Impact of Personal and Academic Factors on Outcome-Based Education of Third-Year Engineering Students in the University of Santo Tomas Delivered Through Full Online Modality

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Abstract

Distance learning has been advancing in today's time given the continuous enhancement of technology in the world. Moreover, with the COVID-19 Pandemic that hit nationwide, the education sector had to turn to distance learning to save the education of students in this generation. The research aims to analyze how engineering students' personal and academic experiences under an unusual online set-up create an impact on their well-being as an individual. Through the dissemination of survey questionnaires to the students, the researchers will measure the results through statistical analysis. With that, the independent variables identified in the study are manipulated into WarpPLS to foresee their relationship with the determined dependent variable through Structural Equation Modeling. It enables a concrete evaluation of which factors affect a student of abundant or sparse weight.

Keywords
Distance learning, Personal and Academic Factors, Structural Equation Model, Outcome-Based Education

1. Introduction
Online learning has emerged as a solution to the dilemma facing the education sector after the start of the COVID-19 pandemic. However, despite the countermeasures, challenges throughout the journey were inevitable. Identifying the factors that influence student performance will greatly assist private and public educational institutions in analyzing and improving the existing systems they use in implementing Outcome-Based Education for engineering students. Moreover, the results of the study will not only help the engineering departments but may also serve as a basis for other educational programs in improving the systems they use to fully utilize the potential of the students.

1.1 Online Modality
There has been a rapid shift in the delivery of course instructions from the traditional way to distance learning. In the Philippines, it became necessary for most schools to pivot to online classes for learning because of the COVID-19 pandemic since most areas in the country are under strict quarantine restrictions. This sudden shift has led to shock and tension among students and faculty members, whether personally or professionally (Khalaf, 2020).

Different video conferencing applications and learning management systems are being used to transmit smooth communication and distribution of learning materials and activities online between teachers and students. This called for institutions to adapt and innovate to continue delivering course content amidst crises.

To properly facilitate this type of education, the preparedness of the institution and the motivation for online learning of the students must also be taken into consideration to form an understanding between the instructor and its students. The communication between the parties involved shall be clear to properly deliver and manifest the goal and objective of this learning shift.

1.2 Outcome-Based Education

Outcome-Based Education (OBE) is an educational system that focuses on student learning outcomes and assessments. It is an approach for organizing the educational system that focuses on the success of the learning experiences of students.

OBE is based on a guiding assumption that coordinates each perspective of the guiding framework with a set of accepted outcomes. This insists on the assurance of learning results as the primary step in course planning. Outcomes selected should go beyond content, instructional techniques, learning experiences, assessment strategies and assessments. Thus, Outcomes-Based Education (OBE) gives an opening to teach differently, naturally, and creatively at the same time. In the CHED Memorandum Order (CMO), in every program outcome, there is a corresponding set of performance indicators.

1.3 Objectives

The study aims to appraise the impact of deployment of online distance learning to the Semester Grade or General Weighted Average (GWA) as a measure of Outcome-Based Education (OBE) to the engineering students at the University of Santo Tomas. GWA is the best representation for OBE since it is an excellent indicator of the students' learnings in the online setup.

The secondary objective of the research is to recommend different strategies that will potentially improve the Outcome-Based Education Grade of the engineering student based on the significant factors that will be identified. Furthermore, the identified variables may be used by the educational institutions and future researchers in developing existing Outcome-Based Education systems in online learning to overcome the current dilemmas that hinder students in maximizing their abilities in certain fields. The results of the study can serve different purposes especially if another situation like this pandemic occurs in the future.
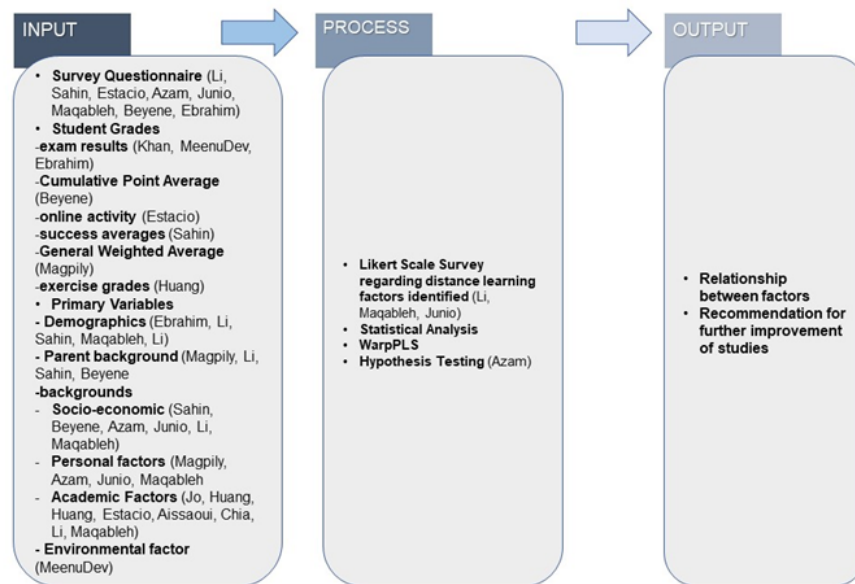
2. Literature Review

