Vol.8 No.2 (2025)

Journal of Applied Learning & Teaching

ISSN : 2591-801X

Content Available at : http://journals.sfu.ca/jalt/index.php/jalt/index

# Direct and indirect effects in learning: A case of learners in a university in Singapore

Jess Wei Chin Tan[A]

[A] School of Business, Singapore University of Social Sciences (SUSS)

## Keywords

Academic performance;
course perceptions;
learning approach;
motivation;
personality traits;
structural equation modelling.

## Correspondence

jesstanwc@suss.edu.sg [A]

## Article Info

Received 17 April 2025
Received in revised form 3 October 2025
Accepted 6 October 2025
Available online 6 October 2025

**DOI:** https://doi.org/10.37074/jalt.2025.8.2.18

## Abstract

The effects of the direct and indirect relationships of academic performance, motivation, learning approach, course perceptions, academic background, personality, learning environment and prior learning are studied here. The analysis is conducted using Structural Equation Modelling (SEM), allowing for a comprehensive examination of these complex relationships within the framework of the expanded Biggs' 3P model.

Some of the notable findings include: (1) the indirect effects of personality traits -conscientiousness and openness on academic performance; (2) the negative effect of a high level of personality trait agreeableness on academic performance; (3) intrinsic motivation as a key mediator in most of the significant indirect effects as well as being an important independent construct; and (4) the direct effects of personality traits (in particular, agreeableness and openness) on students' perceptions of the course. The insights gained from this study could provide universities with valuable information for designing more effective student support and interventions.

## Introduction

Being able to study and understand the various factors that can affect the academic performance of students provides an important handle to design courses and calibrate pedagogical approaches that can bring about effective student learning. This is especially critical in the light of the evolving learning environment, including the disruptions caused by COVID-19 where conventional ways of learning and teaching may no longer be effective in supporting students' learning needs (Sam, 2022).

While there is a fair number of studies attempting to research factors associated with academic performance, the majority of these studies tend to examine these factors as either individual contributions or only for a small set of them. Teaching and learning interactions are often complex, with many factors contributing in a network of influences such that an individual contribution can at best provide an indication, but often the effect needs to take into account the holistic contributions of these factors taken as a whole. In other words, it is likely that interactions in a model are not a causal chain of independently constituted components over time but are the effect of a complex ecology of factors (Trigwell & Prosser, 1997). This is consistent with Chung and Chapman's (2023) affirmation that a student's learning is strongly influenced by multiple factors.

Given the above, the present study seeks to understand the nature and extent of the complex relationships among the factors, or attributes, that can be identified as potential contributors. These would include students, learning and course attributes, linking to the determinants of academic performance. An understanding of how these interact and collectively contribute to effective learning has the potential to guide and facilitate the development of appropriate support and interventions for learning, as well as help to improve the development of curriculum and assessments. While the findings are likely to be context dependent, they can still potentially contribute to theory affirmation and modification.

The study was conducted in a university which offers part- and full-time degree programmes primarily for working adults and students who matriculate directly after pre-university or equivalent education, respectively. This diversity of student profiles would add to the complexity of the interactions of students' attributes and their influence on curriculum and its delivery.

### Framing of the research

This study uses the Biggs 3P model (Biggs, 1989) as its initial framing to provide guidance for its design. In its original form, the 3P model conceptualises the learning process as an interacting system of three sets of variables: the learning environment and student characteristics (presage), students' approach to learning (process) and learning outcomes (product). For this study, the attributes within each set, however, are insufficient to account for the complexities of the interactions examined. This resulted in the need to expand the 3P model in order to investigate directional understanding of direct and indirect relationships across a broader range of presage and process attributes with respect to the product. The expanded 3P model, with the additional attributes (in italics) is as shown in Figure 1.

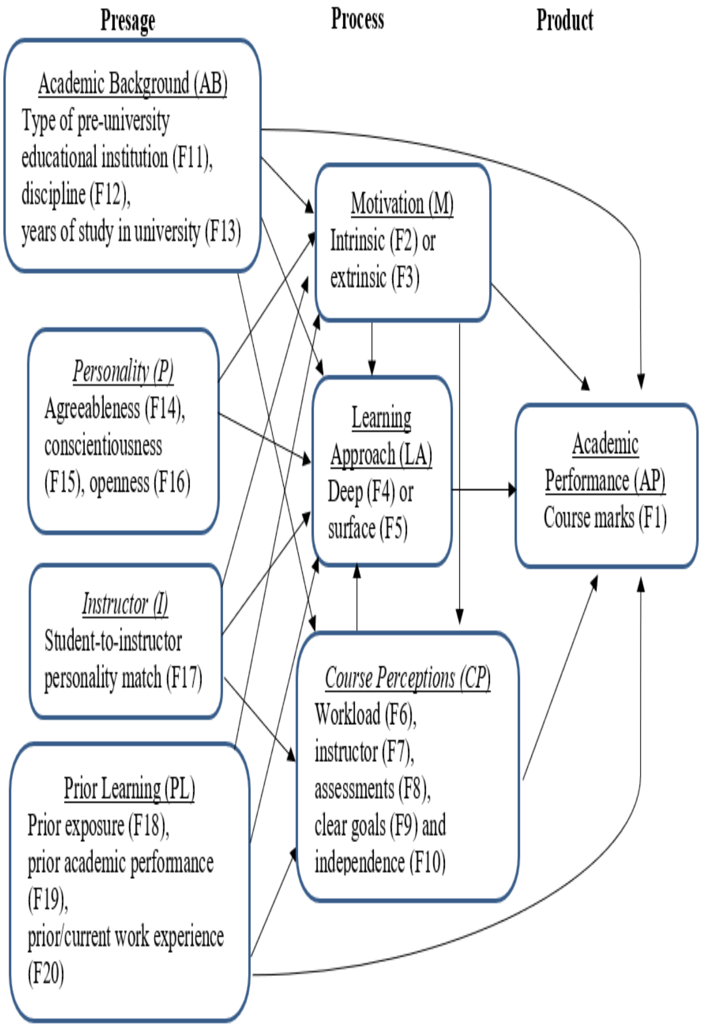



Figure 1. The expanded 3P model of teaching and learning (Research framework).

The expanded model allows for deeper insights that can contribute to how the university can respond in terms of targeted support, appropriate interventions, and refinements of curriculum and its delivery. The expanded model was also discussed by Tan et al. (2024).

### *Presage*

This study aims to investigate various personal characteristics of students as presage factors that may influence academic performance. The attributes covered and the rationale for their inclusion are shared below.

<u>Academic background</u>: Prior studies have suggested that where students come from, in terms of different pre-university educational experiences, could have an impact on their subsequent learning experience in institutions of higher learning (Hassan et al., 2020; Kilishi, 2021). As an illustration, Kilishi (2021) found that the academic performance of

students who attended public schools outperformed those who attended private schools for first-year students majoring in Economics at a university in Nigeria. Also, in a more recent study based on 367 undergraduate accounting students in a Malaysian university, it was found that students from national secondary schools performed significantly better than those from boarding schools and religious secondary schools (Hassan et al., 2020). These different educational experiences are related to, and could have consequence for, which discipline the student would want to pursue. In fact, the selection of discipline to pursue is often complex, involving numerous external (e.g., financial, accessibility and social) and internal (e.g., personality traits and motivation) considerations (Prakasam & Gopinathan, 2019; Vedel, 2014). In addition, it seems that students' adoption of learning approaches depends on the discipline they are in (Smith & Miller, 2005). Taken as a whole, it is crucial to examine the students' discipline selection in this study.

An attribute that has not received sufficient attention is the 'Years of study'. Its inclusion here is motivated by the question of whether a student whose progress through the university programme is taking longer than the norm has any bearing on his/her academic performance. It is noted that the pace of progress can be due to a number of reasons, including work commitments and academic struggles, which would balance against the student being more familiar with the learning environment.

<u>Personality</u>: The personality attributes, specifically agreeableness, conscientiousness and openness, have been found by a meta-analysis conducted by Vedel (2014) to be significantly correlated to academic performance, with conscientiousness being the strongest predictor.

<u>Instructor</u>: Instructors are an important part of the learning environment as they shape students' learning experiences and outcomes. As the personality of instructors could affect their teaching style, as highlighted by Kim and MacCann (2016), and in turn student learning, a student-to-instructor personality attribute match is created, whether the student's core personality trait matches that of the instructor's core personality trait.

