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Motivation, learning strategies, participation and medical school performance

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CONTEXT Medical schools wish to better understand why some students excel academically and others have difficulty in passing medical courses. Components of self-regulated learning (SRL), such as motivational beliefs and learning strategies, as well as participation in scheduled learning activities, have been found to relate to student performance. Although participation may be a form of SRL, little is known about the relationships among motivational beliefs, learning strategies, participation and medical school performance.

OBJECTIVES This study aimed to test and cross-validate a hypothesised model of relationships among motivational beliefs (value and self-efficacy), learning strategies (deep learning and resource management), participation (lecture attendance, skills training attendance and completion of optional study assignments) and Year 1 performance at medical school.

METHODS Year 1 medical students in the cohorts of 2008 (n = 303) and 2009 (n = 369) completed a questionnaire on motivational beliefs and learning strategies (sourced from the Motivated Strategies for Learning Questionnaire) and participation. Year 1 performance was operationalised as students' average Year 1 course examination grades. Structural equation modelling was used to analyse the data.

RESULTS Participation and self-efficacy beliefs were positively associated with Year 1 performance (β = 0.78 and β = 0.19, respectively). Deep learning strategies were negatively associated with Year 1 performance (β = − 0.31), but positively related to resource management strategies (β = 0.77), which, in turn, were positively related to participation (β = 0.79). Value beliefs were positively related to deep learning strategies only (β = 0.71). The overall structural model for the 2008 cohort accounted for 47% of the variance in Year 1 grade point average and was cross-validated in the 2009 cohort.

CONCLUSIONS This study suggests that participation mediates the relationships between motivation and learning strategies, and medical school performance. However, participation and self-efficacy beliefs also made unique contributions towards performance. Encouraging participation and strengthening self-efficacy may help to enhance medical student performance.

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INTRODUCTION

Medical schools wish to better understand why some students excel academically and others have difficulty in passing medical courses. Such an understanding may provide clues with which struggling students can be identified at an early stage and offered timely and specific support, and may also offer medical schools insight into how they might positively influence overall student performance.[1–3] Several researchers have used self-regulated learning (SRL) theory to understand successful learning. Most of these authors have used self-report measures and have found that different components of SRL, such as appropriate motivational beliefs and learning strategies, are positively related to academic performance.[4–7] Others have focused on student participation in scheduled learning activities to explain differences in performance. Student participation, such as in lecture attendance, has been found to be predictive of academic performance.[8,9] Although student participation may be considered part of SRL, the relationships between commonly measured components of SRL and participation, and their joint contribution to predicting medical school performance have not been thoroughly investigated. Participation may mediate the relationships between motivational beliefs and learning strategies, and medical school performance, but these factors may also make unique contributions to performance.[8] Further insight into these relationships would benefit medical schools that seek to enhance their students' performance. Therefore, this prospective study examined the relationships between early measures of motivational beliefs, learning strategies and participation, and performance at medical school.

Self-regulated learning has been defined as learning that occurs when one is 'metacognitively, motivationally, and behaviourally proactive in the learning process'.[10] Thus, self-regulated learners: (i) monitor their own progress towards self-set goals and are therefore able to reflect on the effectiveness of their learning approaches; (ii) tend to view the learning task as intrinsically interesting and worthwhile, and have high levels of self-efficacy, and (iii) engage in and persist with learning behaviours that maximise the degree to which learning occurs.[10,11] One instrument developed to assess SRL as a metacognitive, motivational and behavioural construct is the Motivated Strategies for Learning Questionnaire (MSLQ).[11] The MSLQ has two major sections: Motivation, and Learning Strategies. The Motivation section consists of scales that involve expectancy, value and affect. The Learning Strategies section is further divided into a cognitive–metacognitive section and a resource management section. The motivation, cognitive–metacognitive and resource management sections correspond, respectively, to the three components in the definition of SRL.[10]

In the general education literature, several relationships among the three components of SRL and academic performance have been described. Firstly, the use of deep (cognitive) learning strategies, such as elaboration and organisation, and metacognitive self-regulatory activities, such as planning and monitoring, are related to better academic performance.[12,13] Secondly, higher levels of intrinsic goals for learning, self-efficacy and task value tend to lead to more deep-processing strategies and metacognitive regulation and, consequently, to improved performance.[14–17] Finally, high levels of resource management, using strategies such as effort regulation and time and study environment management, are also related to better academic performance.[11,18] Although it has been suggested that the effect of motivations on academic performance may be mediated by learning strategies,[4,12] studies that incorporated motivations, learning strategies and performance, and tested their inter-relationships, are scarce.[19] In addition, the few studies examining the effects of the different components of SRL on medical student performance showed conflicting results; associations of motivational beliefs, deep learning and resource management with medical school performance were found to be positive, small or even non-present.[20–24]