Figure 1. Theoretical Framework

The different related literature for the study is summarized in the Input-Process-Output model in Figure 1. There are similarities as to the different factors which were used by different authors and similarities in the processes they have undergone. For the output, the majority, if not, all the related studies' objective was to create a predictive model for the academic performance of the students or proponents in their study aside from finding the significant variables based on their chosen variables.

Focusing on engineering education, studies claimed that online learning focuses in terms of design, evaluation of the learning systems, platforms used and, perception and feedback of both students and their instructors (Hsu et al., 2012, cited in Du et al., 2020). Attention has been contemporarily shifted to materialize the emerging development of immersive technologies for both visualization and interactions and the technologies educational applications (Radianti et al., 2020, cited in, Du et al., 2020).

Advantages and disadvantages have been identified since the education system shifted. It opened opportunities despite all the challenges of adapting to the sudden change the world has turned into (Moralista and Oducado, 2020). The modern way, online learning, is innovative in both teaching and learning with the method of using synchronous and asynchronous learning environments wherein students may attend to distance learning in any location, given they have a device and internet connection (Singh and Thurman, 2019, cited in Dhawan, 2020).

Regarding online learning resources and class delivery variables, the communication barrier is one of the challenges that may arise in distance learning for both the professor and the student. Proper utilization of synchronous and asynchronous serves a major impact on the effectiveness of distance education (Arinto, 2016). Furthermore, the generation gap between professors and students is given attention regarding differences in technological capabilities as the older generation is least exposed to the digital world. (Lisenbee, 2016).

In the statistical analysis process, Structural Equation Modeling (SEM) is an effective tool for improving student outcomes and finding out if different factors bring a significant effect. It is a flexible method appropriate for examining a correlation between given latent and observed variables. According to Leon-Mantero, C., et al. (2020), in a Likert scale type survey questionnaire, a high correlation regarding factors is noticed, which compromises the assignment of statements needed, but with SEM's ability to analyze a level of multiplex variables, the researchers estimated factors in coordination with students' weighted average in the mathematics subject. The researchers were able to point out significant differences from their scale basis, Auzmendi, given the results from their structural equation model.
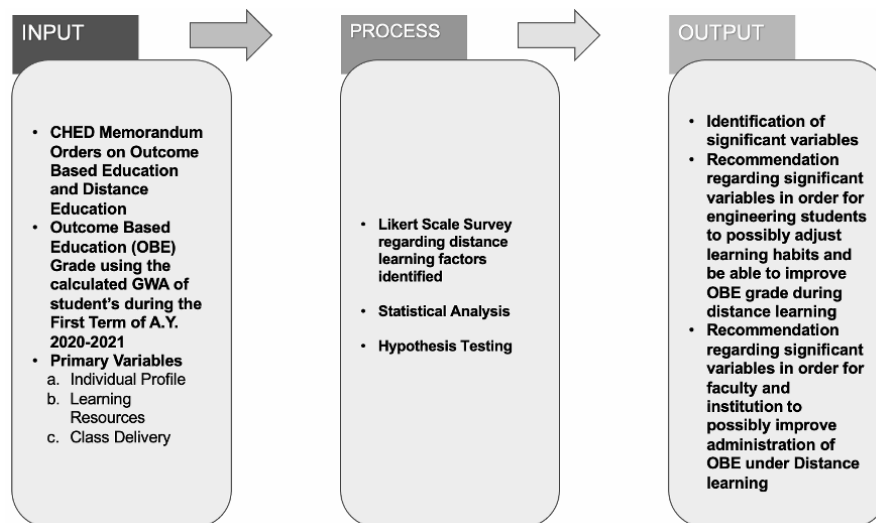
3. Methods

