Validation of competing structural models of inter-relationships in the teaching–learning ecosystem for two Malaysian STEM courses

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Abstract

This study reported the results of Structural Equation Modelling (SEM) analyses on 13 competing structural models on the inter-relationships among academic achievement and student- and course-related attributes. The samples were Malaysian pre-university students enrolled in two STEM courses (biology, $n=326$; mathematics, $n=339$; biology only, $n=92$; mathematics only, $n=105$; biology and mathematics, $n=234$). For both courses, interdisciplinary cross-validation was observed for four models which hypothesized that current academic achievement could be predicted (1) directly by prior academic achievement (high school grades) and student approaches to learning (SAL), and (2) directly and/or indirectly by personality, intrinsic motivation and course experience (CE). For at least one course, all constructs (except intrinsic motivation, clear goals and standards, openness and conscientiousness) significantly and directly predicted current academic achievement. The strongest predictor of current academic achievement was prior (high school) academic achievement, with the largest effect sizes, followed by SAL. Current academic achievement was significantly and positively predicted by all CE constructs (except clear goals and standards) for only mathematics, with moderate and large effect sizes. Only one personality construct (neuroticism) significantly and moderately predicted current academic achievement (biology). SAL partially mediated relationships between current academic achievement with workload appropriateness, assessment for understanding and neuroticism for at least one course. Generally, the strongest predictors of SAL were assessment for understanding, workload appropriateness and intrinsic motivation. Multigroup invariance analysis revealed differences in five hypothesized paths, attributable almost entirely to significant paths found in mathematics but not biology (prior [high school] to current academic achievement, conscientiousness to surface approach to learning, intrinsic motivation to deep and surface approaches to learning). Therefore, this study is the first to report course-nuanced differences in the presence of reduced interpersonal differences. The implications of this study is that, besides the importance of prior high academic achievement which might not be within educators' control, factors in the teaching–learning ecosystem within educators' control which influence current academic achievement are strongly mediated by SAL, which is itself influenced most by assessment, workload and intrinsic motivation.

Keywords Academic achievement · Student approaches to learning · Personality · Motivation · Course experience · Competing models · Structural equation modelling · Confirmatory factor analyses · Multigroup invariance analysis

Introduction

There are various models conceptualizing the relationships among the key factors in the teaching–learning ecosystem. A simple conceptual model which incorporates student attributes with the course environment is Curry's (1983) onion model whereby learning is viewed as a concentric of three layers: (1) cognitive elements of personality (internal and fundamental cognitive processes) at the core, (2) information processing (how information from external stimuli [visual or verbal] is perceived and processed) in the middle and instructional preference at the outermost. Another

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model is Biggs' 3P model of teaching and student learning comprising three components of classroom learning—presage, process and product (Biggs 1993; Biggs et al. 2001). The presage component comprises (1) student characteristics (prior experience, aptitude, conceptions of learning, motivation, work habits, locus of control, perceived self-efficacy, socio-cultural factors and preferred learning approach) and (2) teaching context (synonymous with 'course experience' [CE]) factors such as nature of taught content, teaching and assessment methods, and institutional climate. Process encapsulates learning activities (including ongoing learning approaches), while product refers to qualitative and quantitative learning outcomes. The nature of relationships among all three components is conceptualized as being bi-directional, with all factors affecting one another. For instance, students' preferred approach may adjust in response to a specific course context and success or failure of a learning outcome. Biggs' 3P model is more elaborate than Curry's onion model, because it specifies both student attributes and components of the teaching–learning ecosystem. Curry's model is more learner-centric, focuses on personality and cognitive processes and stops at instructional preferences without addressing the teaching–learning ecosystem in detail.

Serife's model (2008) captured the important relationship between personality and studying by synthesizing Curry's (1983) and Biggs' (1993) models. Curry's personality component was likened to Biggs' Presage component of student, with both being the most stable and least influenced by external factors (e.g. instruction). Curry's cognitive-learning styles and instructional preference were approximated with Biggs' Process and Product components. Instructional preference was conceptualized as being more influenced by learning context (uni-directionality implied), and, hence, the least stable, while at the same time affecting and being affected by learning output (bi-directionality). Furthermore, Serife's model (2008) introduces the link between elements from different sources of psychology, bringing together in one framework mainly theories of SAL, learning style, personality, cognitive and educational psychology. However, it is a re-interpretation based on the superimposition of Curry's and Biggs' model, with little further elaboration of or addition to the individual theories, neither does it describe in detail the elements and interactions among components of the teaching–learning ecosystem.

Entwistle (1998, 2005) proposes a more comprehensive conceptual model of the teaching and learning ecosystem which considers how the variety of components in a teaching–learning environment affects its outcomes or learning quality. They conceptualize that the learning quality which students achieve (deep or surface student approaches to learning [SAL]) is governed by the following components and their interaction with each other, such as student characteristics (personality, prior educational experience,

ability, reasons for studying, prior understanding of the topic area, study organization and habits, time and effort devoted to studying), teaching methods (lectures, labs, tutorials, e-learning, etc.), assessment (procedures and criteria), assignments, feedback and workload (Entwistle 1998). Another model proposed by Richardson (2006) hypothesizes that students' demographic background (e.g. age, gender) might directly influence their perceptions of course experience (i.e. the teaching–learning environment) or be mediated by variations in study behaviour (i.e. student approaches to learning [SAL]). Likewise, student's background might influence SAL or its effect may be mediated by perceptions of course experience. Student's perceptions of course experience might directly influence outcome measures (e.g. academic achievement) or its influence may be mediated by SAL. In Trigwell, Prosser and Waterhouse's (1999) model, teaching approaches influence student approaches to learning.

However, the conceptual models reviewed above remain to be comprehensively tested. Research on such models have been limited in several ways: (1) restricted range of sample attributes (e.g. language, culture, geography), (2) discipline (e.g. mostly the social sciences [psychology, education, business, economics], with a few on pooled samples of hard [science, engineering] and social sciences), (3) examined only relatively few constructs at a time, and (4) statistical methods available (e.g. correlation, factor analysis, multiple regression and path analysis) (Entwistle and McCune 2004). Most studies estimated measured variables (Diseth 2013; Karagiannopoulou and Milienos 2015; Trigwell et al. 2013) instead of latent constructs (Nijhuis et al. 2007). Furthermore, none have presented a competing models strategy beyond two conceptual models, making it difficult to determine which model is more reflective of true relationships (Hair et al. 2010).

Personality and SAL

Empirical data support the conceptual relationship between personality and SAL (Baeten et al. 2010; Swanberg and Martinsen 2010). Studies employing multivariate statistics have consistently reported neuroticism, openness and conscientiousness, as the most significant personality predictors of SAL. However, these studies were not always in agreement in reporting the amount of variance in SAL explained by personality (Diseth 2003; Nijhuis et al. 2007).

Motivation and SAL

Researchers have used certain motivational constructs interchangeably, such as intrinsic motivation, mastery goals and autonomous motivation, all of which have been positively associated with the deep approach to learning (Baeten et al.

2009; Entwistle et al. 2002). As for the surface approach to learning, it has been shown to be negatively related to intrinsic motivation and self-efficacy, but positively with learning avoidance (mastery goals) and performance goals. Intrinsic motivation has been more often associated with quality learning and practical usefulness in education (Richardson and Remedios 2014).

Course experience (CE) and SAL

In the literature, ‘course experience’ (Diseth 2007a, b, 2013; Diseth et al. 2006) has been used interchangeably with the term ‘learning environment’ (Baeten et al. 2010). The constructs which make up course experience include teaching (e.g. quality, approach), clear goals and standards, appropriateness of workload and assessment (referring to assessment for understanding) (Entwistle and McCune 2004).

Perceptions of the teaching–learning environment have been reported to be associated with SAL. Generally, where at least some of these constructs (e.g. teaching quality, clear goals and standards, appropriateness of workload and assessment) have been considered as either separate or composite scales in the presence of none, some or all other CE constructs, multivariate analyses have indicated a positive association between the deep approach to learning with clear goals and standards, both workload and assessment appropriateness, teaching quality and student-centred teaching approach (such as ‘teaching for conceptual change’) (Karagiannopoulou and Milienos 2015; Trigwell and Prosser 2004). In contrast, the aforesaid constructs (clear goals and standards, both workload and assessment appropriateness, teaching quality and student-centred teaching approach) have sometimes been negatively associated with the surface learning approach (Baeten et al. 2010; Beausaert et al. 2013; Diseth et al. 2006, 2010; Diseth 2007a, b; Nijhuis et al. 2007; Teoh et al. 2014; Trigwell et al. 1999). However, in the presence of non-CE constructs, these relationships have not always consistently held true statistically. More studies are needed to confirm these relationships simultaneously as opposed to piecemeal. In particular, studies on the perception of teaching approach together with other CE measures are difficult to trace in the literature.