<u>Prior learning</u>: Prior learning has been identified as an important determinant of academic performance in higher education (Aluko et al., 2016; Ellegood et al., 2019; Robbins et al., 2004). For example, Garon-Carrier et al. (2016) indicated that prior academic achievement could lead to subsequent intrinsic motivation, which has the potential to affect students' academic performance.

On the other hand, some studies indicated that the impact of prior knowledge on academic performance is less certain (Bone & Reid, 2011; Du Plessis et al., 2005; Schneider & Preckel, 2017). Prior studies seem to suggest that the impact of prior knowledge on academic performance might be debatable on a broader scale. Prior exposure (through self-reporting) will be used as a proxy for prior knowledge for this study, as there is an overlap between prior exposure and prior knowledge, and no assessment will be done in this study to assess the level of mastery.

Similarly, there seem to be inconsistent findings across different studies about the relationship between prior work experience and academic performance (Slover & Mandernach, 2018; Mar et al., 2010; Surridge, 2009). Despite the uncertainties, both prior exposure and prior work experience have been included in this study to better understand their effects on students' academic performance.

***Process***

The process factors within the 3P model pertain to how students learn. Naturally, the factor of 'learning approach' falls within the process domain, just as in the original 3P model.

Given that personality traits of students were strongly associated with their intrinsic and extrinsic motivation (Ariani, 2013), 'Motivation' is deliberately placed as part of the process domain, which would allow for the investigation of how the presage attributes can affect motivation (which in turn can affect learning approach and academic performance either directly or indirectly).

As for 'Perception', it is recognised as an individual's primary form of cognitive contact with the world around him/her (Efron, 1969) and hence, course perceptions represent students' form of cognitive contact with their learning environment. These perceptions are formed and continually evolve during the course of learning as students have more contact with their instructor as well as the curriculum. Within this context, course perceptions are arguably part of the process domain.

Several studies have indicated that students tended to adopt deep learning approaches if they had positive perceptions of their course (Abraham, 2006; Faranda et al., 2021; Richardson et al., 2007). However, Nijhuis et al. (2007) had found no direct relationship between personality traits and course perceptions, concluding that the educational programme did not seem to favour any particular kind of students. Despite this, it is prudent to investigate if the relationships between the presage factors and course perceptions could be indirect; thus, course perception is included.

***Product***

Learning outcomes encompass core subject-based outcomes, personal transferable outcomes, and generic academic outcomes (Allan, 1996) – i.e., learning outcomes include both academic performance and non-academic developments. The challenge lies in the design of assessments to capture all these aspects. More often than not, universities tend to rely primarily on students' grade-point average (GPA) as a proxy of their academic performance. GPA – the weighted mean of course marks (or grade points) for courses required to get a formal academic qualification – is, in fact, the most common quantitative measure of cognitive skills and abilities acquisition (Chemers et al., 2001; Plant et al., 2005; Richardson et al., 2012).

Using our university as the reference point, it is hoped that the insights gained from this study can be extended to universities of a similar nature.

### Overview of interactions studied

Various studies have indicated that a student's adoption of a learning approach is influenced by his/her motivation, course perceptions, academic background, personality, learning environment, and prior learning (Beckwith, 1991; Cipra & Müller-Hilke, 2019; Lizzio et al., 2002; Mayya & Roff, 2004; Tohidi & Jabbari, 2012; Trigwell & Prosser, 1997). It was also argued that the interpretation of interactions in a model should not be as a causal chain of independently constituted components over time, but as a holistic contribution of the various factors found to be statistically significant. To date, there is, however, no comprehensive study that examines all these potential determinants simultaneously. As such, two important considerations were applied in the study of these relationships. These are:

(1) Prior studies that examined attributes of interest primarily in isolation or in small sets; and

(2) The importance of examining the complex relationships across the various attributes simultaneously.

The expanded 3P model sketches out the pathways linking the attributes across the three sets of variables – Presage, Process and Product. These pathways are represented by the arrows in Figure 1. A direct relationship refers to the examination of how one attribute affects another, whereas an indirect relationship examines the effect one attribute has on another attribute when mediated by at least one other attribute. These formulations provide a handle to study the complex interactions amongst the attributes, so that the insights gained can inform teaching and learning practices. In examining the myriads of relationships within the expanded 3P model, seven sets of relationships (pathways) have been shown to have statistically significant contributions to understanding factors that affect student learning. These are grouped as hypotheses H01 to H07 and summarised in Figure 2 (see Appendix A for a larger image).

To test the hypotheses, the relationships were examined using structural equation modelling (SEM).

## Methodology

### Participants and instruments

The research sample comprised 475 students from the university. The research was conducted in 2022 using data collected in 2021 by way of a self-administrated and self-rated structured questionnaire comprising four sections: (1) Revised Two-Factor Study Process Questionnaire (R-SPQ-2F) to measure two learning approaches: Deep and Surface (Biggs et al., 2001); (2) Revised Course Experience Questionnaire (CEQ) to measure students' perceptions of

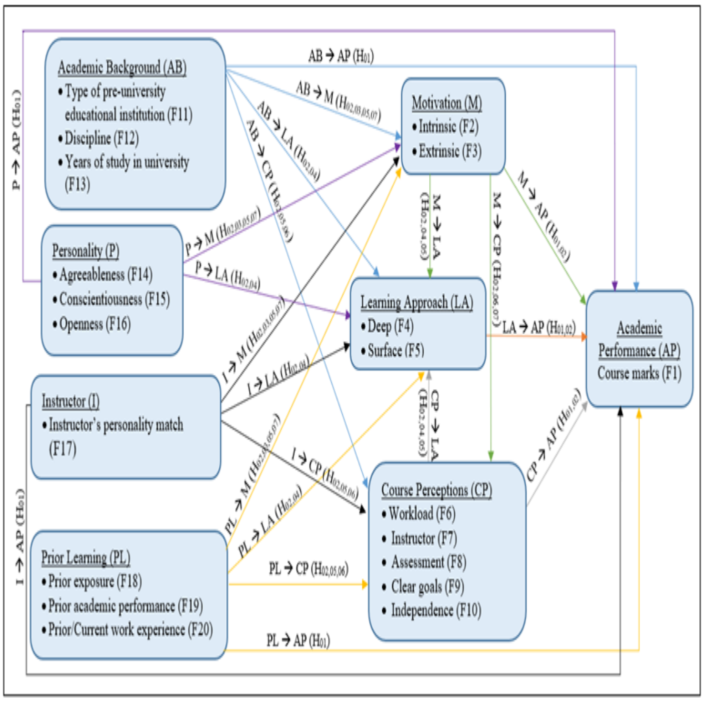



Figure 2. The expanded 3P model of teaching and learning (Research framework).

Instructor (i.e., Teaching), Workload, Assessments, Clear Goals and Independence (Ramsden, 1991); (3) The Big Five Inventory (BFI) to measure personality traits, Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness (John & Srivastava, 1999); and (4) The Motivated Strategies for Learning Questionnaire (MSLQ) to measure the academic motivation of students: Intrinsic and Extrinsic (Pintrich et al., 1993). Consistent with prior studies (see, for example, Guo et al., 2021; Liu et al., 2023), only selected, context-relevant (and not all) MSLQ constructs were used in the research and SEM models. Students' academic performance in the form of course marks was extracted from the student information system. Ethics clearance had been obtained from the Institutional Review Board of the University for this study prior to the data collection.

### Procedure

The survey was administered (via Qualtrics) to students taking analytics and marketing courses in the January and July semesters in 2021. The responses collected were generally within the mean and standard deviation ranges reported by prior studies. Hence, the students' responses were generally typical of those of other students in other settings.

SEM examines the structure of interrelationships represented by a series of equations that illustrates all the relationships among constructs (the dependent and independent variables) involved in the analysis. SEM has the ability to incorporate latent variables into the analysis. Researchers normally first draw upon theory, prior experience, and the research objectives to distinguish which independent variables predict each dependent variable before using SEM for analysis. Through expressing a theory in terms of relationships among measured variables and latent constructs, researchers use SEM to assess how well the theory fits reality as represented by data. Therefore, SEM provides a conceptually appealing way to test theory to analyse the nature and extent of the complex relationships among latent constructs (motivation, learning approaches, course perceptions and personality) and the measured constructs (academic performance, academic background, student-to-instructor personality match and prior learning) to test the hypotheses.