A specific type of study behaviour is participation in scheduled learning activities. In a recent review, Credé *et al.*[8] showed that physical presence at lectures or other modes of instruction was a better predictor of academic performance than any other known predictor, including pre-admission grade point average (GPA), study skills and number of hours spent studying. However, in modern medical curricula, participation involves more than just attending lectures. Participation in small-group work (such as tutorials or skills training) and efficient use of individual study time are also crucial to medical school success.[25] A recent study among nursing students showed that homework completion was a stronger predictor of success than lecture attendance.[9] However, participation in scheduled learning activities appears to be influenced by medical students' personal learning preferences and learning needs at particular times.[26,27]

Aim and hypotheses

In this study we examined how motivational beliefs (value and self-efficacy), learning strategies (deep learning and resource management) and participation relate to Year 1 performance in medical school. On the basis of the reviewed literature, we hypothesised several positive relationships between these variables (Fig. 1). Our aim was to test the hypothesised relationships and to cross-validate our findings with a new, independent sample.

METHODS

Context

This study was performed at Erasmus MC Medical School, Rotterdam, the Netherlands. The integrated and theme-oriented curriculum at this school comprises a 3-year bachelor degree course followed by a 3-year masters degree course. The first year of the Bachelor of Medicine is divided into three thematic blocks of 11–16 weeks, which are organised around pathophysiological systems and cover subjects, starting from the basic sciences, up to and including clinical practice. Each study week covers one topic, such as heart failure, which is dealt with in various learning activities, including large-group learning (lectures and patient demonstrations; 8 hours), small-group learning (skills training and tutorials; 8 hours) and both guided (study assignments; 16 hours) and unguided (8 hours) individual study. Large-group sessions and guided study assignments are undertaken on a voluntary basis; for about a quarter of the small-group sessions student participation is compulsory. The first year includes nine written examinations, consisting of open-ended and multiple-choice questions.

Participants and procedure

The participants in this study were Year 1 students entering in 2008 (n = 408) and 2009 (n = 409). Two months after enrolment, students were invited to return an online questionnaire on SRL and participation, which took 15–20 minutes to complete. Upon completion, participants received automatically generated feedback on the strengths and weaknesses of their study approach, along with tips for improvement. The students were informed about the study, in which participation was voluntary and anonymity was guaranteed. No plausible harm to participants could arise from the study. According to Dutch law, this study was exempt from ethical approval requirements.

Instrument

To measure the three components of SRL, we used parts of a validated Dutch version of the MSLQ.[28,29] Some minor changes to the wording of the items

