ARTICLE

Understanding the Determinants of Academic Performance in a Higher Education Institution Using an Expanded Biggs 3P Model

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ABSTRACT

The Biggs 3P model conceptualises the learning process as an interactive system of three sets of variables: the learning environment and student characteristics (presage), students' approach to learning (process), and learning outcomes (product). Given the learning context that this study examines, it is necessary to not just incorporate additional variables outside of the 3P model, but also to re-categorise some of the existing 3P model variables. As such, an expanded 3P model, built on the framing of the original 3P, has been used. This allows for a more holistic examination of the relationships among a broader range of presage and process variables, potentially providing more incisive insights for the learning environment in the university. Briefly, personality traits and student-to-instructor personality match are included in the expanded model under the presage domain, and course perceptions under the process domain. In addition, motivation is repositioned as a process construct to enable universities to identify determinants (in the presage domain) that influence students' levels of motivation. It is hoped that the expanded 3P model serves as a guide to universities for their curriculum and assessment development as it offers a fresh, and potentially more insightful, perspective on what to focus on to enhance students' learning. These complex relationships (both direct and indirect) are examined using Structural Equation Modelling (SEM) with reference to the expanded Biggs' 3P model for a local university in Singapore.

Keywords: Biggs 3P model, academic performance, motivation, learning approaches, course perceptions, academic background, personality, prior learning

INTRODUCTION

A plethora of research has been conducted to examine the dynamics of learning in higher education with the aim to support students to achieve better academic performance. The 3P model (Biggs, 1989) represents a well-established tool that has been applied for many such studies. Its usefulness lies in the clarity it provides through delineation of the interactions amongst variables that link personal and situational factors that could influence a student's adoption of specific approaches to study, which in turn affects his/her learning outcomes. Figure 1 provides a diagrammatic representation of the 3P model, showcasing an interactive system of three sets of variables: the learning environment and student characteristics (presage), students' approach to learning (process), and learning outcomes (product).

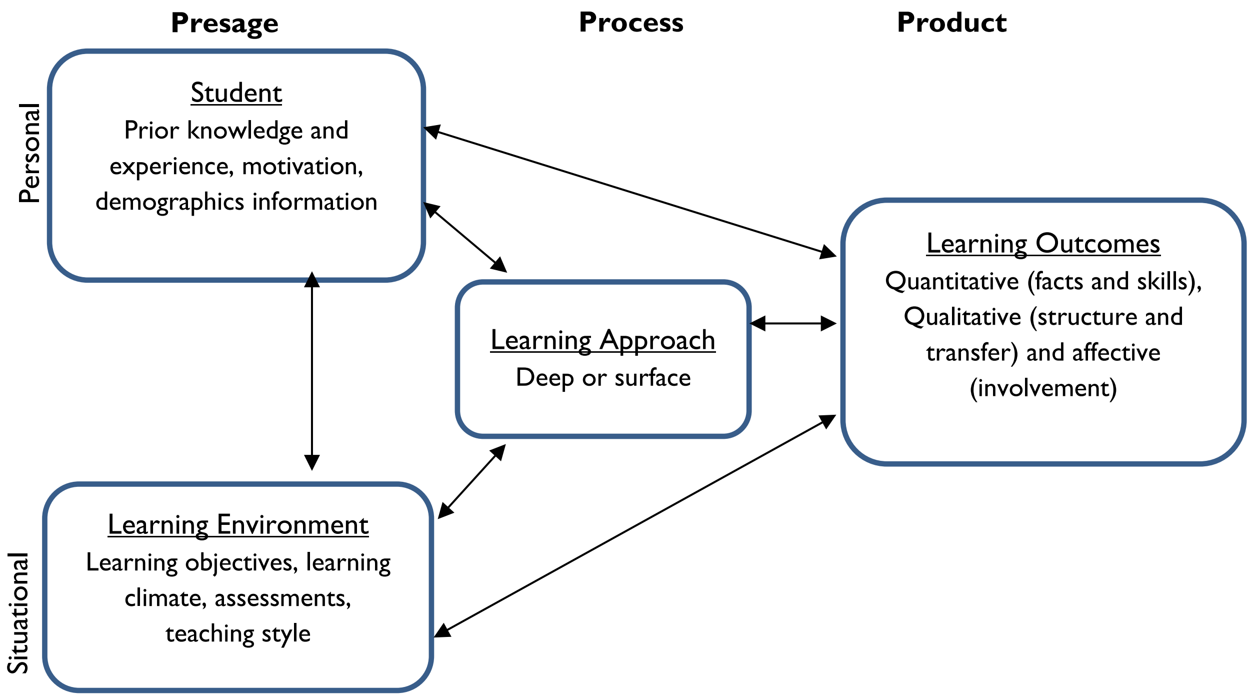

Figure 1. The 3P Model of Teaching and Learning (adapted from Biggs, 2003, p. 19)