Personality, motivation, CE, SAL and academic achievement

Few studies have employed Structural Equations Modelling (SEM) to simultaneously analyse the relationships among the constructs such as personality, motivation, course experience and SAL. While there have been a number of studies on personality and SAL, these relationships appeared to be weaker in the presence of other constructs such as CE, which accounted for greater variance in SAL (Diseth 2013; Nijhuis

et al. 2007). One study which investigated the relationships among SAL and two constructs each of motivation (intrinsic motivation and self-efficacy) and CE (teaching quality and workload appropriateness) reported CE predicting only the surface approach to learning, with motivation predicting both deep and surface approaches to learning (Trigwell et al. 2013). More studies measuring personality, motivation, course experience and SAL are required to ascertain more accurately the relationships among these constructs and their relative influences on SAL. A number of studies have also reported current academic achievement as being predicted by prior academic achievement, personality, motivation and CE constructs, along with SAL (Bonsaksen et al. 2017; Chan et al. 2012; Diseth 2003, 2007a, 2013; Diseth et al. 2010; Karagiannopoulou and Milienos 2015; Swanberg and Martinsen 2010; Trigwell et al. 2013).

Purpose of study

Most of the literature reviewed has been largely done among non-Asian and non-science samples, with no comparison of hypothesized paths between study disciplines. Little has been reported on how different study disciplines influence the pattern of inter-relationships within the teaching–learning ecosystem (Entwistle 2005). This study aimed to test such relationships between mathematics and biology study disciplines in a Malaysian context. It extended previous studies on STEM disciplines by the same authors (Davidson et al. 2014a, b), by (1) adding prior (high school) and current academic achievement to the estimation of models, (2) including an additional course (biology), (3) performing tests for 13 competing structural models, and (4) multigroup invariance analysis.

The research objectives of this study were to determine (1) which model of conceptualization of inter-relationships among personality, intrinsic motivation, CE, SAL, prior (high school) and current academic achievement was statistically acceptable for each study discipline, (2) the extent to which the aforesaid constructs predicted SAL and current academic achievement, and (3) the extent to which the models differed between both study disciplines. The hypotheses for each structural model are presented below. Mathematics and biology were selected for comparison in this study as both were conceptualized as belonging to separate qualitative categories of the ‘pure’ sciences, with the former considered as ‘non-life’ (together with chemistry and physics), and the latter as a ‘life’ science (Laird and Garver 2008). Hence, it was hoped that quantitatively nuanced differences in hypothesized inter-relationships among constructs might emerge based on these qualitative differences. Furthermore, with interpersonal differences reduced due to the high proportion of students common to both study disciplines, any

emerging differences might be more attributable to disciplinary differences instead.

The generalized conceptual framework for this study is presented in Fig. 1. It is a selective amalgamation of several existing conceptual models reviewed above on the relationships among two or more broad components, namely personality, motivation, course experience, SAL, prior high school and current pre-university academic achievement (Biggs 1993; Curry 1983; Entwistle 2005; Richardson 2006; Serife 2008; Trigwell et al. 1999).

In the conceptual framework of the teaching–learning ecosystem shown in Fig. 1, the student-related component comprised three personality constructs (openness, neuroticism and conscientiousness) and intrinsic motivation, while the course experience (CE) component consisted of four constructs (workload appropriateness, assessment for understanding, clear goals and standards and teaching for conceptual change). These constructs were chosen as they have been reported as predictive of SAL and current academic achievement but have not been considered simultaneously in previous studies. The relationships conceptualized in Fig. 1 are presented as unidirectional, based on the conceptualizations of the models of Biggs (1993), Curry (1983), Entwistle (1998, 2005), Serife (2008), Richardson (2006), and Trigwell et al. (1999). A variety of simplified structural models representing conceptual models of the relationships nested in the ecosystem model is presented in Fig. 2.

The structural models tested in this study represented a variety of possible variations in the inter-relationships among components in the teaching–learning ecosystem

Fig. 1 Conceptual framework of the teaching–learning ecosystem. Academic performance: current and prior (high school grades) academic performance; student approaches to learning (‘SAL’; deep and surface); personality (openness, neuroticism and conscientiousness); intrinsic motivation; course experience (‘CE’; workload appropriateness, assessment for understanding, clear goals and standards and teaching for conceptual change)

conceptual framework. In brief, these models hypothesized that current academic achievement was predicted directly by

- prior academic achievement (high school grades) and SAL, and also
 - both directly and indirectly [via SAL] by personality, intrinsic motivation and CE (models 1; model 4 [with personality constructs predicting prior academic achievement as well]);
 - indirectly [via SAL] by personality, intrinsic motivation and CE (model 2; model 5 [personality constructs also predicting prior academic achievement]);
- prior academic achievement (high school grades), SAL, personality, intrinsic motivation and CE (model 3);
- prior academic achievement (high school grades) and SAL, and also
 - indirectly by CE [via SAL], intrinsic motivation and CE [via CE and SAL] (model 6);
 - directly and indirectly by CE [via SAL], personality and intrinsic motivation [both via CE and SAL] (model 7);
 - indirectly by CE [via SAL], personality and intrinsic motivation [both via CE] (model 8);
 - directly and indirectly by CE [via SAL], personality and intrinsic motivation [both via CE] (model 9);
 - indirectly [via SAL] by CE and intrinsic motivation, with CE mediating the relationship between personality with SAL (model 10);
 - indirectly by CE and personality [both via SAL], intrinsic motivation [via CE] (model 11);
 - directly and indirectly by personality [via CE and SAL], intrinsic motivation [via SAL] and CE [SAL-mediated] (model 12); and
 - directly by personality and intrinsic motivation, but also indirectly by intrinsic motivation [via CE then SAL] and CE [via SAL] (model 13).

This paper attempted to fill the aforementioned lack of information on the plausibility of certain conceptualizations derived from the conceptual models reviewed and hypothesized in the 13 models, such as (1) direct and/or indirect (SAL-mediated) relationships among all constructs with current academic achievement (models 1–5) (Curry 1983; Biggs 1993; Serife 2008; Entwistle 2005; Richardson 2006; Trigwell et al. 1999), (2) CE-mediation of inter-relationships among personality and/or intrinsic motivation with SAL and/or current academic achievement (models 6–13) (Baeten et al. 2012; Biggs 1999; Entwistle 1998). Therefore, in all models, current academic achievement was exclusively an endogenous construct, whereas personality constructs and intrinsic

Fig. 2 Simplified variants of the conceptualized relationships within the teaching–learning ecosystem conceptual framework (personality, SAL and CE constructs simplified for brevity). Ac: academic performance (current); p-Ac: prior (high school) academic performance; SAL: student approaches to learning (deep and surface); P: personal-

ity (openness, neuroticism and conscientiousness); IM: intrinsic motivation; CE: course experience (workload appropriateness, assessment for understanding, clear goals and standards and teaching for conceptual change)

motivation were exclusively exogenous. In other models, mediating variables were SAL (all models except model 3) and CE (models 6–13 only). CE constructs were exclusively exogenous only in models 1–5.

Studies employing analyses of latent constructs involving more than one study discipline in the same academic setting are scarce, more so where STEM study disciplines are concerned. The major studies employing multiple constructs and domains reviewed involved only one study discipline such as psychology (Diseth et al. 2006, 2010; Diseth 2007a; Karagiannopoulou and Milienos 2015). Apart from conceptual premises discussed, the selection of constructs for this study was also governed by past work which provided empirical support for such relationships.