Varoquaux (2018) emphasised that cross-validation is a crucial tool to establish model generalisability as it is the only non-parametric method to do so. Weston and Gore (2006) also highlighted that it is ideal to test the SEM model on a separate (cross-validation) sample. To evaluate the comparability of the January and July responses, several statistical analyses were conducted. The t-test results showed no significant differences across all constructs but one, indicating that responses from both semesters were similar. The only exception is the deep learning approach. However, the Cohen's d of -0.27 (small effect) for the deep learning approach indicated that the responses for the January semester were largely similar to those of the July semester. A comparison of the score distributions further confirmed substantial overlap between the two groups, supporting the conclusion that the responses for the deep learning approach between the two semesters were similar. Based on this, responses from the January semester are used to build the SEM model and responses from the July semester are used to cross-validate the model. The cross-validated model is then applied to all the data (both the January and July semesters) to derive the final SEM model.

Table 1. Results for EFA.

| Constructs | Individual Constructs | Removal of Items | Findings | KMO[a] (After removal of items if any) | Cronbach's Alpha (After removal of items if any) |
|---|---|---|---|---|---|
| Motivation (M) | Extrinsic | No items removed | Appropriately loaded with all loadings >0.62 | 0.743 | 0.756 |
| | Intrinsic | No items removed | Appropriately loaded with all loadings >0.61 | | 0.779 |
| Learning Approach (LA) | Deep | No items removed | Appropriately loaded with all loadings >0.49 | 0.810 | 0.851 |
| | Surface | No items removed | Appropriately loaded with all loadings >0.42 | | 0.802 |
| Course Perceptions (CP) | Workload | No items removed | Appropriately loaded with all loadings >0.56 | 0.861 | 0.737 |
| | Instructor | One item removed | Appropriately loaded with all loadings >0.47 | | 0.854 |
| | Assessment | No items removed | Appropriately loaded with all loadings >0.43 | | 0.674 |
| | Clear Goals | Five items removed | Construct was not reliably measured in the local context and hence removed from further analysis | | |
| | Independence | Six items removed | Construct was not reliably measured in the local context and hence removed from further analysis | | |
| Personality (P) | Agreeable -ness | No items removed | Appropriately loaded with all loadings >0.43 | 0.816 | 0.791 |
| | Conscientious -ness | No items removed | Appropriately loaded with all loadings >0.50 | | 0.770 |
| | Openness | Two items removed | Appropriately loaded with all loadings >0.43 | | 0.784 |

a: Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy

## Results

### Exploratory and confirmatory factor analyses

Exploratory (EFA) and confirmatory factor analyses (CFA) were conducted before the final SEM was performed. EFA using varimax rotation with Kaiser normalisation was conducted to explore the underlying factor structure for the four latent constructs (namely, personality, motivation, learning approach and course perceptions) without imposing a preconceived structure on them. Following this, CFA was used to verify the factor structure for these constructs. Table 1 summarises the EFA results.

For course perceptions, the items for clear goals and independence were not appropriately loaded as intended; hence, the misplaced items were removed, EFA was re-performed. In particular, the items for clear goals were loaded onto the assessment as well as independence constructs; for independence, the items were loaded with items for clear goals. As clear goals and independence could not be reliably measured in the local context, they were removed from further analysis. Hence, only workload, instructor and assessment were included in the SEM model. Although one item for instructor was removed (out of seven) and two items for openness were removed (out of ten), Table 1 (showing factor loadings and the Cronbach's Alpha) indicated that these two constructs were measured reliably (Hair et al., 2018) after the removal of these items.
To test the hypothesis that a relationship between the measured items and their underlying latent construct exists, CFA (or the measurement model for each questionnaire) was performed. The model was evaluated using two sets of indices: (1) convergent validity (CV), discriminant validity (DV), R-square, construct reliability (CR), and variance extracted (VE) to examine the validity and reliability of the constructs/models; and (2) the absolute, parsimony and incremental indices to assess the model fit.

Due to low R-Square, two items were removed for motivation, and this improved the validity and reliability of the construct. Parcelling of items (Matsunaga, 2008) was performed for the learning approach and personality to improve the fit of the measurement model, as several of the items did not meet the threshold for R-square. This led to better measurement models for both learning approach and personality. A total of six items were removed for course perceptions due to low R-square. After the removal, the validity and reliability improved, and the fit of the measurement model for course perceptions was acceptable.

To test the measurement model for the four questionnaires in one SEM model, all the remaining items of the 10 latent constructs (i.e., F2 to F10, F14 to F16 – See Figure 2) were included in the model. The CR for all constructs is greater than 0.7 (benchmark), except for assessments (which is slightly below 0.7 at 0.67). However, the level of CR for assessments is deemed to be in the acceptable range

(Hair et al., 2018). The VE for all except two constructs are greater than the benchmark of 0.5. In particular, the VE for intrinsic motivation is very close to 0.5 (0.48); although the VE for assessments is 0.41, its Cronbach Alpha indicated that it is within the acceptable range (Hair et al., 2018). DV is supported as the CR for all the constructs is greater than the squared correlation among the constructs, which range between 0.00 to 0.43 (both inclusive). In addition, the square root of the VE for each construct is greater than its correlations with other constructs (Fornell & Larcker, 1981). The absolute, parsimony and incremental indices are shown in Table 2, with the benchmarks indicated.

Table 2. Fit indices for the four questionnaires.

| | $\chi^2$/DF | SRMR[a] | RMSEA[b] Estimate | RMSEA[b] Lower 90% C.L | RMSEA[b] Upper 90% C.L | CFI[c] |
|---|---|---|---|---|---|---|
| Threshold | <=2 | <=.08 | <=.06 | ~.00 | <=.08 | >=.90 |
| Model | 1.37 | .061 | .045 | .036 | .053 | .936 |

a: Standardised Root Mean Square Residual; b: Root Mean Square Error of Approximation; c: Comparative Fit Index

All the fit indices meet the desired benchmarks. Overall, the results indicate that the measurement of the constructs is appropriate, and hence it is appropriate to proceed with SEM.

**Structured equation modelling**

Structured equation modelling (SEM) was first performed (using SAS programming and IBM-SPSS AMOS v26) on the responses from the January semester. Model modifications were then done to improve the model fit. Based on the Wald test (to delete insignificant paths), Lagrange Multiplier (to add significant paths) and Chi-Square difference test (to assess the path deletions/additions), modified models were then estimated and evaluated (Ullman & Bentler, 2012). Figure 3 shows the paths that were deleted and added after 16 iterations of model modifications (12 paths were deleted and 3 paths were added).

Similar to the evaluation of CFA, the same set of fit indices was examined to determine the model fit. As can be seen from Table 3, the fit indices meet all the benchmarks.

Table 3. Fit indices for the modified model (January semester).

| | $\chi^2$/DF | SRMR | RMSEA Estimate | RMSEA Lower 90% C.L | RMSEA Upper 90% C.L | CFI |
|---|---|---|---|---|---|---|
| Threshold | <=2 | <=.08 | <=.06 | ~.00 | <=.08 | >=.90 |
| Model | 1.43 | .077 | .049 | .040 | .056 | .920 |

The modified model was further cross-validated using the responses from the July semester. Table 4 shows the fit indices of the cross-validated model.

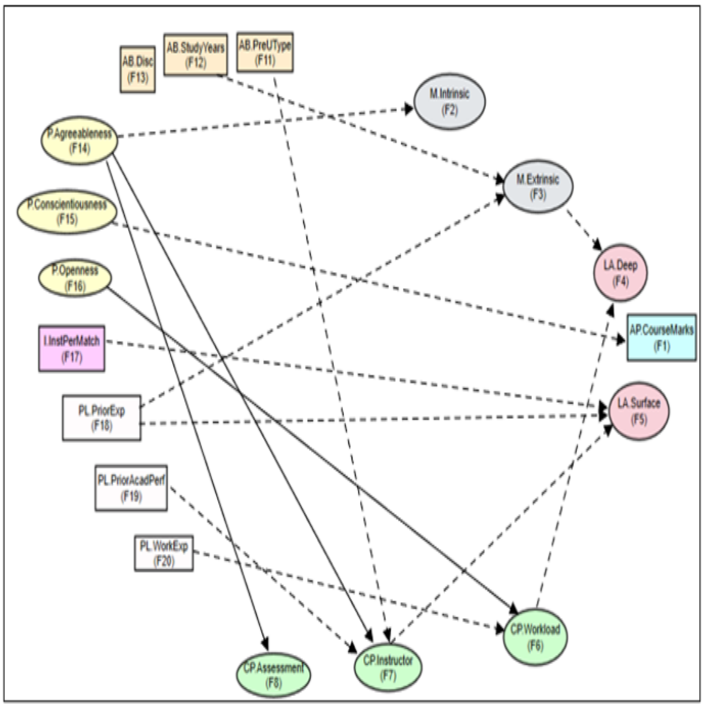



Figure 3. Deletion and addition of paths (Continuous line indicates deletion and dotted line indicates addition).