Presage factors include personal characteristics of the student (i.e., background, motivation, and prior knowledge) and learning environment characteristics (e.g., teaching methods, workload, and course structure) that exist prior to the time of learning. One of the key elements of this theoretical framework is the proposition that a student's perceptions of his/her learning environment—in light of his/her motivations and expectations—determine how situational factors influence approaches to learning and learning outcomes. Process factors describe how a student approaches his/her learning. While there are variations in the terms used, there is a fair amount of empirical evidence indicating that students typically adopt two fundamental approaches, namely deep and surface learning. A deep learning approach refers to the thorough application, comparison, and reflection of ideas for better understanding of the content; while a surface learning approach refers to primarily content regurgitation without good understanding, and with little attempt to integrate information (Marton & Saljo, 1976; Thomas & Bain, 1984). Product factors describe the learning outcomes (quantitative, qualitative, and affective) that a student derives from the learning process. Traditionally, learning outcomes have been measured through academic achievement in terms of grade point average (GPA).

While the Biggs 3P model works well in a wide range of contexts, the learning environment within which this study focuses necessitates the incorporation of variables that are outside this model, in particular, for the presage and process domains. For example, teaching feedback from students seems to indicate that student-to-instructor personality match could play a significant role that affects learning outcomes. As such, these and selected student attributes have been added to the presage domain so that their relationships can be examined. For variables that have been moved into a different category, the primary reason is to recognise that these variables could also play a different role and can inform teaching and learning interactions. Motivation, for instance, can be actively cultivated in the process of learning. By moving this from the presage to the process domain, and studying its potential contribution to learning outcomes, it can serve to inform or reshape teaching and learning interactions that can lead to a better learning experience for the students. Similarly, course perceptions have been included in the process domain.

The next few sections also discuss the expanded 3P model, the research method used, recommendations based on the findings in a local university in Singapore, and suggestions for future research. It is hoped that the expansion of the 3P model will provide universities with a better understanding of the determinants of academic performance, iteratively leading to interventions that serve to enhance students' learning.

EXPANDED 3P MODEL

It is useful to examine the variables as well as the relationships of these variables beyond what are prescribed in the 3P model to gain insights on the determinants of academic outcomes to enhance students' learning. Therefore, the 3P model is expanded to encompass additional attributes under the presage and process domains. Table 2 provides an overview of attributes for the original and expanded 3P models.

Table 2
Presage, process and product attributes for the original and expanded 3P models

Variables	Original 3P Model Domain	Expanded 3P Model Domain
Academic Background • Type of pre-university educational institution • Discipline • Years of study in university	Presage	Presage
Prior Learning (PL) • Prior exposure • Prior academic performance • Prior/Current work experience	Presage	Presage
Personality • Agreeableness • Conscientiousness • Openness	-	Presage
Instructor • Student-to-instructor personality match	-	Presage
Motivation • Intrinsic • Extrinsic	Presage	Process
Learning Approach • Deep • Surface	Process	Process
Course Perceptions • Workload • Instructor • Assessments • Clear goals • Independence	-	Process
Academic Performance • Course marks	Product	Product

Presage

Presage factors comprise the personal characteristics of students and situational characteristics defined by the learning environment. In this study, students' academic background, personality, and prior learning form the personal aspects of the presage domain; and the student-to-instructor personality match forms the situational aspect of the presage domain.

Students' academic background in terms of the type of pre-university educational institution, discipline, and years of study in the university is specific to the respective students. They reflect the (prior) learning experience of the students that is likely to have an influence on their adoption of learning approach(es), ultimately impacting academic performance—hence, positioning them as presage factors. It can be argued that the type of pre-university educational institution is critical to a student's academic success in the university, as different types of pre-university educational institutions prepare him/her for higher education to different degrees. In prior research, it was found that students from government secondary schools (versus private secondary schools) performed better in an accounting programme (Tickell & Smyrnios, 2005) and students from vocational post-secondary institutions were less likely to enrol in any type of higher education programmes compared to students from academic post-secondary institutions (Farias & Sevilla, 2015). On the whole, prior studies suggest that where the students come from could potentially have an impact on their subsequent learning experience in institutes of higher learning.