Definition of terms

The various terms used in this study were defined and operationalized as follows:

- Student approaches to learning (SAL) referred to deep and surface approaches to learning (Entwistle and McCune 2004). The deep learner studies with the intention to understand and employs strategies such as relating ideas and using evidence. The surface learner adopts routine memorizing without understanding, views course knowledge in unrelated bits and uncritically accepts academic content.
- Personality constructs were based on the Five Factor Model of Personality (John et al. 1991). The neurotic

person is anxious, moody, nervous, and temperamental. The individual high on openness to experience is artistic, complex, innovative and intellectual. The conscientious person is characterized as efficient, neat, organized, thorough and systematic.

- Intrinsic motivation was measured in the context of reasons for which students take a particular course including vocational, academic and personal reasons (Entwistle 2005).
- Course experience (CE) covers students' perception of the learning environment (Diseth et al. 2006) and experiences of the teaching environment (Entwistle et al. 2002) such as
 - Assessment for understanding, representing assessment which tests understanding instead of rote memorization.
 - Clear goals and standards, referring to “how clearly the standards of assessment and ends of studying are perceived to be defined” (Ramsden 2005, p. 213).
 - The teaching for conceptual change, striving for conceptual change or understanding among students (Trigwell et al. 1999).
 - Workload appropriateness, reflecting the amount of work demanded of the student within a limited given time.

Methodology

Population and samples

The population of this study were 392 biology and 414 mathematics students at a Malaysian private pre-university centre. The centre conducted 1-year pre-university programmes designed to help students who graduated from high school make the transition to tertiary education. Two samples were randomly selected from a course list. A minimum of 300 respondents per course were targeted to prevent ‘Heywood’ cases while at the same time keeping to below 400 respondents to avoid goodness-of-fit measures performing poorly due to the over-sensitivity to sample size using MLE (Hair et al. 2010). After accounting for incomplete responses or records, the final samples were comprised of 326 students taking a biology course (230 males, 96 females) and 339 students taking a mathematics course (203 males, 136 females). Of these figures, 237 students took both biology and mathematics, leaving 92 and 105 students unique to biology and mathematics, respectively.

Research design

This study used a multivariate correlational survey research design. Correlational analysis was employed to measure the relationships among personality, motivation, course experience and student approaches to learning (SAL) for two science study disciplines. Multivariate analyses were used to predict relationships among the constructs. Previous research has also used the quantitative survey method to test a number of such inter-relationships (Diseth 2003, 2007a, b; Diseth et al. 2006).

Research instruments and measures

All instruments used in this study were from established and validated questionnaires, with existing items either retained or adapted to suit the context of the study. All measures were validated by a panel of experts, and underwent three to four rounds of pilot studies and statistical analyses. Previous studies using instruments identical to those in this study have reported on the validity and reliability of these measures (Davidson et al. 2014a, b). A list of sample original and adapted items is presented in “Appendix”.

Items used to measure SAL (deep and surface approaches [each seven items]) were primarily from the Approaches to Learning and Studying Inventory (ALSI; nine items; Entwistle 2005; Entwistle and McCune 2004; Xu 2004). However, due to the relatively few number of items in the ALSI and reported poor reliability of the Surface approach to learning in some studies, additional items were drawn from its predecessor, namely the Approaches and Study Skills Inventory for Students (ASSIST; four items; Tait et al. 1998) and Revised Two Factor Study Process Questionnaire R-SPQ-2F (one item; Biggs et al. 2001), accepted as the equivalent of the ASSIST (Entwistle and McCune 2004). The construct validity and reliability of the measures used in this study to measure SAL has been reported in a previous study (Davidson et al. 2014b). As for the original source questionnaires, exploratory and confirmatory factor analyses of the ALSI, ASSIST and R-SPQ-2F in English, Chinese, Belgian and Malay languages supported its construct validity (Baeten et al. 2013; Biggs et al. 2001; Entwistle et al. 2002; Remedios and Richardson 2013; Tait et al. 1998; Teoh et al. 2014; Xu 2004).

The Big Five Inventory (BFI) was used as a personality measure, whose construct validity for the English, Spanish and the English–Malay version used in this study was reportedly established via exploratory and confirmatory factor analyses (Benet-Martinez and John 1998; Davidson et al. 2014b; John et al. 1991). Only three personality dimensions of the existing BFI were used in this study neuroticism [eight items], openness and conscientiousness [each nine items]. As reported in a previous study,

another two dimensions (extraversion and agreeableness) were selectively excluded as they have been reported to be unpredictable of SAL and academic achievement in most studies (Swanberg and Martinsen 2010). This would not affect validity and reliability of individual dimensions, as all are independent constructs.

Intrinsic motivation (ten items) was measured by two related questionnaires, namely the Learning and Study Questionnaire (LSQ; four items; Entwistle and McCune 2004) and Experiences of Teaching and Learning Questionnaire (ETLQ; two items; Entwistle and McCune 2004; Entwistle 2005), as the existing scales for these two measures were relatively short. Hence, four items adapted from both questionnaires were added to improve their reliability (sample in “Appendix”). The construct validity and reliability of the original source questionnaires and the English–Malay measure used in this study have been reportedly adequate (Davidson et al. 2014b; Entwistle and McCune 2004; Entwistle 2005; Xu 2004).

Perceptions of CE were comprised of five scales (assessment for understanding, clear goals and standards, workload appropriateness and teaching for conceptual change), with higher scores reflecting more favourable perceptions. Due to the relatively short scales of source questionnaires, items were derived from more than one source questionnaire measuring conceptually similar constructs. These were the Experiences of Teaching and Learning Questionnaire (ETLQ; Entwistle and McCune 2004; Entwistle 2005), Assessment Experience Questionnaire (AEQ; Segers et al. 2008), the Course Experience Questionnaire (CEQ; Ramsden 1991; Ainley and Johnson 2000), Revised Approaches to Teaching Inventory (R-ATI; Trigwell et al. 2005), Approaches and Study Skills Inventory for Students (ASSIST; Tait et al. 1998) and Fox (1983). The construct validity of the aforementioned scales in their original source questionnaires, in both English and Norwegian, has been established (Davidson et al. 2014b; Diseth et al. 2006, 2010; Diseth 2007a).

Clear goals and standards were measured by four items (two each from the CEQ and ETLQ). Adapted items were added to remaining CE scales to increase their reliability (samples in “Appendix”). The assessment for understanding scale was composed on nine items (two from the CEQ, three from the ETLQ, one from the AEQ and two adapted items). Workload appropriateness was comprised of five items (three from the CEQ and two adaptations). Teaching for conceptual change was measured by seven items (five from the R-ATI, one from the ASSIST and one adapted item from Fox 1983). For the aforementioned scales, the construct validity of the English–Malay measures used in this study has been established (Davidson et al. 2014b).

Cronbach reliability alphas for items in source questionnaires as reported by others have somewhat been wide-ranging (Table 1). Scales with reported lower reliability

Table 1 Summary of reliability alphas of SAL, personality, intrinsic motivation and perceptions of course experience constructs of previous studies

Construct	α
SAL	
Deep	0.66–0.79
Surface	0.47–0.77
Personality	
Openness	0.79–0.81
Neuroticism	0.80–0.84
Conscientiousness	0.77–0.82
Intrinsic motivation	0.74
CE	
Appropriate workload	0.65–0.85
Appropriate assessment/assessment for understanding	0.48–0.82
Clear goals and standards	0.72–0.83
Teaching for conceptual change	0.81–0.87

SAL [ALSI: Karagiannopoulou and Milienos (2015), Baeten et al. (2013), Richardson (2013), Remedios and Richardson (2013), Xu (2004); ASSIST: Tait et al. (1998), Diseth (2003), Swanberg and Martinsen (2010), Chen et al. (2011)]; personality (John et al. 1991; Benet-Martinez and John 1998); intrinsic motivation (ETLQ: Xu 2004); CE (CEQ: Baeten et al. 2012; Richardson 2006, 2007, 2009, 2010; Diseth 2013, 2007a; Diseth et al. 2006, 2010; Nijuis et al. 2007; ETLQ: Xu 2004; Karagiannopoulou and Milienos 2015; Beausaert et al. 2013; Teoh et al. 2014)

coefficients necessitated the inclusion of items from more than one source questionnaire as described above.