Table 4. Fit indices for the cross-validated model (July semester).

| | $\chi^2$/DF | SRMR | RMSEA Estimate | RMSEA Lower 90% C.L | RMSEA Upper 90% C.L | CFI |
|---|---|---|---|---|---|---|
| Threshold | <=2 | <=.08 | <=.06 | ~.00 | <=.08 | >=.90 |
| Model | 1.91 | .079 | .056 | .051 | .061 | .880 |

O'Rourke and Hatcher (2014) stated that it is not atypical for an acceptable model to meet only a few desired thresholds but not all. The model indices (see Table 4), except for CFI (which is 0.88 – vis-à-vis the 0.90 benchmark), indicate that the SEM model constructed based on the January data was able to fit the responses for the July semester. Hu and Bentler (1999) acknowledged that in practice, especially in applied fields like education, CFI values of more than 0.85 could be accepted when other indices (e.g., RMSEA) support model adequacy. In addition, Shi et al. (2019) concluded that RMSEA is a more robust index when comparing models of different complexity. Therefore, the model has been cross-validated and hence has model generalisability. Next, the SEM model was applied to the January and July semesters (combined) to test the hypotheses. The fit indices are shown in Table 5.

Table 5. Fit Indices for the SEM model (January and July semesters).

| | $\chi^2$/DF | SRMR | RMSEA Estimate | RMSEA Lower 90% C.L | RMSEA Upper 90% C.L | CFI |
|---|---|---|---|---|---|---|
| Threshold | <=2 | <=.08 | <=.06 | ~.00 | <=.08 | >=.90 |
| Model | 2.09 | .070 | .048 | .044 | .052 | .910 |

The model indices meet the benchmarks. The χ2/DF of 2.09 is very close to 2 and is within the acceptable range (Hooper et al., 2008). Hence, it can be concluded that the SEM model adequately fits the responses for both semesters. Figure 4 shows the final research framework with a new arrow added from personality to course perceptions, indicating the existence of direct effects from agreeableness to instructor, agreeableness to assessment and openness to workload (i.e., three new paths).

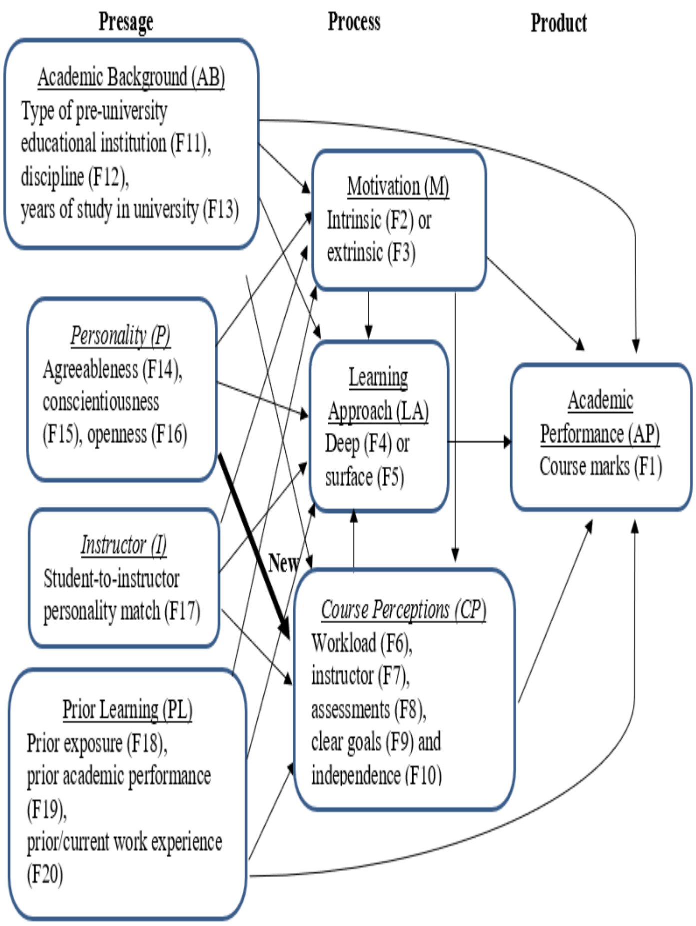



Figure 4. Final research framework based on the SEM model.

With the establishment of model generalisability and applicability, the total effects (TE), direct effects (DE) and indirect effects (IE), along with the respective p-values, are examined to better understand the nature and extent of the complex relationships among students, learning and course attributes, as well as the determinants of academic performance (simultaneously). Appendix B shows the total, direct and indirect effects along with the p-values based on the combined (January and July semesters) data.

## Findings and discussion

Direct Effects on Academic Performance (H01): The SEM results show that the factors that have a positive direct effect on academic performance are: (1) deep learning approach; (2) prior exposure; and (3) prior academic performance. On the other hand, factors that have a negative direct effect are: (1) discipline; (2) number of years of study in the university; and (3) agreeableness.

The results support the notion that students in higher education should strive to develop deep learning approaches to the subject matter, such as learning through application, comparison and critique of ideas. To facilitate such developments, it is important that higher education institutions design their curriculum, assessment and pedagogies to promote deep learning. As other studies have also found (Hailikari et al., 2008; Schneider & Preckel, 2017), students with strong prior knowledge tend to be able to build on that to achieve good academic performance. As such, preparatory classes that focus on building relevant prior knowledge would likely enable students to more successfully navigate their academic learning journey in an institute of higher learning.

It is possible that students become overly confident about a particular discipline that they are already familiar with, resulting in poor performance. As such, it might be beneficial for the universities to state more explicitly the general expectations during the freshman orientation and the specific expectations during programme briefings. More years of study could indicate students' inability to adequately monitor and plan their academic progress, or that there are underlying factors affecting their ability to cope with their studies. This highlights the need to include the years of study as a predictor to identify students at risk so that interventions can be taken. The finding that more years of study than is normally expected have an impact on student performance would suggest that these students were somehow struggling to complete the programme. This could be due to a variety of reasons, including an inability to effectively plan and monitor one's academic progress. While the actual reasons for the negative impact on learning progress are unclear, the finding does point to the potential to use a slower/slowing pace of academic progress as an indicator of potential academic struggle, which the university can then verify and take steps to address.

The finding on the impact of agreeableness requires a more nuanced interpretation. In general, agreeableness includes attributes such as trust, altruism, kindness, affection, and other prosocial behaviours. While this is usually conducive to building strong interpersonal relationships, a student with a high level of agreeableness might be over-obliging and over-compliant, such that they could compromise their understanding of the subject matter by not firmly pursuing lines of questioning so as to refrain from disrupting the learning process for the class. In higher education, there is a need for students to analyse information from differing perspectives in order to form educated judgments and formulate relevant critiques (i.e., defend a disagreement with a concept). Students who are high on agreeableness might find this challenging due to their cooperative and obliging nature, which can adversely affect their academic performance. Workshops on constructive criticism and effective questioning might benefit this group of students.

Indirect Effects on Academic Performance (H02): The following factors have been found to have a positive indirect effect on academic performance: (1) intrinsic motivation; (2) perceptions of the instructor; (3) conscientiousness; and (4) openness. Students who are motivated intrinsically or have positive perceptions of their instructors are more likely to devote more resources to their learning, leading to better academic performance. The effect of personality traits – conscientiousness and openness on academic performance is not direct, in contrast to the findings of prior studies (Komarraju et al., 2011; Vedel, 2014). In this study, it is found that these traits need to be exercised in an environment mediated by factors such as motivation, learning approach and course perceptions in order to achieve positive academic effects.

The finding that students with polytechnic education (polytechnics trained students to be practice-oriented and knowledgeable professionals to support the technological and economic development of Singapore) did not perform academically as well as their counterparts from the more academically oriented pre-university programmes such as the A-levels and International Baccalaureate speaks of the stronger alignment of university and latter's educational experiences. This would likely necessitate the provision of sufficient space and curricular structures to allow polytechnic students to adapt to university settings. For instance, providing preparatory workshops to guide students from the polytechnics on learning approaches and academic writing skills could prove to be beneficial in easing the transition from polytechnics to higher education.