University students have to make a decision on which discipline they want to learn. This decision is often determined by a range of factors, such as personality traits, perceived learning approach, interest (motivation) in the area of studies, and so on. A study on 248 Australian students (93 in psychology and 155 in business) of the effect of discipline on learning approaches found that psychology students scored higher on deep learning and lower on surface learning vis-à-vis the case for business students, and this could be due to the nature of the discipline (Smith & Miller, 2005). A review by Vedel (2014) found that there were substantial differences in personality traits across different disciplines. By extension, given that studies (e.g., John & John, 2020; Poropat, 2009; Stajkovic et al., 2018) have found that personality traits do have a significant relationship with academic performance, it can be argued that discipline has an effect (presumably at least an indirect one) on academic performance. However, it is unclear which is the primary driver.

The number of years of study, which has not been examined in prior studies, is included in this study to examine whether a student who has studied longer in the university (and hence is more familiar with the learning environment or is not progressing enough academically) has any impact on his/her academic performance.

Students' personality exists prior to the time of learning and a meta-analysis conducted by Vedel (2014) found that a student's academic performance was significantly correlated with Agreeableness, Conscientiousness and Openness, with Conscientiousness being the strongest predictor. Another meta-analysis by Poropat (2009) also found that academic performance was significantly related to the personality traits Agreeableness, Conscientiousness and Openness. Interestingly, a study by Trapmann et al. (2007) mentioned that personality traits might become more relevant to academic success in the future as the education landscape moved towards e-learning. This broadly implies that universities would need to adapt or change their way of providing support to their students. Accordingly, personality traits like Agreeableness, Conscientiousness and Openness are included in this study as presage factors to gain a better understanding of their impact on students' motivation, course perceptions as well as learning approaches.

Instructors are an important part of the learning environment as they shape students' learning experiences and outcomes. The personality of instructors might also affect their teaching style, as highlighted by Kim and MacCann (2016). Therefore, a student-to-instructor personality match is included in this study as one of the attributes under the presage domain.

Prior learning, which typically has a strong correlation with prior academic performance has been identified as an important determinant of academic performance in higher education in a number of studies (Aluko et al., 2016; Ellegood et al., 2019; Elias & MacDonald, 2007; Plant, 2005). Prior academic performance could also be an indicator of other attributes such as students' emotional intelligence, motivation, and effort (Goodman et al., 2011; Mohzan et al, 2013). Garon-Carrier et al. (2016) indicated that prior academic achievement could lead to subsequent intrinsic motivation, which could potentially affect their academic performance in higher education. Prior exposure (through self-reporting) is used as a proxy for prior knowledge for this study as there is an overlap between prior exposure and prior knowledge, and no assessment is done to assess the level of mastery. There seems 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, 2008). Hence, prior/current work experience is included in this study to better understand its effect on students' academic performance.

Process

The process factors within the 3P model examine how students approach their learning. The range of process factors is expanded in this study to include factors that are influenced by the presage factors and that affect students' learning experience—in particular, motivation and course perceptions in addition to approaches to learning.

According to Rizkallah and Sietz (2017), students' motivation changes over the academic years as their needs, problems and aspirations change. Sogunro (2015) also highlighted eight factors that affect students' motivation, including factors that existed during learning such as classroom interaction, quality of instructions and curriculum, and timely feedback. A study done by Kusurkar et al. (2013) found that relative autonomous motivation (a measure of the balance between autonomous motivation and controlled motivation) was positively associated with the use of a good study strategy which, in turn, was positively associated with higher study effort resulting in better academic performance in terms of GPA. A study administered in a first-year undergraduate financial accounting course showed that students with a high level of motivation (both intrinsic and extrinsic) tended to use deep learning that led to better academic performance (Everaert et al., 2017). The effect of motivation on academic performance (see, for example, Almalki, 2019; Liu et al., 2012; Sogunro, 2015) might not be clear-cut; however, motivation does influence students' adoption of a learning approach. For this study, motivation is cast as part of the process domain as prior studies (e.g., Ariani, 2013) had found that personality traits of students were strongly associated with their level of intrinsic as well as extrinsic motivation. Motivation is also purposefully moved from the presage domain to process domain so that a better understanding of how the presage attributes can affect motivation (which in turn can affect learning approach and academic performance either directly or indirectly) can be obtained. This understanding will help universities identify the appropriate interventions to further motivate students to achieve academic success.