All instruments employed were self-report measures with a five-point Likert scale. For Teaching for Conceptual Change (TCC), this ranged from ‘5’ for ‘almost always’ to ‘1’ for ‘rarely or never’. For all other constructs, responses ranged from ‘5’ for ‘agree strongly’ to ‘1’ for ‘disagree strongly’. Each construct was scored by averaging all item scores. Where items were worded in meaning opposite to the other items of a scale, reverse scoring was employed. All items were bilingual (English–Malay). The Malay version was obtained using backtranslation (Brislin 1986). Items were first translated by one of the authors proficient in Malay and subsequently verified by a Malay language expert. Next, items were subjected to backtranslation by language experts proficient in both Malay and English, who then assessed if the backtranslations adequately reflected the intent of existing items.

High school grades as indicated by academic performance on a standardized government exam (the Malaysian Certificate of Education or *Sijil Pelajaran Malaysia*, equivalent to the O-levels), which was a prerequisite for entry into the centre, was used as measure of prior academic performance. Current academic performance was measured by examination scores of end of semester exams, obtained with official permission from institutional records.

Data collection

Questionnaires were administered on paper and via an online student portal during curriculum time on two different occasions during the semester. The first surveyed students' personality in the second week of the 14-week semester, while the second surveyed intrinsic motivation, CE and SAL in week nine. Before survey administration, respondents were briefed on the purpose of the survey and given instructions on answering the survey. In return for participation, all students were given online academic advice on their learning approaches based on their responses. Prior ethical clearance was provided by an institutional committee before administering questionnaires.

Data analysis

A two-step SEM process of the study was performed, the first step being the estimation of a measurement model in order to perform confirmatory factor analysis (CFA) and the second being Structural Equations Modelling (SEM) using the AMOS programme (Arbuckle 2007). The variance–covariance matrices of samples were analysed and maximum likelihood estimation was employed.

In this study, the partial aggregation of items was employed, in which there were both parcelled and non-parcelled measured indicators (Hall et al. 1999). All constructs had aggregated item parcels, while two constructs (clear goals and standards and workload appropriateness) consisted of parcelled and non-parcelled measured indicators, so as to meet the minimum three-indicator rule required for model identification (Hair et al. 2010). All items were

Table 2 Descriptive statistics and reliability of latent and measured constructs for two STEM study disciplines

Construct	Discipline	Mean	SD	Factor loadings ^a			Reliability	
				IP1	IP2	IP3	CR	α
Deep	Biology	3.80	0.54	0.72	0.65	0.81	0.91	0.68
	Mathematics	3.92	0.62	0.80	0.72	0.88	0.94	0.79
Surface	Biology	2.99	0.79	0.81	0.61	0.69	0.70	0.75
	Mathematics	2.78	0.88	0.88	0.69	0.76	0.76	0.82
Openness	Biology	3.29	0.63	0.76	0.68	0.68	0.83	0.72
	Mathematics	3.27	0.60	0.95	0.57	0.78	0.92	0.68
Neuroticism	Biology	2.83	0.74	0.77	0.77	0.81	0.92	0.78
	Mathematics	2.88	0.72	0.80	0.78	0.77	0.89	0.74
Conscientiousness	Biology	3.38	0.61	0.81	0.71	0.67	0.80	0.75
	Mathematics	3.38	0.62	0.83	0.67	0.66	0.88	0.75
Intrinsic motivation	Biology	2.79	0.82	0.91	0.87	0.78	0.90	0.87
	Mathematics	3.76	0.77	0.89	0.90	0.84	0.97	0.87
Workload appropriateness	Biology	2.39	0.85	0.78	0.81	0.66	0.85	0.81
	Mathematics	2.74	1.02	0.87	0.91	0.73	0.80	0.90
Assessment for understanding	Biology	3.96	0.52	0.70	0.70	0.76	0.93	0.72
	Mathematics	4.20	0.56	0.84	0.79	0.87	0.98	0.83
Clear goals and standards	Biology	3.46	0.70	0.72	0.68	0.74	0.86	0.64
	Mathematics	3.84	0.70	0.74	0.71	0.77	0.82	0.69
Teaching for conceptual change	Biology	3.10	0.69	0.75	0.64	0.74	0.72	0.76
	Mathematics	3.47	0.89	0.90	0.76	0.81	0.85	0.88
High school achievement	Biology	70.89	31.47					
	Mathematics	92.11	11.34					
Current academic achievement	Biology	64.25	13.56					
	Mathematics	60.89	17.95					

CR Composite Reliability of IP indicators, α Cronbach alpha coefficient of measured indicators

^aLatent constructs measured by parcelled item parcel (IP) indicators. Each IP comprises one or more items: (1) IP1 and 2 (three items each) and IP3 (four items): intrinsic motivation; (2) IP1 (three items) and IP2 and 3 (two items each): deep and surface approaches to learning, teaching for conceptual change; (3) IP1 and 2 (three items each) and IP 3 (two items): neuroticism, (4) IP1-3 (three items each): openness, conscientiousness and assessment for understanding, (5) IP1 and 2 (two items each) and IP3 (one item): workload appropriateness; (6) IP 1 and 2 (one item) and IP3 (two items): clear goals and standards. Factor loading of item parcels, significant at $p < .001$

parcelled into composites of two or more items, according to empirical equivalence in which items of similar means, variances and reliabilities were parcelled (Landis et al. 2000). All constructs consisted of three item parcels with the number of items per parcel stated in Table 2. The empirical equivalence method produces superior model fit over other existing methods and produces item parcels that are similar to each other and reflect the dimensionality (if any) of the underlying construct, as similar items measuring the same dimensions are forced into different composites. All constructs formed single scales as defined conceptually and tested empirically in their original source questionnaires and previous reports on EFA or CFA. CFA was performed on all constructs mentioned above to assess construct validity of latent constructs (measurement model in Fig. 3).

Structural models were compared using a competing models strategy to determine the most plausible model of conceptualization of the relationships among constructs (sample structural model in Fig. 3). A test of competing theories is superior to that of only one, as a model may show acceptable fit, without excluding that no other model would fit either equally well or better (Hair et al. 2010). Apart from the χ^2 statistic and its associated degrees of freedom, the CFI, RMSEA and SRMR as prescribed by Hair et al. (2010), the Expected Cross-Validation Index (ECVI) was used additionally to ascertain how stable or well a model fit would replicate in another similarly sized sample and when comparing models (Schumaker and Lomax 2004). In order to compare hypothesized inter-relationships across both STEM study disciplines, configural and metric invariance was established via multigroup invariance analyses performed on measurement and structural models (Ho 2006).

This paper presented extended SEM analyses aimed at estimating the path relationships among current and prior (high school) academic performance, SAL (deep and surface); personality (openness, neuroticism and conscientiousness), intrinsic motivation and perceptions of course experience (workload appropriateness, assessment for understanding, clear goals and standards and teaching for conceptual change).

Results

Construct validity

The construct validity of the measures employed were subjected to convergent and discriminant validation via CFA. Indicators of convergent validity computed were factor loadings, composite reliability (CR) and Average Variance Extracted (AVE). For both measurement models, each item parcel was below the recommended limits for skewness (<3) and kurtosis (<7 ; Byrne 2010). All factor loadings exceeded

the minimum requirement of 0.5, while CR of all parcelled constructs met the ideal value of 0.7 (Table 2; Chen et al. 2009; Hair et al. 2010).

All constructs showed acceptable levels of convergent validity as they met the ideal 0.5 value for AVE (Table 3). Therefore, by the factor loadings, CR and AVE, all constructs were deemed to have exhibited sufficient convergent validity. All constructs showed discriminant validity, as ascertained by the squared correlations between pairs of constructs being lower than the AVE of individual constructs (Hair et al. 2010). Hence, convergent and discriminant validity indicators indicated sufficient construct validity of the measures employed in this study. The significant bivariate correlations among current academic achievement, SAL and personality, intrinsic motivation and CE variables provided empirical support for the view that SAL is associated with the aforesaid constructs and allowed for the estimation of inter-relationships among them in the context of SEM and CFA.

Measurement and structural models

The model fit indices of measurement and competing structural models are reported in Table 4. All indices, for measurement models were above the recommended cutoff values (in parentheses): normed χ^2 (χ^2/df , <3), CFI (>0.90), RMSEA (<0.07) and SRMR (≤ 0.08) (Hair et al. 2010; Schumacker and Lomax 2004). This indicated adequate fit of the sample data to the model.