Figure 2. Conceptual Framework

Figure 2 presents the conceptual framework of the study. The research will utilize statistical analysis in identifying how personal and academic factors would influence the Outcomes Based Education (OBE) grade of students in the Faculty of Engineering. OBE grade based on the calculated Grade Weighted Average (GWA) of students during the First Term of A.Y. 2020-2021 will be the data going to be used in conducting the statistics. CHED Memorandum Orders regarding the implementation of OBE and Distance Education are to be used to support the results going to be derived from the statistical data in the study.

Likert Scale survey questionnaires are going to be distributed to students regarding the distance learning factors identified in the study and be able to infer how it affects them. Aside from the statistical analysis, hypothesis testing will be conducted to examine if the survey conveyed significant results. Gathered data will then be analyzed through Structural Equation Modeling using WarPLS statistical software.

Out of all the inputs and processes the study will undergo, its aimed output will be the identification and eventual recommendation of significant variables for the benefit of the UST engineering students, faculty, and institution. The recommendations will acknowledge the significance of the study and aim to present future outcomes that may occur regarding the impact of personal and academic factors on the OBE of students under distance education and may serve as suggestive evidence for the beneficiaries of the study.

4. Data Collection

The data gathering instrument that will be used is through disseminating a survey questionnaire which was accomplished by each of the six departments of the faculty which are Civil Engineering, Mechanical Engineering, Electronics Engineering, Electrical Engineering, Chemical Engineering, and Industrial Engineering. The procedure that will be done is disseminating the questionnaire to students from the different departments until the needed sample size is obtained for the study. The researchers will be using a survey method that focuses more on a quantitative approach and using a type of survey which is the Likert Scale. All types of data are combined and analyzed to determine the impact of deployment of online distance learning to the semester grade as a measure of Outcome-Based Education to the engineering students at the University of Santo Tomas. This approach will help the researchers get quantitative results that will help formulate a better approach to the system of online learning and will help identify the factors that greatly affect the students' performances.

Through gathering the data in each department, the researchers plan to use 2 different methods for the respondents to accomplish the survey willingly. First, the survey will be disseminated through social media, since students nowadays, this platform is important because it is often easier and more convenient to access information, it can also communicate and provide information using social media. This will be done by posting it in different Facebook groups where students in each department are members of the group mentioned. Second is disseminating via email, this will be done through using group email per department where a listed number of students were chosen. Since students focus on academics to earn knowledge, using email is one way to get the attention of students to accomplish the survey again, willingly. Using this method is very effective to get the attention of students since the source of information is coming through online communication. This way it would be beneficial for this study to get as much as information needed to achieve the said sample size of this study.

For Independent Variables:
Individual Profile, Learning Resources, and Class Delivery

Unit of Measurement on the Survey Questionnaire, the score "1" chosen by the student indicates that the same Strongly agree with the statement shown. A score "2" Chosen by the student would indicate that the student only Agrees with the said statement. A score of "3" that was selected by the student indicates that the student disagrees with the statement mentioned. A score of "4" that was picked by the student indicates that the student Strongly Disagrees with the statement mentioned.

For Dependent Variable:
The procedure that will be done regarding the OBE grade, is the respondent who is the student in each department will input their semestral average into the questionnaire that will serve as a basis of the dependent variable in this study.

5. Results and Discussion
5.1 Numerical Results

Table 1. Path Analysis of the SEM Model

Path Analysis	Path Coefficients	p-value	Decision
Individual Profile	-0.292	0.000	Significant
Learning Resources	-0.054	0.256	Not Significant
Class Delivery	0.006	0.469	Not Significant

Table 1 shows the path analysis of the SEM Model. Based on the results, Individual Profile (Path = -0.292, p = 0.000) has a significant relationship to OBE Grade. Looking at the column under path coefficient for individual profile, there is a negative correlation (-0.292) between Individual Profile and OBE Grade. The negative correlation means that the individual factors (learning style, community, social connection, geographical location, self-motivation, learning environment, and financial capability) inversely influence OBE Grade. The result is valid for our respondents since the University of Santo Tomas follows a 4.0 numerical grading system with 1.0 as the highest. Therefore, it appears true that these factors have a positive impact on OBE Grade wherein having a positive influence on I.P aspects lowers student's grades which ultimately means having a higher grade for them.