Perception is an individual's primary form of cognitive contact with the world around him/her (Efron, 1969); hence, course perceptions are students' form of cognitive contact with their learning environment. Potentially, students can form perceptions of the course based on their previous experiences and attitudes towards the relevant subjects before embarking on university subjects[1]. However, perceptions are also formed or changed

[1] We would like to thank the reviewers for their insightful comments.

during the course of learning as students have more contact with their instructor as well as the curriculum. As the study aims to inform on what the university can do to enhance the learning experience, focusing on the process stage allows for intervention to be fruitfully designed and implemented which, hopefully, can make a positive difference to student's learning. Prior studies (Abraham, 2006; Faranda et al., 2021; Lizzio et al. 2002; Richardson et al., 2007) indicated that students' perceptions played a critical role in affecting students' learning in terms of their adoption of learning approaches and academic performance, either directly or indirectly. Therefore, these are subsumed under the process domain so that it is examined as both an independent and mediator construct to facilitate an examination of their effects on academic performance directly or indirectly. The placement of course perceptions as part of the process domain can also help generate insights on how the presage attributes can affect them so that institutions can devise interventions to promote more favourable perceptions. Nijhuis et al. (2007) found no relationship between personality traits and course perceptions, concluding that the educational system did not seem to favour any particular kind of students. However, Diseth (2013) found that two course experience factors of good teaching and appropriate workload were negatively predicted by neuroticism. These conflicting findings of how personality affects course perceptions could be due to a variety of reasons, principal among them is likely the context within which the learning takes place. Despite ambiguous prior findings, it is prudent to include course perceptions in this study as the relationships between personality traits and course perceptions may not be direct.

Prior studies indicated that students' perceptions played a critical role in affecting students' learning in terms of their adoption of learning approaches and academic performance, either directly or indirectly. Therefore, these are subsumed under the process domain so that they are examined as both independent and mediator constructs to study their effects on academic performance directly or indirectly. The placement of course perceptions as part of the process domain can also help generate insights on how the presage attributes can affect them so that institutions can devise interventions to promote more favourable perceptions.

Students' adoption of a learning approach depends on the context, content, and the demands of the learning tasks (Richardson, 2000). In response to perceived demands of the learning environment, students change their approaches to learning accordingly (Aggarwal and Bates, 2001). More generally, the same learning environment may be perceived differently by students of the same cohort, and in different situations, the same student may use a different learning approach. Similar to the original 3P model, learning approach is placed under the process domain.

Product

Product factors describe the learning outcomes (quantitative, qualitative, and affective) which a student derives from the learning process. Quantitative learning outcomes are typically assessed via tests of how well the students had comprehended the facts and application of the skills learnt. On the other hand, qualitative learning outcomes relate to the integration (structure and transfer) of both previously and newly learned information. Affective learning outcomes are measures of students' motivation, course satisfaction and liking for the learning task. Affective learning outcomes focus on the students' feelings, rather than the cognitive outcomes (quantitative and qualitative) in terms of what was learned.

As such, the measurement of learning outcome is not confined to academic performance but would include non-academic outcomes that are developed as students interact within the university ecosystem that provides diverse learning opportunities. The challenge lies in the design of assessments that are capable of capturing these aspects. While this is intellectually desirable, it often represents a gargantuan task that requires a huge injection of resources and transformed ways of teaching and learning. As such, most universities still rely on students' GPA as a proxy of their academic performance, and assessment of non-academic aspects are generally not defined and reflected in the university transcript. The GPA is, in fact, the most common quantitative measure of cognitive skills and abilities acquisition (Chemers, 2001; Madigan, 2019; Richardson et al., 2012).

Noting the challenge in measuring learning outcomes through non-academic quantifications, this study used students' course marks (total of marks awarded to two assignments and an examination), which are part of core subject-based outcomes, to represent the quantitative aspect of learning outcomes similar to that of other prior studies. Figure 2 illustrates the expanded 3P model.