Thirteen structural models were estimated and described (Fig. 2). Judging from the same recommended cutoff values used to evaluate the measurement models, only four structural models (1, 2, 4 and 5) indicated that the sample data fitted the hypothesized models adequately. In order to determine if a structural model had adequate fit vis-à-vis a measurement model, the criterion of a ΔCFI of less than 0.01 was employed (Cheung and Rensvold 2002). By this criterion, only the structural models 1, 2, 4 and 5 indicated adequate structural fit when compared with the measurement models. All other models (i.e. models 3, 6 to 13) failed to meet this criterion (Table 4). Model fit indices indicated that models 1, 2, 4 and 5 were equivalent models ($\Delta\text{CFI} < 0.01$; Cheung and Rensvold 2002). Nevertheless, model 1 (Fig. 4) yielded more indices useful for comparing across models and which registered more favourable values (Table 4). This meant that across models, model 1 had superior fit, especially where it replicated in another similarly sized sample as indicated by the ECVI (Schumaker and Lomax 2004).

Predictors of current academic achievement

Generally, for biology and/or mathematics, all constructs hypothesized to predict current academic achievement did

were, generally, in-between those of CE and prior academic achievement. Effect sizes were defined after Fryer et al. 2014 (small < medium < large): $0.05 < 0.15 < 0.24$; $-0.10 < -0.20 < -0.29$.

Prior academic achievement significantly predicted current academic achievement, with large effect sizes for both study disciplines. Prior academic achievement was the strongest predictor of current academic achievement, with approximately double the effect size of the nearest predictor variable (surface approach to learning).

SAL significantly predicted current academic achievement for both study disciplines. The deep approach to learning predicted current academic achievement positively and

Table 3 Average variance extracted^a for latent constructs, bivariate and squared correlations^b of constructs for two STEM study disciplines

Discipline	Con	Dp	Su	Op	Neu	Con	Mot	Wkl	AsU	CGS	TCC	HS	Ac
Biology	Dp	0.53	0.15	0.05	0.05	0.05	0.04	0.00	0.20	0.11	0.10	0.03	0.07
	Su	-0.39	0.50	0.02	0.06	0.03	0.06	0.17	0.03	0.15	0.05	0.01	0.05
	Op	0.22	-0.14	0.50	0.02	0.08	0.01	0.00	0.01	0.01	0.00	0.00	0.01
	Neu	-0.23	0.25	-0.14	0.61	0.28	0.00	0.02	0.01	0.00	0.05	0.01	0.01
	Con	0.23	-0.16	0.29	-0.53	0.54	0.00	0.02	0.06	0.02	0.01	0.00	0.00
	Mot	0.20	-0.24	0.11	-0.05	0.06	0.73	0.02	0.01	0.23	0.02	0.01	0.00
	Wkl	0.01	-0.41	0.01	-0.16	0.15	0.13	0.57	0.01	0.05	0.03	0.00	0.00
	AsU	0.45	-0.17	0.10	-0.07	0.24	0.12	-0.11	0.52	0.20	0.06	0.01	0.00
	CGS	0.33	-0.38	0.09	-0.06	0.15	0.48	0.23	0.45	0.51	0.11	0.02	0.01
	TCC	0.32	-0.22	-0.01	-0.23	0.12	0.14	0.17	0.25	0.33	0.51	0.01	0.00
	HS	0.17	-0.11	-0.04	0.11	-0.02	0.09	0.01	0.08	0.16	-0.11		0.30
	Ac	0.27	-0.22	-0.08	0.11	-0.04	0.00	0.03	0.06	0.12	0.01	0.55	
Mathematics	Dp	0.64	0.17	0.04	0.00	0.04	0.34	0.02	0.41	0.36	0.13	0.03	0.06
	Su	-0.41	0.61	0.01	0.02	0.11	0.31	0.31	0.08	0.13	0.01	0.03	0.11
	Op	0.19	-0.10	0.62	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00
	Neu	-0.06	0.16	-0.07	0.61	0.33	0.00	0.03	0.00	0.01	0.00	0.00	0.00
	Con	0.20	-0.33	0.13	-0.57	0.53	0.05	0.04	0.01	0.02	0.00	0.01	0.01
	Mot	0.59	-0.56	0.08	-0.03	0.22	0.77	0.17	0.20	0.31	0.11	0.04	0.09
	Wkl	0.15	-0.55	0.04	-0.18	0.21	0.41	0.70	0.00	0.09	0.01	0.00	0.02
	AsU	0.64	-0.28	0.10	0.00	0.12	-0.44	0.05	0.70	0.28	0.06	0.00	0.00
	CGS	0.60	-0.36	0.10	-0.11	0.15	0.56	-0.30	0.53	0.55	0.25	0.01	0.04
	TCC	0.36	-0.12	0.04	-0.03	0.03	0.33	-0.10	0.25	0.50	0.68	0.00	0.02
	HS	0.16	-0.17	0.00	0.02	0.09	0.20	-0.05	0.07	0.10	-0.02		0.47
	Ac	0.24	-0.34	-0.03	0.01	0.08	0.31	0.13	0.03	0.19	0.13	0.69	

Con constructs, Ac Academic performance (current), HS high school academic performance, Dp deep, Su surface, Op openness, Neu neuroticism, Cons conscientiousness, Mot intrinsic motivation, Wkl workload appropriateness, AsU assessment for understanding, CGS clear goals and standards, TCC teaching for conceptual change

^aAverage variance extracted for latent constructs only (diagonal); Bio (biology); Mat (mathematics)

^bSquared correlations (above diagonal—bold italics); bivariate (below diagonal—bold italics); significance depicted by font type: bold ($p \leq .001$), underscored ($p \leq .01$), italics ($p \leq .05$), plain font ($p > .05$)

moderately for only biology. On the other hand, the surface approach to learning negatively predicted current academic achievement for both study disciplines. The effect sizes were moderate and strong for biology and mathematics, respectively. The effect sizes of the relationship between the surface approach to learning and current academic achievement were approximately half of those between prior and current academic achievement (above). Therefore, the surface approach to learning negatively predicted current academic achievement in both study disciplines.

CE

Model 1 hypothesized the direct prediction between CE and current academic achievement. This was true for mathematics and three CE constructs only, with moderate and large

effect sizes. For mathematics only, three CE constructs positively predicted current academic achievement. The effect sizes of the relationship between predictor constructs and current academic achievement were largest and strong for assessment for understanding, but followed by weak effect sizes for both workload appropriateness and teaching for conceptual change.

Personality

Only neuroticism significantly, positively and moderately predicted current academic achievement for biology. These results indicated a diminished role of personality on current academic achievement when non-personality constructs which reportedly influence SAL (e.g. CE and

Table 4 Model fit indices for measurement and competing structural models of inter-relationships among academic achievement, SAL, personality, intrinsic motivation and CE of two STEM study disciplines