<u>Direct effects on motivation (H03)</u>: It can be concluded from the results that: (1) conscientiousness; and (2) openness have a positive direct effect on intrinsic motivation. Prior studies (John & John, 2020; Poropat, 2009) have found that personality traits of agreeableness, conscientiousness and openness were associated with better academic performance, and that intrinsic motivation was significantly and positively associated with academic performance. This study highlighted that students with higher levels of conscientiousness and/or openness are more intrinsically motivated (with openness having the higher positive direct effect), and that both traits have a positive indirect effect on academic performance. This suggests that universities can consider enhancing intrinsic motivation through cultivating a higher level of conscientiousness (such as self-discipline and planning skills) and openness (such as cultivating an open mindset).

Students who have: (1) a higher level of agreeableness; (2) conscientiousness; and (3) better prior academic performance are associated with a higher level of extrinsic motivation. Prior studies indicate that extrinsic motivation in higher education is unlikely to be sufficient for successful learning where the demand for deep understanding of the content is often required (Wu et al., 2020). Therefore, students would need to cultivate a higher level of intrinsic (rather than extrinsic) motivation to enhance their potential for better academic performance (Wu et al., 2020) and allow for greater adoption of deep learning (Ariani, 2013). The effects of extrinsic and intrinsic motivation can be highlighted through universities' student advisory.

On the other hand, students with (1) polytechnic education and (2) prior/current work experience are associated with a lower level of extrinsic motivation. The reasons for this are unclear, although the fact these students have direct experience in real-life working environment (whether through internship or employment) could indicate a useful place to examine for possible connections.

<u>Direct effects on learning approach (H04)</u>: Students who: (1) are more intrinsically motivated; (2) have a more favourable perception of their instructor; and (3) have a higher level of conscientiousness are more likely to engage in deep learning practices. These findings are aligned with those of prior studies (Chamorro-Premuzic et al., 2007; Faranda et al., 2021). The results also show that students who have: (4) a similar personality trait as that of their instructor are more likely to use deep learning. It can be argued that these students could better relate to their instructor; hence, are more "receptive" to use deep learning to better understand the content.

On the other hand, the results show that students: (1) who graduated from polytechnics, and (2) taking a course related to their discipline are less likely to use deep learning approaches. Students who are: (1) more extrinsically motivated, and (2) who graduated from a similar polytechnic discipline, tend to use more surface learning. The findings provide a better understanding of the challenges that students from the polytechnics might face when they enter the university and could indicate that the type of pre-university educational institution that students come from has an impact on their subsequent learning experience in institutes of higher learning.

Students who are extrinsically motivated tend to focus on the successful completion of learning requirements, and surface learning is generally deemed as the more efficient way to achieve this with minimum learning effort.

On the flip side, students who are: (1) more intrinsically motivated; (2) have a more favourable perception of their assessments; and (3) have a higher level of conscientiousness are more likely to use less surface learning. These findings are aligned with prior studies (Chamorro-Premuzic et al., 2007; Lizzio et al., 2002; Tohidi & Jabbari, 2012). However, prior studies had examined these effects in isolation, while this study has analysed the effects collectively.

<u>Indirect effects on learning approach (H05)</u>: The SEM results show that students who have a higher level of: (1) intrinsic motivation (via course perceptions); (2) openness; and (3) conscientiousness are also more likely to use deep learning (vis-à-vis surface learning via intrinsic motivation). The findings highlight the importance of intrinsic motivation and perceptions that students had of the course, making these potential handles for universities to leverage to encourage students to use more of deep learning.

Students who have a higher level of agreeableness are associated with less use of surface learning through a positive perception of assessments. Riding on this finding, universities can make explicit explanations of the purpose and learning outcomes of the assessments to help students better appreciate the assessments so that they will use less surface learning.

Direct effects on course perceptions (H06): Students who are more intrinsically motivated are more likely to have favourable perceptions of workload, instructor and assessments. These students enjoy learning for intrinsic rewards (such as a sense of satisfaction or achievement), and they might perceive the workload, instructor and assessments as guiding them to achieve their goals. In contrast, students who are more extrinsically motivated are more likely to have a less favourable perception of the workload. Students who are extrinsically motivated tend to focus on the successful completion of learning requirements and may perceive the workload as a hinderance.

Students who have a polytechnic education or have studied longer in university also have a less favourable perception of workload. These findings could reinforce the argument that there is a misalignment between the expectations in polytechnic and those in higher education, and students who have studied longer in university may have underlying factors affecting their ability to cope with their studies, leading to a less favourable perception of workload. Students who are studying a course that is related to their discipline also tend not to have a favourable perception of their instructor. Similarly, this adds to the argument that such students might be overly complacent; hence, they do not see how their instructor can aid them in their learning.

Students with better prior academic performance have more favourable course perceptions of workload and assessments. These students might have experienced similar workload and assessments that had led them to better prior academic results; therefore, they understood the benefits of the workload and assessment. On the other hand, students who have prior exposure to the content have a significant negative direct effect on the course perception of assessments. Students with prior/current work experience are associated with less favourable perceptions of their instructor and assessments. With prior exposure or prior/current work experience, these students might not comprehend how the instructor or assessments can help them gain a deeper understanding of the content.

Indirect effects on course perceptions (H07): Students with polytechnic education have a less favourable perception of assessments. This finding, along with the finding that students with a polytechnic education have a less favourable perception of workload, provides stronger evidence that the type of pre-university educational institution that students come from has an impact on their subsequent learning experience in institutes of higher learning.

Students with a higher level of agreeableness tend to adapt their perspectives to what they are faced with. This alignment process (i.e., adapting one's perspective to the circumstances) would likely be easier if they are intrinsically motivated, whereas if it is extrinsic motivation, the alignment process may face more challenges, and hence the difference in terms of favourable or unfavourable perception. Students who have a higher level of conscientiousness or openness have more favourable perceptions of workload, instructors and assessments through (intrinsic) motivation. Personality traits of students seem to work hand-in-hand with their level of motivation in influencing their perceptions of workload, instructor and assessments, especially so for personality traits – openness and conscientiousness. The findings may shed some light on why personality traits were not found to have any relation with students' perceptions of the course as motivation (which was not included in the prior studies) plays a critical role as a mediator.

Direct effect based on new paths: Results of the two new paths show that students who have a higher level of agreeableness are more likely to have more favourable perceptions of their instructor and assessments. Prior studies found no relationship between personality traits and course perceptions, although Diseth (2013) found that two course experience factors (good teaching and appropriate workload) were negatively predicted by neuroticism. However, this finding is consistent with the characteristics associated with agreeableness. Students who are high on agreeableness tend to be tolerant, kind and friendly; hence, it makes good sense for them to seek satisfactory relationships with others. Therefore, they have a more favorable perception of their instructor. Students who are high on agreeableness are also benevolent and warm, so they are more likely to be driven by affective motives. This enhances their perception of assessments.

Another new path highlights that students who have a higher level of openness have a less favourable perception of workload. Students who are high on openness are more open to trying new things. This might lead them to perceive workload as taking up too much of their time and hindering their ability to try new things. (Incidentally, this significant negative direct effect is counter-balanced by a significant positive indirect effect, leading to an insignificant total effect.)

In conclusion, all seven null hypotheses can be rejected based on the responses collected, and this provides empirical support for, or affirmation of, a number of related theoretical propositions. In addition, the new paths highlighted that the personality traits of students do have an effect on their perceptions of the course. It can be seen from the results that the relationships from one construct to another are complex.

## Concluding remarks

Today, the relationships among student profiles, learning environment, course attributes and learning outcomes are central in the field of education. In this study, the Biggs 3P model was examined and expanded with reference to theories and prior studies as well as the empirical results based on this study, so as to enable a better understanding of the nature and extent of these complex relationships and the determinants that affect students' academic performance (both directly and indirectly). The examination of the effect of personality on course perceptions is made possible through the use of the expanded 3P model. Structural Equation Modelling (SEM), which allows the examination of the complex relationships among student, learning, and course attributes and academic performance, was constructed and cross-validated based on responses gathered in a local university in Singapore.