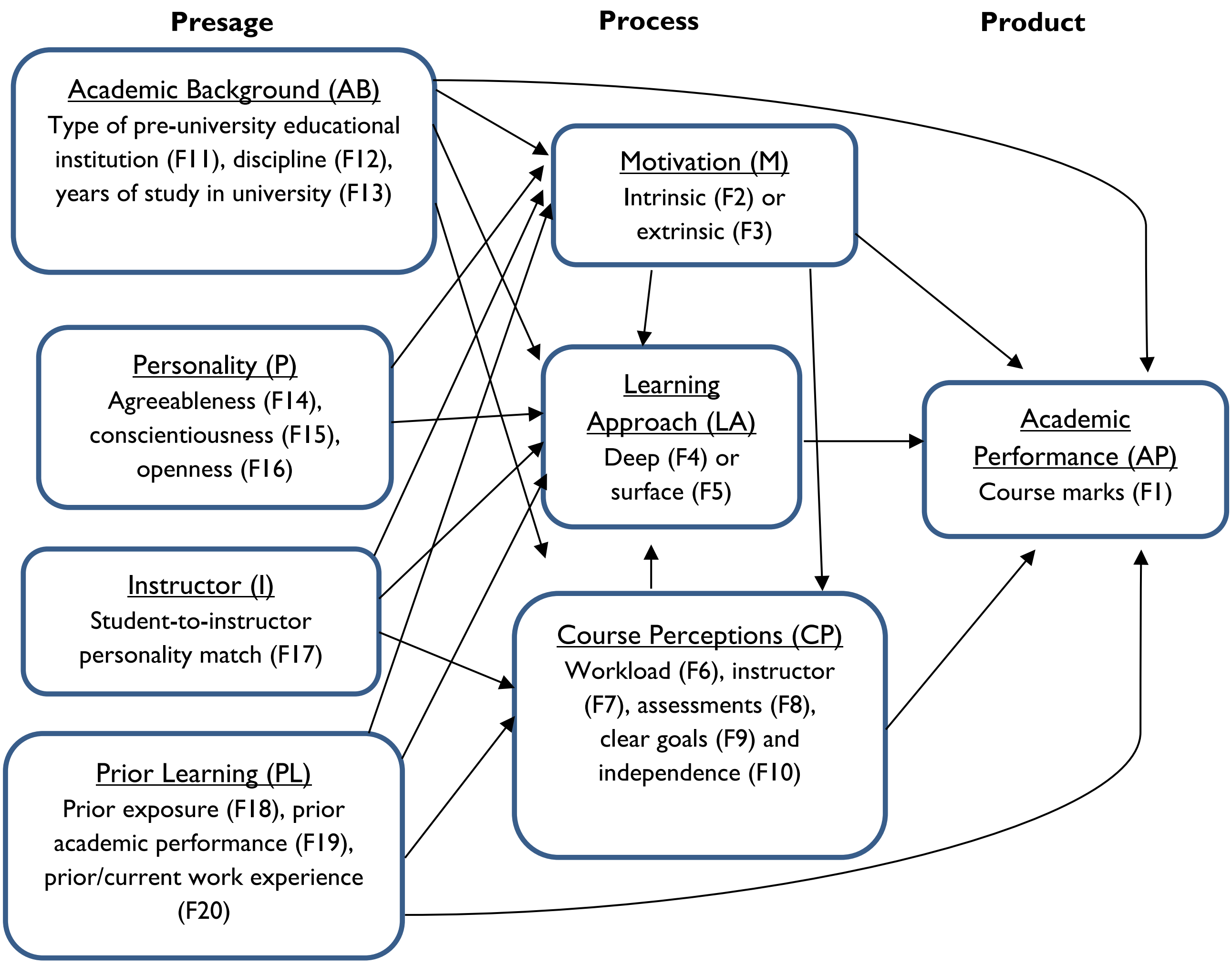

Figure 2. The expanded 3P model of teaching and learning (research framework)

RESULTS

Research data were collected through a self-administrated and self-rated structured questionnaire. The questionnaire comprises five sections as shown in Table 3.

Table 3
Summary of questionnaire used

Questionnaire	Constructs	Number of items
Participant Information Sheet	Academic Background and Prior Learning	6
Socio-Demographic (Age, Gender, Race)	-	3
Motivated Strategies for Learning Questionnaire (MSLQ)	Motivation	8
Revised Two-Factor Study Process Questionnaire (R-SPQ-2F)	Learning Approach	20
Revised Course Experience Questionnaire (CEQ)	Course Perceptions	16
Big Five Inventory (BFI)	Personality	28

As discussed under presage, based on prior studies (Poropat, 2009; Vedel, 2014), only Agreeableness, Conscientiousness, or Openness (28 items) which have a stronger association with academic performance are used in this study. Besides the students' responses to the survey, their course marks for the course were extracted from SUSS' student information system.

The same questionnaire on personality is also administered to the instructors to capture their personality trait, which was then compared to the students' personality to derive a match indicator/measure.