Discipline	Mod ^a	χ^{2b}	df	χ^2/df	$\Delta\chi^{2c}$	Δdf	RMSEA			CFI	SRMR	ECVI		
							90% CI					90% CI		
							Low	High				Low	High	
Biology	M	580.77	400	1.45			0.037	0.030	0.044	0.949	0.0460			
	S1	604.65	403	1.50	23.88	3	0.039	0.033	0.046	0.944	0.0492	2.63	2.44	2.85
	S2	621.95	411	1.51	41.18	11	0.040	0.033	0.046	0.941	0.0508	2.63	2.44	2.85
	S3	756.77	419	1.81	176.00	19	0.050	0.044	0.055	0.906	0.0945	3.00	2.77	3.25
	S4	617.39	408	1.51	36.62	8	0.040	0.033	0.046	0.941	0.0521	2.64	2.44	2.86
	S5	634.66	416	1.53	53.89	16	0.040	0.034	0.046	0.939	0.0530	2.64	2.45	2.86
	S6	705.82	422	1.67	125.05	22	0.045	0.040	0.051	0.921	0.0643	2.82	2.61	3.06
	S7	695.31	414	1.68	114.54	14	0.046	0.040	0.052	0.921	0.0639	2.84	2.63	3.08
	S8	724.19	430	1.68	143.42	30	0.046	0.040	0.052	0.918	0.0664	2.83	2.62	3.07
	S9	713.66	422	1.69	132.89	22	0.046	0.040	0.052	0.919	0.0661	2.85	2.63	3.09
	S10	789.39	432	1.83	208.62	32	0.050	0.045	0.056	0.900	0.0835	3.02	2.79	3.27
	S11	739.98	436	1.70	159.21	36	0.046	0.041	0.052	0.915	0.0740	2.84	2.62	3.09
	S12	779.08	424	1.84	198.31	24	0.051	0.045	0.056	0.901	0.0832	3.04	2.81	3.29
S13	729.37	428	1.70	148.60	28	0.047	0.041	0.052	0.916	0.0737	2.86	2.64	3.10	
Mathematics	M	623.70	400	1.56			0.041	0.034	0.047	0.960	0.0440			
	S1	629.36	403	1.56	5.66ns	3	0.041	0.035	0.047	0.959	0.0457	2.60	2.41	2.82
	S2	657.33	411	1.60	33.63	11	0.042	0.036	0.048	0.956	0.0443	2.64	2.44	2.86
	S3	995.96	419	2.38	372.26	19	0.064	0.059	0.069	0.896	0.1452	3.59	3.33	3.88
	S4	642.32	408	1.57	18.62	8	0.041	0.035	0.047	0.958	0.0483	2.61	2.42	2.83
	S5	670.32	416	1.61	46.62	16	0.043	0.037	0.048	0.954	0.0498	2.65	2.45	2.87
	S6	783.03	422	1.86	783.03	422	0.050	0.045	0.056	0.935	0.0641	2.94	2.72	3.19
	S7	753.04	414	1.82	753.04	414	0.049	0.044	0.055	0.939	0.0622	2.90	2.69	3.14
	S8	830.07	430	1.93	830.07	430	0.052	0.047	0.058	0.928	0.0677	3.04	2.81	3.29
	S9	800.83	422	1.90	800.83	422	0.052	0.046	0.057	0.932	0.0660	3.00	2.77	3.25
	S10	910.93	432	2.11	910.93	432	0.057	0.052	0.062	0.914	0.0639	3.26	3.02	3.53
	S11	825.82	436	1.89	825.82	436	0.051	0.046	0.057	0.930	0.0693	2.99	2.76	3.24
	S12	880.90	424	2.08	880.90	424	0.056	0.051	0.062	0.918	0.0621	3.22	2.98	3.49
S13	796.36	428	1.86	796.36	428	0.050	0.045	0.056	0.934	0.0677	2.95	2.72	3.19	

CI confidence interval, Low/High lower/higher bounds

^aMod: Model type (M: measurement; S: structural) and number (Figs. 2, 3)

^bStatistically significant ($p < .001$)

^cWith reference to measurement model; statistically different ($0.00 < p < 0.05$) unless denoted as 'ns' (not significant)

intrinsic motivation) were simultaneously included in model estimation.

Predictors of the deep approach to learning

For biology and/or mathematics, all constructs positively predicted the deep approach to learning except for neuroticism, conscientiousness and workload appropriateness. The effect sizes ranged from moderate to large. The strongest predictor of the deep approach to learning was assessment for understanding, followed by intrinsic motivation, clear goals and standards, teaching for conceptual

change and openness. For both study disciplines, assessment for understanding positively and strongly predicted the deep approach to learning. For only mathematics, intrinsic motivation positively and strongly predicted the deep approach to learning, whereas clear goals and standards did so moderately. Similarly, teaching for conceptual change positively and moderately predicted the deep approach to learning for only biology. The deep approach to learning was also positively predicted by openness for both study disciplines, with moderate and weak effect sizes for biology and mathematics, respectively. For both study disciplines, assessment for understanding was the

Fig. 4 Parameters of structural model 1 path estimates of science students reading biology and mathematics. Only significant paths are shown. B: biology and M: mathematics. Format of parameters accompanying drawn paths: 'Standardized regression weights

(Unstandardized regression weights $p \pm SE$ [critical ratio]). Dotted circles represent standardized residuals. Italicized numbers outside endogenous constructs represent explained variance. p values $*p \leq .05$; $**p \leq .01$; $***p \leq .001$

strongest predictor of the deep approach to learning, with large effect sizes.

Predictors of the surface approach to learning

For biology and/or mathematics, the surface approach to learning was predicted significantly by all constructs except teaching for conceptual change and openness. Two comparable and strongest predictors of the surface approach to learning were workload appropriateness and intrinsic motivation, followed, in descending order, by clear goals and standards, neuroticism, assessment for understanding and conscientiousness. Neuroticism positively predicted the surface approach to learning, whereas workload appropriateness and intrinsic motivation, clear goals and standards and assessment for understanding did so negatively.

For both study disciplines, workload appropriateness negatively and strongly predicted the surface approach to learning. Intrinsic motivation negatively and strongly predicted the surface approach to learning for only mathematics. Clear goals and standards negatively and moderately predicted the surface approach to learning but only for biology. Neuroticism positively and moderately predicted the surface approach to learning for only biology, whereas conscientiousness did so negatively and weakly for only

mathematics. As for assessment for understanding, it negatively and weakly predicted the surface approach to learning for only mathematics.

Mediation by SAL

Generally, for biology and/or mathematics, partial mediation by SAL was observed for relationships between current academic achievement with workload appropriateness, assessment for understanding and neuroticism (Fig. 4). For mathematics only, the relationship between current academic achievement with assessment for understanding was partially mediated by both deep and surface approaches to learning, with greater direct than indirect effects (-0.245 vs. 0.091). Also for mathematics only, just the surface approach to learning partially mediated the relationship between current academic achievement and workload appropriateness, with similar direct and indirect effects (0.12 vs. 0.11). For biology only, partial mediation by the surface approach to learning was observed between current academic achievement and neuroticism, with direct effects greater than indirect ones (0.15 vs. -0.08).

For biology and/or mathematics, the relationships of all other constructs with current academic achievement were fully mediated at least by one SAL. For biology only, the

Table 5 Model fit indices for multigroup invariance measurement and structural models of two STEM study disciplines

Invariance model ^a	Mod ^b	χ^2 ^c	df	χ^2 /df	$\Delta\chi^2$ ^d	Δ df	RMSEA			CFI	SRMR	ECVI		
							90% CI					90% CI		
							Low	High				Low	High	
<i>n</i> = 665 (pooled)														
Configural	MM	1204.47	800	1.51			0.028	0.024	0.031	0.956	0.0437	2.59	2.45	2.74
Metric	MM	1218.38	820	1.49	13.90 ns	20	0.027	0.024	0.030	0.956	0.0458	2.55	2.41	2.70
Configural	1	1241.88	824	1.51			0.028	0.024	0.031	0.954	0.050	2.57	2.44	2.72
Metric	1	1440.26	851	1.69	198.38 ^c	27	0.032	0.029	0.035	0.936	0.053	2.79	2.64	2.96

CI confidence interval, *Low/High* lower/higher bounds, *ns* not significant

^aConfigural (baseline); Metric (factor loadings invariant)

^bMM (measurement model); Model 1 (structural model)

^cStatistically significant at $p < .001$

^dWith reference to baseline (configural) model

influence of workload appropriateness on current academic achievement was fully mediated by the surface approach to learning. For both study disciplines, the deep approach to learning did not mediate this relationship. Also for biology, the influence of teaching for conceptual change on current academic achievement was fully mediated by the deep approach to learning. For both study disciplines, the surface approach to learning did not mediate this relationship.

The influence of clear goals and standards on current academic achievement was fully mediated by the deep approach to learning for mathematics, and the surface approach to learning for biology. The relationship between intrinsic motivation and current academic achievement was fully mediated by the deep and surface approaches to learning for mathematics, but not for biology.

Full mediation of the influence of personality by SAL was registered for all three personality constructs depending on the study discipline. The influence of openness was fully mediated by the deep approach to learning for biology and mathematics. The influence of neuroticism and conscientiousness were fully mediated by the surface approach to learning for biology and mathematics, respectively.

Overall, the greater amount of variance explained for all predicted constructs was for mathematics (current academic achievement: 57%; deep: 58%; surface: 49%), followed by biology (current academic achievement 36%; deep: 32%; surface: 33%). (Note: variance explained for constructs are not meant to add up to 100% as they refer to only individual latent constructs and the variance contributed by their respective predictors.)

Multigroup invariance analyses

In order to compare if and how the nature of hypothesized inter-relationships of structural models differed between

study disciplines, multigroup invariance analyses were performed on measurement and structural models (Ho 2006). All measurement models achieved configural and metric measurement invariance (Δ CFI < 0.01, Table 5). This meant that the groups studied were comparable, permitting group comparisons at the structural model level (Hair et al. 2010).