Compared to prior studies, this study uncovers:

- A more comprehensive understanding of determinants of academic performance;
- Mediation effects among the attributes and their impact on academic performance; and
- A deeper layer of understanding of the attributes and their complex interactions.

The findings are made possible in this study as the relationships between the various attributes are examined simultaneously (direct and indirect) using an expanded 3P model, which is not done in many of the prior studies. With the contributions of this study, it is hoped that institutions will be able to provide greater student support, identify appropriate interventions and design a more integrated curriculum and assessments to help students succeed academically.

### Research limitations

The main purpose of this research is to determine the factors associated with academic performance in the following areas – student support, intervention and design of curriculum and assessments, so as to improve it. The generalisability of the findings may be affected by the following factors.

The learning outcome of this study is measured by the course marks of the students, which comprises only a part of the learning outcome. It is noted that learning outcomes also include aspects that are beyond the cognitive skills and abilities acquisition as measured by the course marks.

While the CEQ questionnaire asked the students for their perceptions of a particular course, the sampled students might have responded based on their perceptions of the learning environment in the university as a whole, i.e., perceptions based on all the courses that they had taken. This may confound the interpretation of the findings. Similarly, for R-SPQ-2F (Revised Two-Factor Study Process Questionnaire) and MSLQ (The Motivated Strategies for Learning Questionnaire), students might have responded based on perceptions of the learning environment in the university, among other things. In addition, the different factors that can influence students' perceptions of workload, instructors and assessments are not examined in this study. For example, the perceptions of workload, instructor and assessments can be influenced by the students' previous learning experience in their prior educational institutions.

While SEM is a powerful, multivariate technique to test and evaluate multivariate relationships, it is not without limitations. For example, although SEM can represent causal relationships (under a specific context), a well-fitting SEM does not necessarily provide information on the causal relationships. Hence, testing the fit of an SEM does not equate to a test of causality (Nachtigall et al., 2003). For this research, the relationships are examined with reference to theories and prior research. This strengthens the support for any relationships suggested by the research framework.

Compared to prior studies, this study uncovers a deeper layer of understanding of the nature and extent of the complex relationships among students, learning and course attributes, as well as the determinants of academic performance (simultaneously). It is hoped that this study can make a significant contribution to the existing literature, as well as help improve student success in universities.

## Acknowledgements

I am sincerely grateful to Professor Cheah Horn Mun and Emeritus Professor Koh Hian Chye for their invaluable support and encouragement throughout the course of this project.

## References

Abraham, A. (2006). Teaching and learning in accounting education: Students' perceptions of the linkages between teaching context, approaches to learning and outcomes. In R. Juchau & G. Tibbits (Eds.), *Celebrating accounting* (pp. 9-21). University of Western Sydney.

Allan, J. (1996). Learning outcomes in higher education. *Studies in Higher Education, 21*(1), 93-108.

Aluko, R. O., Adenuga, O. A., Kukoyi, P. O., Soyingbe, A. A., & Oyedeji, J. O. (2016). Predicting the academic success of architecture students by pre-enrolment requirement: using machine-learning techniques. *Construction Economics and Building, 16*(4), 86.

Ariani, D. W. (2013). Personality and learning motivation. *European Journal of Business and Management, 5*(10).

Beckwith, J. (1991). Approaches to learning, their context and relationship to assessment performance. *Higher Education, 22*(1), 17–30.

Biggs, J. B. (1989). Approaches to the enhancement of tertiary teaching. *Higher Education Research and Development, 8*, 7–25.

Biggs, J., Kember, D., & Leung, D. Y. (2001). The revised two-factor study process questionnaire: R-SPQ-2F. *British Journal of Educational Psychology, 71*(1), 133-149.

Bone, E. K., & Reid, R. J. (2011). Prior learning in biology at high school does not predict performance in the first year at university. *Higher Education Research & Development, 30*(6), 709-724.

Chamorro-Premuzic, T., Furnham, A., & Lewis, M. (2007). Personality and approaches to learning predict preference for different teaching methods. *Learning And Individual Differences, 17*(3), 241-250.

Chemers, M. M., Hu, L.-T., & Garcia, B. F. (2001). Academic self-efficacy and first year college student performance and adjustment. *Journal of Educational Psychology, 93*(1), 55-64.

Chung, C., & Chapman, E. (2023). Intent to transfer learning amongst adult learners with differential learning orientations. *Journal of Applied Learning and Teaching, 6*(1), 136-150. https://doi.org/10.37074/jalt.2023.6.1.3

Cipra, C., & Müller-Hilke, B. (2019). Testing anxiety in undergraduate medical students and its correlation with different learning approaches. *PloS One, 14*(3), e0210130.

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.

Du Plessis, A., Muller, H., & Prinsloo, P. (2005). Determining the profile of the successful first-year accounting student. *South African Journal of Higher Education, 19*(4), 684-698.

Efron, R. (1969). What is perception?. In *Proceedings of the Boston Colloquium for the Philosophy of Science 1966/1968* (pp. 137-173). Springer, Dordrecht.

Ellegood, W. A., Bernard Bracy, J., Sweeney, D. C., Duncan, M., & Burns, K. (2019). Measuring the impacts of administrative policies on student performance in higher education. *Journal of further and Higher Education, 43*(3), 418-433.

Faranda, W. T., Clarke, T. B., & Clarke III, I. (2021). Marketing student perceptions of academic program quality and relationships to surface, deep, and strategic learning approaches. *Journal of Marketing Education, 43*(1), 9-24.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Garon-Carrier, G., Boivin, M., Guay, F., Kovas, Y., Dionne, G., Lemelin, J. P., ... & Tremblay, R. E. (2016). Intrinsic motivation and achievement in mathematics in elementary school: A longitudinal investigation of their association. *Child Development, 87*(1), 165-175.

Guo, H., Tong, F., Wang, Z., Tang, S., Yoon, M., Ying, M., & Yu, X. (2021). Examining self-regulated learning strategy model: A measurement invariance analysis of MSLQ-CAL among college students in China. *Sustainability, 13*(18), 10133.

Hailikari, T., Katajavuori, N., & Lindblom-Ylanne, S. (2008). The relevance of prior knowledge in learning and instructional design. *American Journal of Pharmaceutical Education, 72*(5), 1-113.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2018). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hassan, H., Mohamad, R., Ali, R. H. R. M., Talib, Y. Y. A., & Hsbollah, H. M. (2020). Factors affecting students' academic performance in higher education: Evidence from accountancy degree programme. *International Business Education Journal, 13*(1), 1-16.

Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modeling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods, 6*, 53–60.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55.

John, O. P., & Srivastava, S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (Vol. 2, pp. 102–138). New York: Guilford Press.

John, R., & John, R. (2020). The Big Five personality traits and academic performance. *Journal of Law & Social Studies (JLSS), 2*(1), 10-19.

Kilishi, A. A. (2021). Explaining academic performance of first–year undergraduate students in Economics. *Ilorin Journal of Economic Policy, 8*(1), 78-88.

Kim, L. E., & MacCann, C. (2016). What is students' ideal university instructor personality? An investigation of absolute and relative personality preferences. *Personality and Individual Differences, 102*, 190-203.

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.

Liu, Z., Yu, P., Liu, J., Pi, Z., & Cui, W. (2023). How do students' self-regulation skills affect learning satisfaction and continuous intention within desktop-based virtual reality? A structural equation modelling approach. *British Journal of Educational Technology, 54*(3), 667-685.

Lizzio, A., Wilson, K., & Simons, R. (2002). University students' perceptions of the learning environment and academic outcomes: Implications for theory and practice. *Studies in Higher Education, 27*(1), 27-52.

Mar, E., Barnett, M. J., Tang, T. T., Sasaki-Hill, D., Kuperberg, J. R., & Knapp, K. (2010). Impact of previous pharmacy work experience on pharmacy school academic performance. *American Journal of Pharmaceutical Education, 74*(3).

Matsunaga, M. (2008). Item parceling in structural equation modeling: A primer. *Communication Methods and Measures, 2*(4), 260-293.

Mayya, S. S., & Roff, S. (2004). Students' perceptions of academic environment: A comparison of academic achievers and under-achievers at Kasturba Medical College, India. *Education for Health, 17*(3), 280-291.

Nachtigall, C., Kroehne, U., Funke, F., & Steyer, R. (2003). Pros and cons of structural equation modeling. *Methods Psychological Research Online, 8*(2), 1-22.