The survey was administered (via Qualtrics) to all 2,250 students taking business analytics and marketing courses in the January and July 2021 semesters. A total of 475 students responded to the survey. Table 4 summarises the demographics, academic background, and course marks for the 475 participants:

Table 4
Summary of participants and course information

Variable	Description	Values
Age	Average age	24.6
	Standard deviation of age	5.6
Gender	Female	254 (53%)
	Male	221 (47%)
Race	Chinese	392 (82%)
	Malay	30 (6%)
	Indian	24 (5%)
	Eurasian	2 (1%)
	Others	27 (6%)
Type of Pre-University Institution	Polytechnic	403 (85%)
	Non-Polytechnic	72 (15%)
Discipline	Course taken is similar to discipline of programme	205 (43%)
	Course taken is different from discipline of programme	270 (57%)
Years of Study in SUSS	Average years in SUSS	1.2
	Standard deviation of years in SUSS	1.1
Prior Exposure	Have	259 (55%)
	Do not have	216 (45%)
Prior Academic Performance	Average entry score	52.8
	Standard deviation of entry score	23.5
	(Total possible score is 100)	
Prior/Current Work Experience	Experience related to course	68 (14%)
	No experience related to course	407 (86%)
Course Marks	Mean score	64.4
	Standard deviation of score	7.5

The responses from 475 students collected were generally within the mean and standard deviation ranges reported by prior studies (Astika & Sumakul, 2020; John & John, 2020; Peck et al., 2018; Richardson et al., 2007). Hence, the students' responses were generally typical of those of other students in other settings. To gain a better understanding of the determinants of academic performance using an expanded 3P model, structural equation modelling (SEM) is used as the research framework.

Exploratory (EFA) and confirmatory factor analyses (CFA) were conducted before the final SEM was performed. EFA was used 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. For course perceptions, the items for clear goals and independence were not appropriately loaded as intended; hence, the misplaced items were removed and EFA was re-performed (see Appendix A). The data collected support the underlying factor structures for personality, motivation, learning approach, and course perceptions (after the removal of the misplaced items).

Following this, CFA was used to verify the factor structure for these constructs. Based on the CFA results, two items were removed for motivation due to low R-square. This improved the validity and reliability of the construct. Parcelling of items to improve the fit of the measurement model (Matsunaga, 2008) was performed for learning approach and personality as several of the items did not meet the threshold for R-square. An R-Square value of 0.4 or higher is considered acceptable (O'Rourke & Hatcher, 2014). 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 constructs (i.e., F2 to F8 and F12 to F14 – See Figure 2) were included in the model. The convergent validity (CV) for all constructs is greater than 0.7 (benchmark based on Hair et al., 2018), except for assessments (0.67, which is slightly below 0.7). The variance extracted (VE) for all constructs are greater than 0.5 (benchmark based on Hair et al., 2018) and for intrinsic motivation, the VE is very close to 0.5 (0.48). The exception is assessments (0.41). The construct reliability (CR) for all the constructs is also greater than the squared correlation among the constructs, which range between 0.00 to 0.43 (both inclusive). Therefore, discriminant validity (DV) is supported (Hair et al., 2018).

The absolute fit indices [Chi-Square/DF < 2 and Standardised Root Mean Square Residual (SRMR) < 0.08, both based on Hooper et al., 2008), parsimony fit indices [Root Mean Square Error of Approximation [RMSEA] < 0.06 and its lower and upper 90% confidence limits (0 – 0.08) based on Hooper et al., 2008] and incremental fit index [Bentler Comparative Fit Index (CFI) > 0.90 based on O'Rourke & Hatcher, 2014] meet the desired benchmarks. Taken together, the results indicate that the measurement of the constructs is appropriate, and hence it is appropriate to proceed with SEM.

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). A total of 12 paths were deleted and three paths were added, as shown in Figure 5.