Model fit indices indicated that multigroup invariance structural models were found to be group variant for academic study discipline (Table 5), implying that the nature of hypothesized paths differed between study disciplines. The critical ratios of pairwise comparisons of path coefficients between both study disciplines were examined, with only significant (> 1.96) ones reported: prior (high school) to current academic achievement, conscientiousness to the surface approach to learning, intrinsic motivation to both deep and surface approaches to learning, and neuroticism to the surface approach to learning. Of the aforesaid paths, all but the path between prior (high school) to current academic achievement were significant for either biology (surface approach to learning $\leftarrow$ neuroticism) or mathematics (all other remaining paths).

Discussion

Competing models

Of the variety of conceptual models on the relationships among current and prior academic achievement, SAL, personality, intrinsic motivation and CE, most have largely been either untested or without full empirical support, owing to the potentially large number of variables involved. Of the four reviewed empirical studies on three of the four domains using path analysis or SEM, none have adopted a rigorous

competing models strategy to test various conceptualizations of such relationships (Diseth 2013; Karagiannopoulou and Milienos 2015; Nijhuis et al. 2007; Trigwell et al. 2013). Besides, none have presented a measurement model to compare against a structural model to validate the latter (Hair et al. 2010).

This study was unique among previous ones in that it presented statistical tests of 13 competing structural models which represented mostly untested conceptualizations of the possible inter-relationships among SAL, motivation and CE simultaneously, and variations thereof. The strongest test of a model is performed by comparing different, yet, plausible models of hypothesized structural relationships. This is closely akin to testing competing theories, which is stronger than testing an isolated model on its own (Hair et al. 2010). For both STEM study disciplines, the comparison of fit indices among structural models and between structural and measurement models revealed that only models 1, 2, 4 and 5 were acceptable and had the best fit and greatest parsimony. Thus, these findings supported the hypothesis that personality, intrinsic motivation and course experience (CE) directly predicted SAL, all of which, together with prior academic performance (high school grades), directly (models 1 and 4) and indirectly (models 2 and 5) predicted current academic achievement (Table 4). In particular, these results empirically supported conceptualized inter-relationships among current academic achievement, SAL and one or more domains, such as (i) personality (Price 2004), (ii) the teaching–learning environment (synonymous with CE) alone (Trigwell et al. 1999), (iii) CE with personality (Serife 2008), and (iv) motivation and all preceding domains (Biggs 1993; Biggs et al. 2001; Entwistle 1998, 2005; Prosser and Trigwell 1999).

Models 3 and 6 to 13 did not show adequate structural model fit against the measurement model, and, thus, the conceptualizations which they represented could not be supported empirically. In general, such unsupported structural models could be divided into two categories: those that (1) omitted SAL as a mediator between personality and intrinsic motivation with current academic achievement; and (2) hypothesized any form of CE-mediated relationships between personality and/or intrinsic motivation with SAL and/or current academic achievement. Unsuccessful models 8, 9 (Entwistle 1998; Biggs 1999) and 11 and 13 (Baeten et al. 2012) reflected a position shared by some researchers that student characteristics, such as personality and motivation, influenced student perception of CE. Therefore, this study did not support the positions that CE mediated the relationships of personality and/or intrinsic motivation with SAL and/or current academic achievement as conceptualized by these researchers.

A few studies were comparable in terms of selection of constructs. One such work by Diseth et al. (2010)

concurred with the findings of this study, namely that there was no support for structural models of the first category, namely those which omitted SAL as a mediator between personality and intrinsic motivation with current academic achievement (model 3) compared to one which allowed SAL-mediation of CE (models 1, 2, 4 and 5). Another study by Diseth (2013) reported acceptable fit indices for a model similar to model 8, which belonged to the second category of unsupported models in this study, namely those which hypothesized any form of CE-mediated relationships with SAL and current academic achievement. However, the statistical methods used in that study were less rigorous, having a small sample size ($n=70$) potentially compromising reliability of estimates, and did not compare among alternative structural models and against a measurement model.

While four models showed adequate fit and were found to be statistically equivalent, model 1 yielded more favourable indices for comparing across models (Hair et al. 2010). Therefore, while statistically equivalent, model 1 demonstrated superior fit judging by cross-model comparisons of the aforesaid indices. It contained all important direct and indirect paths nested in the other models and yielded very similar path coefficients.

Inter-relationships

This section discusses significant paths for direct and indirect (SAL-mediated) relationships common to both study disciplines followed by those unique to any one study discipline.

Predictors of current academic achievement common to both study disciplines

For both study disciplines, prior academic achievement was the strongest predictor of current academic achievement, in agreement with previous studies which reported that prior academic achievement predicted current academic achievement more strongly (large effect sizes) than did either SAL (weak, moderate and large effect sizes; Diseth 2007a; Diseth et al. 2010) or personality (weak effect size; Swanberg and Martinsen 2010).

In this study, as far as SAL was concerned, only the surface approach to learning significantly predicted current academic achievement in both study disciplines. This concurred with most studies which have reported a consistently significant and negative influence of the surface approach to learning on academic performance, with weak to strong effect sizes (Diseth 2007b; Diseth et al. 2010; Karagiannopoulou and Milienos 2015; Swanberg and Martinsen 2010; Trigwell et al. 2013).

SAL-mediation of relationships with current academic achievement common to both study disciplines

In this study, the influence of openness on current academic achievement was fully mediated by the deep approach to learning for biology and mathematics, corroborating the findings of other studies (Diseth 2003; Swanberg and Martinsen 2010). While conscientiousness was reportedly mediated by the surface approach to learning in those studies, this was not the case for this study.

Predictors of SAL common to both study disciplines

Since SAL emerged as the second strongest predictor of current academic achievement, due attention must be accorded to factors which influence SAL. Generally, the significant predictors of the deep approach to learning in this study were also reported in previous comparable studies. In this study, assessment for understanding most strongly and positively predicted the deep approach to learning for both study disciplines in agreement with the findings reported by another study (Karagiannopoulou and Milienos 2015). This study also showed that, for both study disciplines, the surface approach to learning was predicted positively by workload appropriateness, in agreement with previous reports (Nijhuis et al. 2007; Trigwell et al. 2013).

Predictors of current academic achievement unique to any one study discipline

In this study, the deep approach to learning significantly predicted current academic achievement in only biology, concurring with other studies on psychology (Diseth 2003) and secondary school students of undefined disciplines (Chan et al. 2012). The findings of this study were similar to Diseth's (2003) findings in that the deep approach to learning predicted current academic achievement in only one of two courses studied, namely for psychology but not philosophy (Diseth 2003). In Diseth's (2003) study, the difference was attributed to student motivation. However, motivation was not measured in Diseth (2003). Instead, it was surmised that, in a study discipline for which interest and study motivation was lacking, only students who studied with understanding would be rewarded for their intrinsic motivation. While intrinsic motivation was measured in the current study and found to be lower in biology than mathematics, it neither predicted current academic achievement nor the deep approach to learning for biology.

In this study, CE directly predicted current academic achievement for only mathematics (i.e. workload appropriateness and teaching for conceptual change), whereas these were indirect for biology. In a study by Diseth (2007b), a construct similar to workload appropriateness positively

predicted current academic achievement, with a strong effect size larger than that of SAL. The absence of a significant and direct prediction between CE and current academic achievement for biology concurred with findings from some previous studies, in which the effects of course experience on current academic achievement were indirect, being mediated by student approaches to learning in non-STEM study disciplines such as psychology (Diseth et al. 2006, 2010; Diseth 2007a; Karagiannopoulou and Milienos 2015). Studies on constructs similar to teaching approach have mainly been confined to its relationship with SAL instead of current academic achievement (Beausaert et al. 2013; Teoh et al. 2014; Trigwell et al. 1999), and were, thus, not comparable with the findings of this study. Nevertheless, this study showed that teaching for conceptual change predicted current academic achievement, albeit weakly, and for mathematics only.