Nijhuis, J., Segers, M., & Gijselaers, W. (2007). The interplay of perceptions of the learning environment, personality, and learning strategies: A study amongst international business studies students. *Studies in Higher Education, 32*, 59-77.

O'Rourke, N., & Hatcher, L. (2014). *A step-by-step approach using SAS for factor analysis and structural equation modelling.* SAS Inc., North Carolina, USA.

Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and Psychological Measurement, 53*(3), 801-813.

Plant, E. A., Ericsson, K. A., Hill, L., & Asberg, K. (2005). Why study time does not predict grade point average across college students: Implications of deliberate practice for academic performance. *Contemporary Educational Psychology, 30*, 96-116.

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin, 135*(2), 322.

Prakasam, G. R., & Gopinathan, R. (2019). Enrolment by academic discipline in higher education: Differential and determinants. *Journal of Asian Business and Economic Studies.*

Ramsden, P. (1991). A performance indicator of teaching quality in higher education: The course experience questionnaire. *Studies in Higher Education, 16*, 129-150.

Richardson, J. T., Dawson, L., Sadlo, G., Jenkins, V., & Mcinnes, J. (2007). Perceived academic quality and approaches to studying in the health professions. *Medical Teacher, 29*(5), e108-e116.

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin, 138*(2), 353.

Robbins, S. B., Lauver, K., Davis, H. L. a. D., & Langley, R. (2004). Do psychosocial and study skill factors predict college outcomes? A meta-analysis. *Psychological Bulletin, 130*(2), 261-288.

Sam, C. Y. (2022). Post-COVID-19 and higher education. *Journal of Applied Learning and Teaching, 5*(1), 156-164. https://doi.org/10.37074/jalt.2022.5.1.21

Schneider, M., & Preckel, F. (2017). Variables associated with achievement in higher education: A systematic review of meta-analyses. *Psychological Bulletin, 143*(6), 565.

Shi, D., Lee, T., & Maydeu-Olivares, A. (2019). Understanding the model size effect on SEM fit indices. *Educational and Psychological Measurement, 79*(2), 310-334.

Slover, E., & Mandernach, J. (2018). Beyond online versus face-to-face comparisons: The interaction of student age and mode of instruction on academic achievement. *Journal of Educators Online, 15*(1), n1.

Smith, S. N., & Miller, R. J. (2005). Learning approaches: Examination type, discipline of study, and gender. *Educational Psychology, 25*(1), 43-53.

Surridge, I. (2009). Accounting and finance degrees: Is the academic performance of placement students better?. *Accounting Education: An International Journal, 18*(4-5), 471-485.

Tan, W. C. J., Cheah, H. M., & Koh, H. C. (2024). Understanding the determinants of academic performance in a higher education institution using an expanded Biggs 3P model. *Asian Journal of the Scholarship of Teaching and Learning, 14*(1), 55-73. https://ctlt.nus.edu.sg/wp-content/uploads/2024/07/v14n1_Tan-et-al-4.pdf

Tohidi, H., & Jabbari, M. M. (2012). The effects of motivation in education. *Procedia-Social and Behavioral Sciences, 31,* 820-824.

Trigwell, K., & Prosser, M. (1997). Towards an understanding of individual acts of teaching and learning. *Higher Education Research and Development, 16,* 241–252.

Ullman, J. B., & Bentler, P. M. (2012). *Structural equation modeling. Handbook of Psychology* (2nd Ed.).

Varoquaux, G. (2018). Cross-validation failure: Small sample sizes lead to large error bars. *Neuroimage, 180*, 68-77.

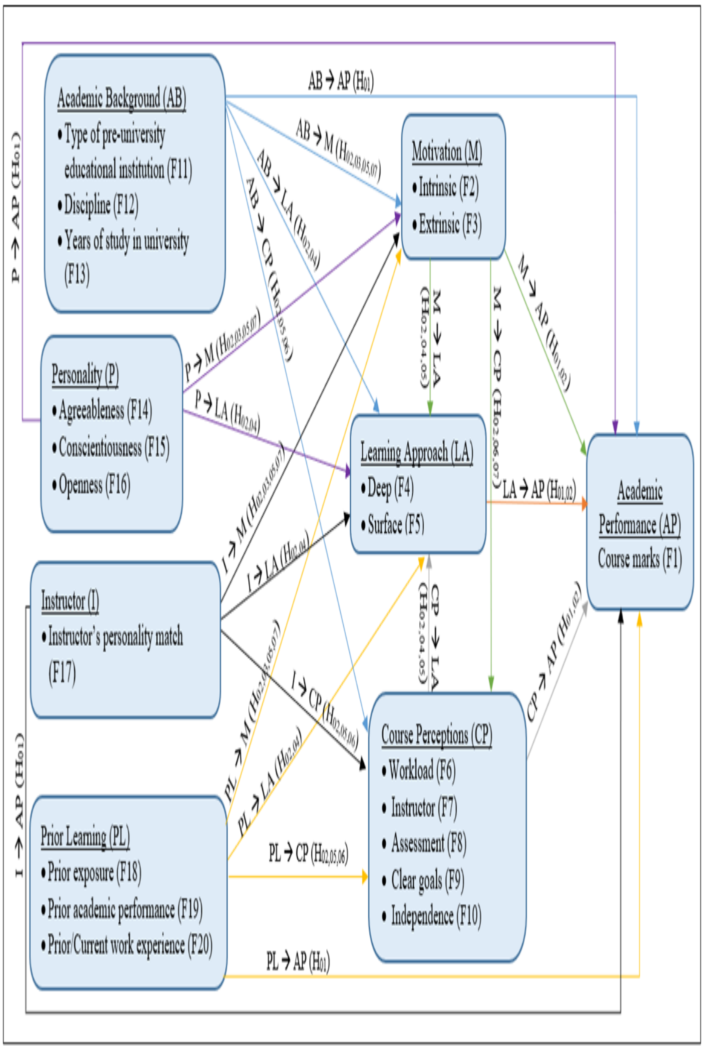
Vedel, A. (2014). The Big Five and tertiary academic performance: A systematic review and meta-analysis. *Personality and Individual Differences, 71*, 66-76.

Weston, R., & Gore Jr, P. A. (2006). A brief guide to structural equation modeling. *The Counseling Psychologist, 34*(5), 719-751.

Wu, H., Li, S., Zheng, J., & Guo, J. (2020). Medical students' motivation and academic performance: The mediating roles of self-efficacy and learning engagement. *Medical Education Online, 25*(1), 1742964.

## Appendices

### Appendix A: The Expanded 3P Model of Teaching and Learning (Research Framework).




### Appendix B: Total Effects (TE), Direct Effects (DE) and Indirect Effects (IE) with P-Values.

| | | $H_{01}$ to $H_{02}$ | $H_{03}$ | | $H_{04}$ to $H_{05}$ | | $H_{06}$ to $H_{07}$ and New Paths | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Effects On | | | | | | | |
| From | | AP.FRS (F1) | M.Intrinsic (F2) | M.Extrinsic (F3) | LA.Deep (F4) | LA.Surface (F5) | CP.Workload (F6) | CP.Instructor (F7) | CP.Assessment (F8) |
| M.Intrinsic (F2) | TE | 0.142**(0.019) | - | - | 0.532*(<.0001) | -0.349*(<.0001) | 0.371*(<.0001) | 0.325*(<.0001) | 0.247*(<.0001) |
| | DE | 0.003(0.971) | - | - | 0.486*(<.0001) | -0.212*(0.005) | 0.371*(<.0001) | 0.325*(<.0001) | 0.247*(<.0001) |
| | IE | 0.139*(0.008) | - | - | 0.046***(0.084) | -0.137*(0.001) | - | - | - |
| M.Extrinsic (F3) | TE | 0.033(0.478) | - | - | -0.013(0.309) | 0.18*(0.001) | -0.184*(0.002) | -0.018(0.715) | 0.092(0.111) |
| | DE | 0.048(0.333) | - | - | - | 0.214*(<.0001) | -0.184*(0.002) | -0.018(0.715) | 0.092(0.111) |
| | IE | -0.016(0.430) | - | - | -0.013(0.309) | -0.035(0.262) | - | - | - |
| LA.Deep (F4) | TE | 0.176**(0.013) | - | - | - | - | - | - | - |
| | DE | 0.176**(0.013) | - | - | - | - | - | - | - |
| | IE | - | - | - | - | - | - | - | - |
| LA.Surface (F5) | TE | -0.088(0.168) | - | - | - | - | - | - | - |
| | DE | -0.088(0.168) | - | - | - | - | - | - | - |
| | IE | - | - | - | - | - | - | - | - |
| CP.Workload (F6) | TE | 0.007(0.908) | - | - | - | -0.052(0.389) | - | - | - |
| | DE | 0.002(0.972) | - | - | - | -0.052(0.389) | - | - | - |
| | IE | 0.005(0.466) | - | - | - | - | - | - | - |
| CP.Instructor (F7) | TE | 0.057(0.303) | - | - | 0.221*(<.0001) | - | - | - | - |
| | DE | 0.018(0.748) | - | - | 0.221*(<.0001) | - | - | - | - |
| | IE | 0.039**(0.032) | - | - | - | - | - | - | - |
| CP.Assessment (F8) | TE | 0.057(0.387) | - | - | *-0.104(0.101)* | -0.477*(<.0001) | - | - | - |
| | DE | 0.033(0.671) | - | - | *-0.104(0.101)* | -0.477*(<.0001) | - | - | - |
| | IE | 0.024(0.485) | - | - | - | - | - | - | - |