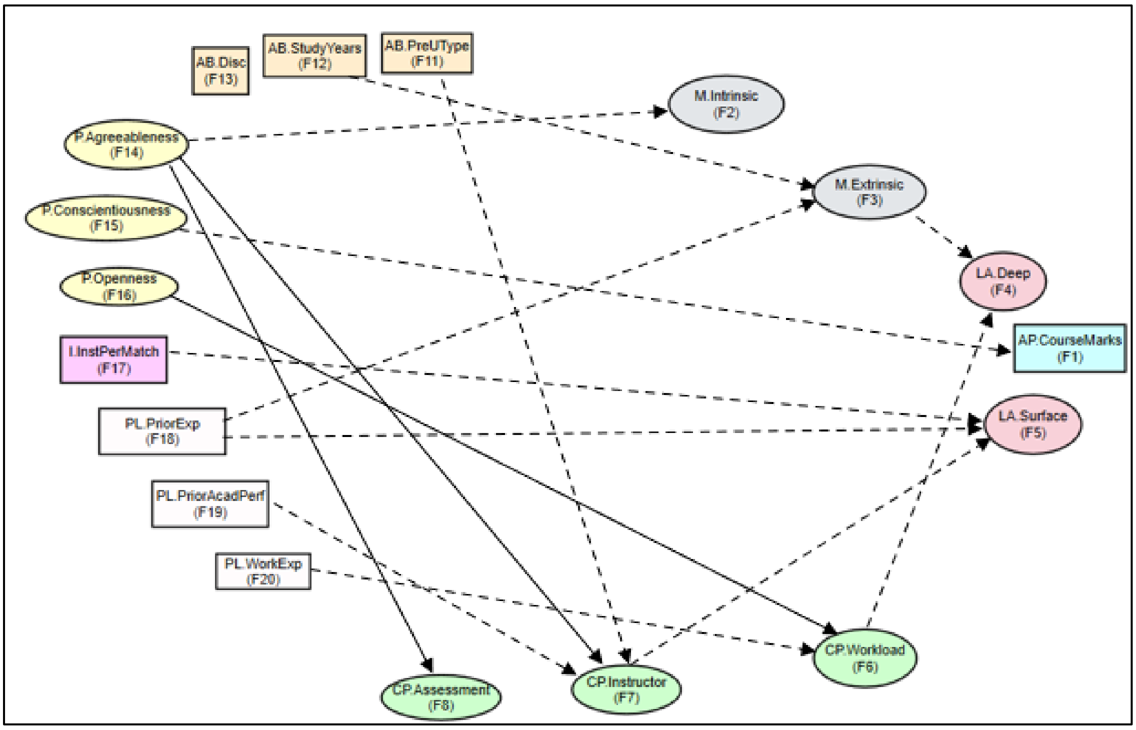

Figure 5. Deletion and addition of paths
(Continuous line indicates deletion and dotted line indicates addition)

Similar to the evaluation of CFA, the same set of fit indices was examined to determine the model fit. The fit indices meet all the benchmarks. The expanded model was further cross-validated using the responses from the July semester. The model indices, expect for CFI (which is 0.88—vis-à-vis the 0.90 benchmark), meet the benchmarks. This indicates that the SEM model constructed based on the January data was able to fit the responses for the July semester. It is not atypical for an acceptable model to meet only a few desired thresholds but not all (O'Rourke & Hatcher, 2014). Therefore, the model can be deemed as cross-validated and hence has model generalisability. Next, the SEM model was applied to the January and July semesters (combined) to gain a better understanding of the determinants of academic performance.

The model indices meet the benchmarks. Hence, it can be concluded that the SEM model adequately fits the responses for both the semesters.

FINDINGS AND DISCUSSION

With the establishment of model generalisability and applicability, the direct effects and indirect effects along with the respective *p*-values were examined. Appendix B presents the direct and indirect effects based on the combined (January and July semesters) data. The key findings are summarised as follows:

1. Students have better academic performance if they are more intrinsically motivated, use more of deep learning, have more favourable perceptions of the instructor, higher levels of conscientiousness, openness and prior exposure, and better prior academic performance.
2. Students have poorer academic performance if they are in a course that match their discipline, have polytechnic education, more years of study, and a higher level of agreeableness.
3. Students with a higher level of agreeableness, conscientiousness or openness, and better prior academic performance are more motivated.
4. Students from the polytechnics and have prior/current working experience are less motivated.
5. Students use more of deep learning if they are intrinsically motivated, have more favourable perceptions of their instructor, higher levels of conscientiousness and openness, and an instructor whose personality matches their personality.
6. Students use more of surface learning if they are extrinsically motivated, have polytechnic education and have prior/current working experience.
7. Students have more favourable course perceptions if they are intrinsically motivated, have a higher level of agreeableness (for perceptions of instructor and assessments), conscientiousness and openness, and better prior academic performance.
8. Students have less favourable course perceptions if they are extrinsically motivated, in a course that match their discipline, have a higher level of agreeableness (for perceptions of workload), polytechnic education, more years of study, prior exposure to the course, and prior/current work experience.

These key findings provide an opportunity for a deeper understanding of the determinants of academic performance. In particular:

(1) Prior academic performance is an important determinant of university academic performance. This indicates that prior academic performance is "translatable" to learning environments that the learners have been unfamiliar with up to that point in their education journey. This implies that universities could use prior academic performance as a useful proxy to proactively provide appropriate learning support.