In this study, only one personality construct (i.e. neuroticism) predicted current academic achievement and that only for biology, despite the reduced interpersonal differences between both samples due to common students. The effect size was smaller than those of SAL. These results were in agreement with findings from previous studies which have reported either an equivalent (Swanberg and Martinsen 2010) or a lower influence of personality compared to SAL on academic performance (Diseth 2003). These results indicated that other factors in the teaching–learning ecosystem (e.g. CE and intrinsic motivation) may play a more defining role on shaping SAL than simply personality.

SAL-mediation of relationships with current academic achievement unique to any one study discipline

Full SAL-mediation of the relationship between intrinsic motivation and current academic achievement as seen in this study (for mathematics only) has also been reported previously. Like this study, SAL-mediation was full in one study (Chan et al. 2012) but partial in another (Trigwell et al. 2013). Nevertheless, the latter study showed that SAL was a stronger predictor of current academic achievement than intrinsic motivation. As for the relationship between neuroticism and current academic achievement, this was mediated by the surface approach to learning as seen for biology, corroborating findings reported in previous studies (Diseth 2003; Swanberg and Martinsen 2010).

Predictors of SAL unique to any one study discipline

For only mathematics, this study's findings corroborated the results from past studies, in that the deep learning approach was predicted positively by intrinsic motivation (Trigwell et al. 2013) and clear goals and standards (Nijhuis et al. 2007). In this study, teaching for conceptual change positively predicted the deep approach to learning for only

biology but not mathematics, concurring with most experimental studies which indicated that student-centred learning (synonymous with ‘teaching for conceptual change’) did not always increase the use of the deep learning approach (Baeten et al. 2010, 2013; Loyens et al. 2013; Reid et al. 2012).

This study showed that, for any one study discipline only, the surface approach to learning was predicted positively by intrinsic motivation, clear goals and standards, assessment for understanding and conscientiousness, but negatively by neuroticism. These findings concurred with those reported previously, with particular differences in terms of the relative strengths of effect sizes among constructs (Trigwell et al. 2013; Nijhuis et al. 2007). In one study with a conceptually similar assessment construct to assessment for understanding, it moderately and negatively predicted the surface approach to learning (Karagiannopoulou and Milienos 2015).

Differences between study disciplines

Differences between both study disciplines were observed from both the variance accounted and significant differences between path coefficients. More variance in current academic achievement and SAL was accounted for by mathematics than biology. Across both study disciplines, the variance explained for current academic achievement and SAL was relatively large (32–58%) compared to those reported by previous studies. The variance explained in this study for current academic achievement well exceeded those of comparable studies but were almost similar in the variance explained for SAL (Diseth 2013; Trigwell et al. 2013; Nijhuis et al. 2007). The lower variance accounted for in biology indicated that other constructs which were not measured deserve attention in future studies. For instance, teacher-centred teaching, type of assessment and assignment have been found to influence SAL (Baeten et al. 2010).

This study also confirmed expectations of nuanced differences between study disciplines in terms of hypothesized significant paths among constructs (Entwistle 2005). Critical ratios of pairwise comparisons of path coefficients revealed that significant differences in path estimates were mainly attributable to certain paths found significant in one study discipline only but not the other. In a previous study on two study disciplines, namely mathematics and chemistry, sharing 80% common students, such differences were also observed (Davidson et al. 2014b). While metric measurement invariance was achieved indicating no test bias for or against a certain study discipline for the instruments employed, future studies could consider measures more specific to the context and nature of each study discipline, as context is conceptualized to govern such inter-relationships (Entwistle 2005; Schumacker and Lomax 2004).

Conceptualized qualitative differences among study disciplines also warrant further study to ascertain to what extent certain constructs consistently exhibit a significant influence on endogenous constructs across different disciplines. Academic disciplines have been categorized as soft versus hard (i.e. no consensus on knowledge and methods versus a consensus), pure versus applied (favours creating over applying knowledge) and life versus non-life (deals with living systems versus inanimate objects) (Laird and Garver 2008). According to such a classification, both biology and mathematics fall within the same classification of ‘hard’ and ‘pure’. Yet, a distinction remains between them, with the former categorized additionally as ‘Pure-Life’ and the latter as ‘Pure-non-life’.

Practical implications

Common predictors of current academic achievement found in both STEM study disciplines, namely prior academic achievement and the surface approach to learning, highlight their importance over others which were found in any one study discipline only. As prior academic achievement most strongly predicted current academic achievement, an institution which attracts high achievers (e.g. via scholarships and bursaries) is likely to achieve better academic results. However, influencing factors which influence the surface approach to learning, which directly predicts current academic achievement, may lie more within educators’ control. As such, educators need to pay heed to the influence of factors fostering it, namely workload appropriateness, which was found to consistently predict the surface approach to learning in both study disciplines. Thus, workload across study disciplines must be regulated such that they do not overwhelm students.

The collective variance explained for both SAL exceeded that of current academic achievement, making the consideration of factors which influence SAL deserving of attention, as both directly predicted current academic achievement. Accompanying recommendations that might help in the promotion of the deep approach to learning and decrease the surface approach to learning are

- intrinsic motivation—fostering interest in a course, emphasizing relevance of course to future course and vocation;
- clear goals and standards—clarifying course aims and demands;
- teaching for conceptual change—should foster understanding instead of rote memorization;
- assessment for understanding—designed so as to demand and measure understanding versus factual rote memorization;

- openness and conscientiousness—modelling and rewarding desirable characteristics of such behaviour (e.g. curiosity, efficiency); and
- neuroticism—directing students towards productive strategies (e.g. structured self-study schedule) versus worrying alone.

Limitations and future research

This study was limited to the conceptualization of unidirectional (i.e. recursive) relationships among constructs, mainly Malaysian ethnic minority students (Chinese and Indian diaspora) in Southeast Asia and selected constructs of student- and teaching–learning-related domains. The unaccounted variance for all predicted constructs (~40–70%) suggested that there remains other predictors that need to be considered. While there were significant structural path differences between both study disciplines, it cannot be concluded that these were primarily due to the nature of each discipline, as there was a high proportion of students common to both study disciplines. Other samples are required to validate these differences. Nevertheless, this study showed that, in the presence of reduced interpersonal differences, such differences were detected. Therefore, further research is warranted to confirm the pattern of structural relationships by including (1) alternative conceptual models which hypothesize either bi-directional or alternative inter-relationships among such constructs, and (2) across a wider selection of constructs or domains, STEM study disciplines (i.e. independent samples with no common respondents), ethnic majority (e.g. native or *bumiputera*) of

Malaysian pre-university students, Chinese and Indian or their diaspora in other geographical regions.

Conclusion

This study has tested conceptual models of the relationships in the teaching–learning ecosystem using SEM analyses of latent constructs. Of four equivalent structural models, for both study disciplines, model 1 had relatively more favourable indices and represented the conceptualization that high school grades and SAL could directly predict current academic achievement, and so, too, could personality, intrinsic motivation and CE also, both directly and indirectly. Prior academic achievement was the strongest predictor of current academic achievement, followed by SAL and jointly so by personality and perceived course experience (CE) constructs. These findings point educators towards factors within their control which determine academic performance and increase the deep but lower surface approaches to learning, of which the most influential are, depending on course and context, assessment for understanding, workload appropriateness and intrinsic motivation. This would include attempts to increase assessment for understanding and reduce workload and fostering intrinsic motivation.

Appendix

See Table 6.

Table 6 Sample of existing and adapted items measuring constructs (Davidson et al. 2014a)

Construct	Sample item ^a
Deep approach	...I tried to relate ideas I came across to those in other topics or other Units whenever possible
Surface approach	...I didn't think through topics for myself, I just relied on what we're taught
Neuroticism	...can be tense
Openness	...is curious about many different things
Conscientiousness	...is a reliable worker
Intrinsic motivation	This Unit is not what I would have chosen but it's compulsory I took this Unit because I had no other choice. ^{A, ®}
Workload appropriateness	The workload was too heavy. [®] The amount of work given was too much to handle. ^{A, ®}
Assessment for understanding	I was tested more on what I had understood than what I had memorized The tests given tested my understanding more than my ability to memorize. ^A
Clear goals and standards	It was clear to me what was expected in the work for this course unit
Teaching for conceptual change	...my lecturer encouraged us to think for ourselves and showed us how he/she thought ...encouraged us to come up with our own opinions or answers instead of just giving us their own opinions and answers. ^A

^aAll original items unless otherwise indicated 'A'—adapted; ®—reverse-scored

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