On the other hand, Learning Resources (Path = -0.054, p = 0.256) and Class Delivery (Path = 0.006, p = 0.469) have a relationship to grades but not to a significant extent since their p>0.05 (Garson, 2012).

Table 2. Collinearity, Validity, and Reliability Tests of the Constructs

Construct / Item	Indicator Loadings	VIF	AVE	CR	CA
Individual Profile		2.326	0.437	0.735	0.819
IP1	0.671				
IP 2	0.610				
IP 3	0.545				
IP 4	0.759				
IP 5	0.816				
IP 6	0.512				
Learning Resources		2.034	0.571	0.809	0.868
LR1	0.607				
LR 2	0.799				
LR 3	0.803				
LR 4	0.760				
LR 5	0.789				
Class Delivery		1.622	0.599	0.828	0.880
CD1	0.739				
CD 2	0.868				

CD 3	0.816				
CD 4	0.595				
CD 5	0.823				

*Notes: All item indicators are significant at 0.001 (p < 0.001). AVE = average variance extracted;
VIF = variance inflation factor; CR = composite reliability; CA = Cronbach's alpha*

Table 2 shows the collinearity, validity, and reliability tests of the questionnaire constructs. For the constructs to have convergent validity, the p-values of each item must be equal to or lower than 0.05, and the loadings are equal to or higher than 0.5 (Hair et al., 2009; Kock, 2017). Based on the results, all constructs or item loadings for Individual Profile, Learning Resources, and Class Delivery are more significant than 0.5 with a p-value < 0.001. Thus, it can be concluded that the survey construct has convergent validity.

Moreover, constructs/items should have VIF < 5 to conclude that the data do not show multicollinearity (Ringle et al., 2015) and since all computed VIF are < 5 thus no multicollinearity exists. Also, according to Fornell and Larcker (1981), the AVE must be equal to or higher than 0.5, and since Learning Resources (AVE = 0.571) and Class Delivery (AVE = 0.599) are more significant than 0.5, it can be concluded that the constructs and loadings satisfied the acceptable validity except for Individual Profile (AVE = 0.437).

Lastly, to measure the reliability of the constructs or items, the researcher used composite reliability and Cronbach's alpha. Fornell and Larcker (1981) suggested that one of the reliability coefficients should be greater than 0.7 to achieve acceptable reliability. Since all computed coefficients from composite and Cronbach's alpha are greater than 0.7, thus it can be concluded that the constructs and items used in this study have acceptable reliability.

Table 3. Model Fit and Quality Indices

Index	Values	Parameters
APC	0.118, p = 0.037	0.05
ARS	0.083, p = 0.078	0.05
AARS	0.063, p = 0.110	0.05
AVIF	1.178	Less than 3.3
AFVIF	1.754	Less than 3.3
Tenenhaus GoF	0.232	small >= 0.1, medium >= 0.25, large >= 0.36

Table 3 presents the coefficients of model fit and quality indices. In evaluating the model fit with the acquired data, there are several recommended criteria to check. According to WarPLS User Manual: Version 6, Kock indicated that the p-values of average path coefficient or APC, average R-squared or ARS, and average adjusted R-squared or AARS should be equal or less than the significance level of 0.05 for it to be identified if it is acceptable or not acceptable (Kock, 2011c cited in, Kock, 2017). Based on the results, APC = 0.118 with p-value = 0.037 or interpreted as acceptable, ARS = 0.083 with p-value = 0.078 or interpreted as not acceptable, and AARS = 0.063 with p-value = 0.110 or interpreted as not acceptable. For the average block inflation factor or AVIF and average full collinearity VIF or AFVIF, it is ideal that the p-value of both indices is equal to or lower than 3.3, specifically to models wherein variables are measured by two or more indicators (Kock and Lynn, 2012 cited in Kock, 2017). Also,