(2) A higher level of personality trait agreeableness has a negative direct effect on academic performance, contrary to prior studies that report agreeableness is positively and directly related to academic performance. On the other hand, agreeableness has a positive indirect effect on academic performance mediated by course perceptions of the instructor, followed by deep learning. This finding highlights the complexity of the relationship between agreeableness and academic performance.

(3) Personality traits of students seem to work hand-in-hand with their level of motivation in influencing their perceptions of workload and the instructor, as well as the use of deep learning, especially so for the personality traits of openness and conscientiousness. This indicates that the effects of the personality traits conscientiousness and openness on academic performance are not direct.

(4) Intrinsic motivation has a positive indirect effect on academic performance, and intrinsically motivated students are more likely to have more favourable perceptions of workload, the instructor and assessments. This result re-affirms that intrinsic motivation transcends different learning conditions/environments and universities can help ensure that the learning environment

it provides contributes positively to enhancing and/or strengthening intrinsic motivation, leading to better academic performance.

The findings that certain determinants are 'transferable', coupled with those that showed greater complexity than initially indicated by the existing literature, provide evidence that the expanded 3P model could potentially be beneficial. The proposed expanded 3P model examines motivation and course perceptions as presage factors affecting students' adoption of learning approaches (i.e., process) and process factors affecting academic performance (i.e., product), as illustrated in Figure 2. The expanded model also allows universities to gain a better understanding of the factors that can affect motivation and course perceptions. By incorporating motivation, learning approach, and course perceptions that serve as presage and process factors in the model, the expanded 3P model can help universities take a more nuanced approach in their development of curriculum and assessments. At the same time, the expanded 3P model can provide greater depth and understanding in the university's attempt to structure a more holistic and coherent learning environment; linking pedagogies, assessments and curriculum delivery in ways that provide mutually reinforcing support for learners. For example, universities can make explicit its teaching and learning environment as well as assessment approach so that the students with poorer prior academic performance are able to reflect (through reflective learning) upon what is required of them and the gaps that they have to close in order to perform well. In particular, the results show that intrinsic motivation needs to be more explicitly integrated throughout the teaching and learning interactions. Hence, it will be useful for instructors to provide guided opportunities for students to explore new ideas using inquiry-based learning pedagogy as higher level of openness is associated with higher levels of intrinsic motivation. The deeper understanding could also enhance the ability of universities to devise more targeted and efficient student support and interventions as the relationships among these factors can now be established simultaneously.

It is hoped that the expanded 3P model can serve as a guide to universities in terms of their curriculum and assessment development as it offers a fresh, and potentially more insightful, perspective on what to focus on in order to enhance students' learning.

LIMITATIONS AND FUTURE DIRECTIONS

In this study, the Biggs' 3P model was applied in a local university in Singapore. To examine the external validity of the model, the model can be applied in a wider variety of contexts, including other local universities in Singapore and other universities in other regions. Also, more data can be collected – in terms of quantity and diversity (e.g., from other universities). This will enrich the research and provide more insights on the relationships among student profiles, learning environment, course attributes and academic performance.

Due to the scope of this study and sample size, not all potential variables that can affect academic performance are included in the SEM model. Future research can incorporate, for example, socio-demographic data (as presage factors) about the students. In addition, students' satisfaction defined as a short-term attitude resulting from an evaluation of students' educational experience, services and facilities, is a potential construct to include as a process factor in the 3P model (Weerasinghe & Fernando, 2017). Dhaqane and Afrah (2016), Martirosyan et al. (2014), and Sembiring (2015) found strong positive correlation between students' satisfaction and academic performance. Rubin et al. (2018) also found that there was a relationship between learning approach and students' satisfaction of a course, although the direction of the relationship was unclear. This indicates that students' satisfaction can affect their academic performance both directly and indirectly. Therefore, the inclusion of students' satisfaction in the model may generate more insights into the nature and extent of the complex relationships among student attributes, learning attributes, course attributes, and academic performance. However, due to the scope of the study, students' satisfaction is not included.

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 of this study so to enable a better understanding of the nature and extent of these complex relationships and the determinants that affect student's academic performance (both directly and indirectly). It is hoped that this study can make a significant contribution to the existing literature, as well as help enhance students' learning in universities.

APPENDIX A

APPENDIX B

DISCLOSURE STATEMENT

The authors report there are no competing interests to declare.

ETHICS APPROVAL

Approval (APL-0098) was obtained from SUSS Institutional Review Board (SUSS-IRB), signed by Associate Professor Adrian Kwek. Participants' consents were obtained via Qualtrics upon submission of the survey..

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