ED579379

Kara, M., Erdoğdu, F., Kokoç, M., & Cagiltay, K. (2019). Challenges faced by adult learners in online distance education: A literature review. *Open Praxis*, *11*(1), 5–22. https://doi.org/10.5944/openpraxis.11.1.929

Keller, H., & Karau, S. J. (2013). The importance of personality in students' perceptions of the online learning experience. *Computers in Human Behavior*, *29*(6), 2494–500. https://doi.org/10.1016/j.chb.2013.06.007

Kirschner, P. A. (2017). Stop propagating the learning styles myth. *Computers & Education*, *106*, 166–171. https://doi.org/10.1016/j.compedu.2016.12.006

Komarraju, M., Karau, S. J., Schmeck, R. R., & Avdic, A. (2011). The Big Five personality traits, learning styles, and academic achievement. *Personality and Individual Differences*, *51*(4), 472–477. https://doi.org/10.1016/j.paid.2011.04.019

Köseoglu, Y. (2016). To what extent can the Big Five and learning styles predict academic achievement. *Journal of Education and Practice*, *7*(30), 43–51. https://files.eric.ed.gov/fulltext/EJ1118920.pdf

McCarty, C., Bennett, D., & Carter, S. (2013). Teaching college microeconomics: Online vs. traditional classroom instruction. *Journal of Instructional Pedagogies*, *11*. https://eric.ed.gov/?id=EJ1097170

Mirza, M. A., & Khurshid, K. (2020). Impact of VARK learning model at tertiary level education. *International Journal of Educational and Pedagogical Sciences*, *14*(5), 359–366. https://publications.waset.org/10011198/impact-of-vark-learning-model-at-tertiary-level-education

Nakayama, M., Mutsuura, K., & Yamamoto, H. (2017). Effectiveness of student's note-taking activities and characteristics of their learning performance in two types of online learning. *International Journal of Distance Education Technologies*, *15*(3), 47–64. https://doi.org/10.4018/ijdet.2017070104

Noroozi, O., Hatami, J., Bayat, A., van Ginkel, S., Biemans, H. J., & Mulder, M. (2018). Students' online argumentative peer feedback, essay writing, and content learning: Does gender matter? *Interactive Learning Environments*, *6*, 698–712. https://doi.org/10.1080/10494820.2018.1543200

Page, J., Meehan-Andrews, T., Weerakkody, N., Hughes, D. L., & Rathner, J. A. (2017). Student perceptions and learning outcomes of blended learning in a massive first-year core physiology for allied health subjects. *Advances in Physiology Education*, *41*(1), 44–55. https://doi.org/10.1152/advan.00005.2016

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*(2), 322–338. https://doi.org/10.1037/a0014996

Redecker, C., Leis, M., Leendertse, M., Punie, Y., Gijsbers, G., Kirschner, P., Stoyanov, S., & Hoogveld, B. (2011). *The future of learning: Preparing for change*. Publications Office of the European Union. https://doi.org/10.2791/64117

Rice, M. F., Lowenthal, P. R., & Woodley, X. (2020). Distance education across critical theoretical landscapes: Touchstones for quality research and teaching. *Distance Education*, *41*(3), 319–325. https://doi.org/10.1080/01587919.2020.1790091

Sandu, M. (2019). *Investigating personality traits and intelligence as predictors of academic performance and academic motivation*. [Doctoral dissertation, National College of Ireland]. Semantic Scholar. https://www.semanticscholar.org/paper/Investigating-Personality-Traits-and-Intelligence-Sandu/ce27950afc1482a94d002c515994a77a4e0f99f0

Seaman, J. E., Allen, I. E., & Seaman, J. (2018). *Grade increase: Tracking distance education in the United States*. Babson Survey Research Group. https://eric.ed.gov/?id=ED580852

Siemens, G., Gašević, D., & Dawson, S. (2015). *Preparing for the digital university: A review of the history and current state of distance, blended, and online learning*. https://doi.org/10.13140/RG.2.1.3515.8483

Simonson, M., Zvacek, S. M., & Smaldino, S. (2019). *Teaching and learning at a distance: Foundations of distance education* (7th ed.). IAP.

Stojilović, M., Filiposka, S., Krsteska, A., Vidosavljević, A., Janev, V., & Vraneš, S. (2012). Students' perception of IT curricula and career opportunities in Serbia and Macedonia. In A. Béraud, A. S. Godfroy, & K. Michel (Eds.), *GIEE 2011: Gender and Interdisciplinary Education for Engineers* (pp. 241–253). SensePublishers. https://doi.org/10.1007/978-94-6091-982-4_18

Talebian, S., Mohammadi, H. M., & Rezvanfar, A. (2014). Information and communication technology (ICT) in higher education: Advantages, disadvantages, conveniences and limitations of applying e-learning to agricultural students in Iran. *Procedia-Social and Behavioral Sciences*, *152*, 300–305. https://doi.org/10.1016/j.sbspro.2014.09.199

Tawfik, Y., Samy Eldeeb, M., & Elwy, E. (2017). *Behaviourism, cognitivism and constructivism paradigm for teaching and learning*. University of Greenwich. http://central-library.msa.edu.eg:8009/xmlui/handle/123456789/2706

Toquero, C. M. (2020). Challenges and opportunities for higher education amid the COVID-19 pandemic: The Philippine context. *Pedagogical Research*, 5(4). https://doi.org/10.29333/pr/7947

Tseng, K. C., & Chu, S. Y. (2010). Traditional versus online courses, efforts, and learning performance. *The Journal of Human Resource and Adult Learning*, *6*(1), 115–121. http://www.hraljournal.com/Page/14%20Kuang-Cheng%20Tseng.pdf

Uliaszek, A. A., Al-Dajani, N., Sellbom, M., & Bagby, R. M. (2019). Cross-validation of the demoralization construct in the Revised NEO Personality Inventory. *Psychological Assessment*, *31*(2), 159–166. https://doi.org/10.1037/pas0000655

Wu, F., & Lai, S. (2019). Linking prediction with personality traits: A learning analytics approach. *Distance Education*, *40*(3), 330–349. https://doi.org/10.1080/01587919.2019.1632170

Wu, J. Y., & Cheng, T. (2019). Who is better adapted in learning online within the personal learning environment? Relating gender differences in cognitive attention networks to digital distraction. *Computers & Education*, 128, 312–329. https://doi.org/10.1016/j.compedu.2018.08.016

Zhang, X., Chen, G., & Xu, B. (2020). The influence of group Big-Five personality composition on student engagement in online discussion. *International Journal of Information and Education Technology*, *10*(10), 744–750. https://doi.org/10.18178/ijiet.2020.10.10.1452