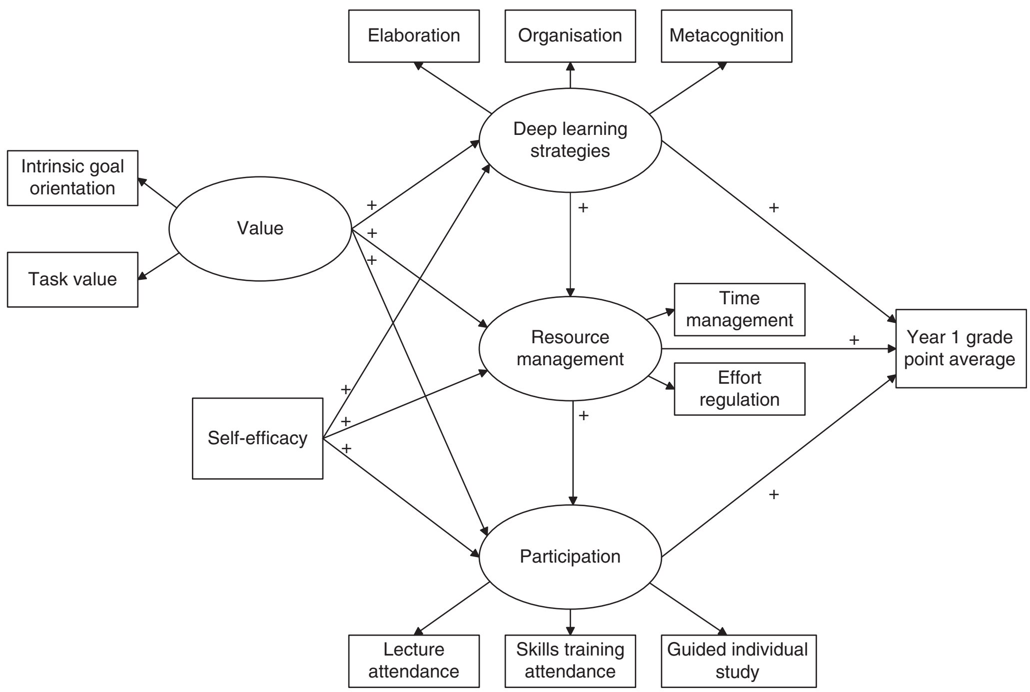

Figure 1 Hypothesised model of Year 1 performance

Motivational beliefs

'In a course like this, I prefer course material that arouses my curiosity, even if it is difficult to learn' (Intrinsic goal orientation)

'Understanding the subject matter of this course is very important to me.' (Task value)

'I expect to do well in this course.' (Academic self-efficacy)

Deep learning strategies

'When I study for this course, I pull together information from different sources, such as lectures, readings and discussions' (Elaboration)

'When I study the readings for this course, I outline the material to help me organize my thoughts' (Organisation)

'I ask myself questions to make sure I understand the material I have been studying for this course' (Metacognitive self-regulation)

Resource management

'I make sure I keep up with the weekly readings and assignments for this course' (Time and study environment management)

'I work hard to do well on this course even if I don't like what we are doing' (Effort regulation)

Figure 2 Example items from the subscales selected from the Motivated Strategies for Learning Questionnaire

were made to make them more suitable for our medical school context. The MSLQ consists of 81 items divided into six motivation subscales and nine learning strategies subscales. Items are scored on a 7-point Likert scale (1 = not at all true of me, 7 = very true of me). As the MSLQ subscales are designed to be modular, they can be used to fit the needs of a particular study.[12] The present study used eight subscales of the MSLQ, comprising 49 items.

To measure students' motivational beliefs, we used three motivation subscales: Intrinsic Goal Orientation; Task Value, and Academic Self-Efficacy. Deep learning strategies were measured using three subscales on cognitive and metacognitive strategies: Elaboration; Organisation, and Metacognitive Self-Regulation. To measure the extent to which students manage their resources, we used two resource management subscales: Time and Study Environment, and Effort Regulation. Figure 2 shows example items from the selected subscales.

Three items were added to the questionnaire to measure participation. Students were asked to rate their lecture attendance, skills training attendance and completion of individual study assignments using a 5-point scale.

Outcome measure: Year 1 performance

Year 1 performance was calculated as the mean of the grades obtained on the nine course examinations. We considered only grades obtained at the first attempt. Grades were given on a 10-point scale (1 = poor, 10 = excellent) and 5.5 was the cut-off pass/fail mark. Student grades were retrieved from the university student administration system.

Statistical analysis

Prior to statistical analyses, datasets were screened for accuracy of data entry and missing values, and study variables were checked for normality. Next, the subscales of the MSLQ were subjected to reliability analysis, and descriptive statistics and Pearson correlations were calculated for the study variables. We used *t*-tests to identify differences in variable scores between the cohorts of 2008 and 2009. Data were then subjected to structural equation modelling (SEM), using AMOS 18.0 (SPSS, Inc., Chicago, IL, USA).[30] Structural equation modelling is a statistical tool that builds on techniques such as correlation, regression, factor analysis and analysis of variance (for an explanation of SEM, see Violato and Hecker[31]). We used SEM to test the significance of the hypothesised relationships among variables and the fit of the overall model. The final model derived for the 2008 cohort was cross-validated using data from the 2009 cohort.

A two-stage approach, as recommended by Anderson and Gerbing,[32] was used to test the hypothesised model. The first stage involved testing the validity of the measurement model. To this end, two separate confirmatory factor analyses (CFAs) were conducted; one of these applied to the three latent factors measured by the MSLQ (Value, Deep Learning, Resource Management), and one applied to the latent factor Participation (Fig. 1). Self-efficacy beliefs were not hypothesised to load on a latent variable and therefore were not included in the CFAs.

The second stage involved testing the full structural model depicted in Fig. 1.