for the Tenenhaus GoF, Wetzels et al. (2009), cited in Kock (2017), proposed the following threshold of GoF: small if equal to or greater than 0.1, medium if equal to or greater than 0.25, and large if equal to or greater than 0.36. The table shows that AVIF = 1.178 or interpreted as acceptable, AFVIF = 1.754 or interpreted as acceptable, and Tenenhaus GoF = 0.232 or interpreted as a medium.
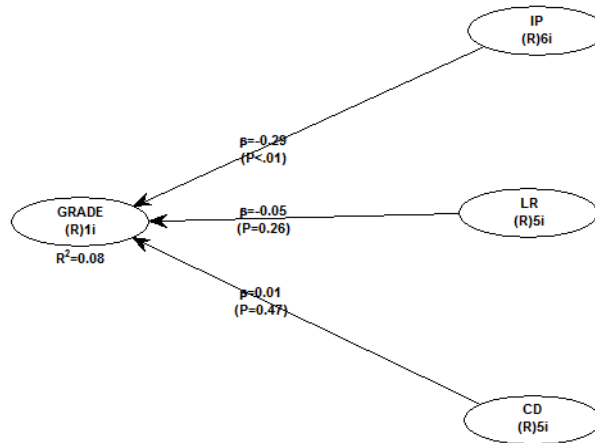
5.2 Graphical Results

Figure 3. Structural Equation Model

A Structural Equation Model via WarpPLS as presented in Figure 3 was made to analyze the relationship between the dependent variable (OBE Grade of a student), the three latent variables (Individual Profile, Learning Resources, and Class Delivery), and the observed variables under it.

5.3 Proposed Improvements

Given that only one independent variable is significant, the researchers suggest improvements by reconstructing the SEM model/reducing or adding survey questions to obtain a suitable data result specifically to meet the threshold of =>0.05 in Average Variance Extracted (AVE). Moreover, further studies may consider a slight correlation between the significant independent variable to the other two observed variables (Learning Resources and Class Delivery) and testing of normality in different software can be conducted.

There can also be further improvements on the survey questionnaire itself by looking individually and thoroughly through the different questions and testing the validity and reliability of each question if it is relevant for the category of Individual Profile, Learning Resources, and Class Delivery. With that, possible regrouping of questions may be performed to achieve more properly sorted variables and increase the survey's validity and reliability.

As with the sample size, future researchers can look at deploying surveys to larger sample sizes and with different students from different schools to determine if there is a significant difference or similarity between the results. This change in sample size could give a larger view of the scope of the study, which may be a great research opportunity for the educational sector.

6. Conclusion

Since there are abrupt changes in implementing online distance learning to recommence education on newly established systems, the study specifically sought to find out the significance of the three latent variables, Individual Profile, Learning Resources, and Class Delivery on the OBE Grade of UST Engineering students during the first semester when full-time Enriched Virtual Mode of learning was implemented by the institution, which was during the first semester of A.Y. 2020-2021.

The researchers sorted the variables based on the formulated survey questionnaire and subsequently constructed a Structural Equation Model on the software WarpPLS to simplify and carry out the statistical analysis. After running the data, results showed that one independent variable, Individual Profile, was found significant among the three Independent Variables. There are six (6) observed variables under Individual Profile which are the following: Learning Style, Community, and Social Connection, Geographical Location, Self-motivation, Learning Environment, and Financial Capability.

Considering the aim of the study to aid engineering students regarding their distance learning practices and techniques, the results from statistical analysis displayed satisfactory and specific outcomes. It allows the educational sector, including students, teachers, and academic institutions, to focus on students' Individual Profiles in creating new and improved learning approaches for the betterment of the whole educational system after being affected by one of the most challenging phenomena nationwide, the COVID-19 Pandemic.

Highlighting the technical subjects being undergone in the Engineering course, implementation of various laboratory activities became a challenge for the institution to conduct virtually. The Individual Profiles of students are different under distance learning and possession of resources is one of the major issues encountered, taking into account that these classes would require several tools or machines. Also, with the limited hands-on experience that became unavailable for students, ensued a lack of confidence in the following entry to the professional engineering world.

On the other hand, with the convergent validity of all the three latent variables, it can be concluded that despite Individual Profile being the only one of significance, all three variables still have a small interrelation. The study allows the concerned bodies to tackle the Learning Resources and Class Delivery variables after primary comprehension with Individual Profile.

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Biography

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