| | | $H_{01}$ to $H_{02}$ | $H_{03}$ | | $H_{04}$ to $H_{05}$ | | $H_{06}$ to $H_{07}$ and New Paths | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Effects On | | | | | | | |
| From | | AP.FRS (F1) | M.Intrinsic (F2) | M.Extrinsic (F3) | LA.Deep (F4) | LA.Surface (F5) | CP.Workload (F6) | CP.Instructor (F7) | CP.Assessment (F8) |
| AB.PreUType (F11) | TE | -0.103**(0.013) | -0.055(0.255) | -0.114**(0.015) | -0.103**(0.020) | 0.181*(<.001) | -0.105***(0.054) | -0.016(0.341) | -0.106**(0.041) |
| | DE | -0.059(0.168) | -0.055(0.255) | -0.114**(0.015) | -0.083**(0.043) | 0.138*(0.003) | -0.105***(0.053) | - | -0.082(0.117) |
| | IE | -0.044*(0.01) | - | - | -0.019(0.479) | 0.044(0.171) | 0(0.989) | -0.016(0.341) | -0.024***(0.098) |
| AB.Disc (F12) | TE | -0.108**(0.012) | 0.047(0.354) | 0.063(0.189) | -0.078***(0.095) | -0.067(0.180) | 0.017(0.764) | -0.116**(0.012) | 0.019(0.719) |
| | DE | -0.102**(0.020) | 0.047(0.354) | 0.063(0.189) | -0.073***(0.089) | -0.061(0.196) | 0.011(0.842) | -0.13*(0.004) | 0.002(0.971) |
| | IE | -0.006(0.694) | - | - | -0.005(0.874) | -0.007(0.832) | 0.006(0.782) | 0.014(0.403) | 0.017(0.215) |
| AB.StudyYears (F13) | TE | -0.161*(<.0001) | 0.04(0.417) | - | 0.021(0.635) | -0.03(0.534) | -0.114**(0.033) | 0.044(0.330) | 0.015(0.770) |
| | DE | -0.169*(<.0001) | 0.04(0.417) | - | -0.006(0.878) | -0.02(0.662) | -0.129**(0.017) | 0.031(0.482) | 0.005(0.916) |
| | IE | 0.008(0.559) | - | - | 0.028(0.321) | -0.01(0.745) | 0.015(0.424) | 0.013(0.421) | 0.01(0.426) |
| P.Agreeableness (F14) | TE | -0.13*(0.006) | - | 0.119**(0.044) | 0.049(0.340) | -0.16*(0.006) | -0.022***(0.088) | 0.389*(<.0001) | 0.416*(<.0001) |
| | DE | -0.179*(0.004) | - | 0.119**(0.044) | 0.007(0.918) | 0.012(0.854) | - | 0.391*(<.0001) | 0.405*(<.0001) |
| | IE | 0.049(0.189) | - | - | 0.043(0.248) | -0.172*(<.0001) | -0.022***(0.088) | -0.002(0.723) | 0.011(0.192) |
| P. Conscientiousn (F15) | TE | 0.079*(<.001) | 0.223*(<.0001) | 0.161*(0.01) | 0.303*(<.0001) | -0.154**(0.011) | 0.053***(0.075) | 0.07*(0.002) | 0.07*(0.001) |
| | DE | - | 0.223*(<.0001) | 0.161*(0.01) | 0.187*(<.001) | -0.105***(0.09) | - | - | - |
| | IE | 0.079*(<.001) | - | - | 0.116*(<.001) | -0.049***(0.084) | 0.053***(0.075) | 0.07*(0.002) | 0.07*(0.001) |
| P.Openness (F16) | TE | -0.023(0.645) | 0.433*(<.0001) | 0.004(0.942) | 0.285*(<.0001) | -0.039(0.493) | -0.1(0.116) | 0.141*(<.0001) | 0.107*(<.001) |
| | DE | -0.084(0.181) | 0.433*(<.0001) | 0.004(0.942) | 0.055(0.351) | 0.098(0.146) | -0.26*(<.0001) | - | - |
| | IE | 0.061***(0.076) | - | - | 0.23*(<.0001) | -0.137*(0.001) | 0.16*(<.0001) | 0.141*(<.0001) | 0.107*(<.001) |
| I.InstPerMatch (F17) | TE | 0.043(0.302) | 0.029(0.563) | 0.068(0.149) | 0.082***(0.075) | 0.012(0.691) | -0.002(0.967) | -0.053(0.246) | -0.007(0.895) |
| | DE | 0.028(0.511) | 0.029(0.563) | 0.068(0.149) | 0.079***(0.06) | - | 0(0.994) | -0.061(0.171) | -0.02(0.690) |
| | IE | 0.016(0.207) | - | - | 0.003(0.915) | 0.012(0.691) | -0.002(0.929) | 0.008(0.623) | 0.013(0.330) |

| | | $H_{01}$ to $H_{02}$ | $H_{03}$ | | $H_{04}$ to $H_{05}$ | | $H_{06}$ to $H_{07}$ and New Paths | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Effects On | | | | | | | |
| From | | AP.FRS (F1) | M.Intrinsic (F2) | M.Extrinsic (F3) | LA.Deep (F4) | LA.Surface (F5) | CP.Workload (F6) | CP.Instructor (F7) | CP.Assessment (F8) |
| PL.PriorExp (F18) | TE | 0.081***(0.051) | 0.05(0.312) | - | 0.098**(0.031) | 0.03(0.302) | 0.018(0.742) | 0.002(0.970) | -0.087***(0.087) |
| | DE | 0.069***(0.098) | 0.05(0.312) | - | 0.064(0.124) | - | -0.001(0.991) | -0.015(0.746) | -0.1**(0.052) |
| | IE | 0.012(0.347) | - | - | 0.034(0.241) | 0.03(0.302) | 0.019(0.321) | 0.016(0.318) | 0.012(0.327) |
| | | | | | | | | | |
| PL.PriorAcadPerf (F19) | TE | 0.36*(<.0001) | 0.011(0.831) | 0.207*(<.0001) | -0.039(0.388) | 0.019(0.702) | 0.073(0.183) | 0(0.992) | 0.12**(0.023) |
| | DE | 0.355*(<.0001) | 0.011(0.831) | 0.207*(<.0001) | -0.031(0.451) | 0.038(0.43) | 0.107***(0.055) | - | 0.098***(0.069) |
| | IE | 0.006(0.737) | - | - | -0.007(0.796) | -0.019(0.575) | -0.034(0.148) | 0(0.992) | 0.022(0.217) |
| | | | | | | | | | |
| PL.WorkExp (F20) | TE | 0.027(0.533) | -0.043(0.403) | -0.088***(0.069) | -0.053(0.257) | 0.002(0.972) | 0(0.988) | -0.131*(0.005) | -0.132**(0.013) |
| | DE | 0.048(0.282) | -0.043(0.403) | -0.088***(0.069) | -0.017(0.695) | -0.052(0.284) | - | -0.119*(0.009) | -0.114**(0.033) |
| | IE | -0.021(0.200) | - | - | -0.036(0.236) | 0.053***(0.1) | 0(0.988) | -0.012(0.473) | -0.019(0.197) |
| | | | | | | | | | |

* = significant at a .01 significance level

** = significant at a .05 significance level

*** = significant at a .10 significance level