Maximum likelihood estimations were used to estimate the model's parameters and a chi-squared test was conducted to assess model fit. Although, in general, a non-significant chi-squared result indicates a good model fit, the chi-squared test is influenced by the sample size and the magnitudes of correlations between variables. Therefore, several additional fit indices were considered, including: the chi-squared statistic divided by the degrees of freedom (CMIN/d.f.); the comparative fit index (CFI), and the root mean square error of approximation (RMSEA). A well-fitting model should have a CMIN/d.f. of < 3.0,[33] a CFI of ≥ 0.95 and an RMSEA of ≤ 0.06.[34]

To improve model fit, we first added paths one at a time based on the modification indices, and then dropped paths one at a time based on Wald tests of the significance of the structural coefficients (at an α-level of 0.05). Theory was taken into account in both the adding and dropping of paths.[31,35] To compare non-nested models, we used the expected cross-validation index (ECVI). The model with the smallest ECVI value is considered best.[35]

A risk of adding and dropping paths (i.e. post hoc model fitting) is that model modification may be driven by characteristics of the particular sample on which the model was tested.[35] One approach to addressing this risk for over-fitting involves employing a cross-validation strategy whereby the final model derived from the post hoc analyses is tested on a second independent sample from the same population. In this study, the 2008 cohort served as the calibration sample and the 2009 cohort as the validation sample; the final model for the 2008 cohort was tested on the 2009 cohort. We tested across the two cohorts for invariance related to the measurement and structural model. Both the chi-squared difference and CFI difference were used to determine whether the parameters tested (i.e. factor loadings and structural paths) were operating equivalently across the groups. The chi-squared difference should be non-significant and the CFI difference should be < 0.01.[35]

RESULTS

Respondents

In 2008, 303 students (74%), of whom 97 (32%) were male, completed the questionnaire. Their mean ± standard deviation (SD) age at the start of medical school was 19.3 ± 1.49 years. In 2009, 369 students (90%), of whom 135 (37%) were male, completed the questionnaire. Their mean ± SD age at the start of medical school was 19.4 ± 1.59 years. These gender and age distributions were representative of those of the total student cohorts for 2008 and 2009 and differences between the two cohorts were not statistically significant. Furthermore, pre-university GPA did not differ between the two cohorts. All respondents completed all items on the questionnaire.

Descriptive statistics and Pearson correlations

The reliabilities of the subscales from the MSLQ ranged from 0.62 to 0.88 (Cronbach's α; Table 1). Table 1 also presents the descriptive statistics for the study variables and their correlations. All study variables were positively related to one another; only Organisation was not related to Year 1 performance.

Confirmatory factor analyses

For the first CFA, the MSLQ subscales for Intrinsic Goal Orientation and Task Value were hypothesised to load on the latent variable Value Beliefs. The subscales for Elaboration, Metacognitive Self-Regulation and Organisation were hypothesised to load on the latent variable Deep Learning, and the subscales for Time Management and Effort Regulation were hypothesised to load on the latent variable Resource Management (Fig. 1). This proposed measurement model showed a good fit with the data ($\chi^2[11, n = 303] = 22.15$, p = 0.02; CMIN/d.f. = 2.01, CFI = 0.99, RMSEA = 0.058). For the second CFA, the three items Lecture Attendance, Skills Training Attendance and Guided Study Assignments were hypothesised to load on the latent factor Participation. This model also showed a good fit with the data ($\chi^2[1, n = 303] = 1.145$, p = 0.29; CMIN/d.f. = 1.15, CFI = 0.99, RMSEA = 0.022).

Evaluating the structural model

The hypothetical model for Year 1 performance, as displayed in Fig. 1, was tested with SEM. This model did not fit the data well and could not be accepted ($\chi^2[45, n = 303] = 146.56$, p = 0.00; CMIN/d.f. = 3.26, CFI = 0.93, RMSEA = 0.086). Modification indices suggested that an error covariance should be added between Lecture Attendance and Skills Training Attendance and a link should be included between Self-Efficacy and Year 1 GPA. Both suggestions were incorporated because they were considered substantively meaningful. This

Table 1 Descriptives, Cronbach's α-values and Pearson correlations for the study variables (2008 cohort, n *= 303)*

Variable	Mean	SD	Median	α	Items, *n*	1	2	3	4	5	6	7	8	9	10	11	12
Motivational beliefs																	
1 Intrinsic goal orientation	5.67	0.79	5.75	0.62	4	–	0.63*	0.51*	0.52*	0.31*	0.38*	0.34*	0.36*	0.23*	0.21*	0.19*	0.22*
2 Task value	5.73	0.78	5.83	0.84	6		–	0.49*	0.46*	0.32*	0.38*	0.36*	0.43*	0.26*	0.20*	0.23*	0.21*
3 Self-efficacy	4.77	0.89	4.75	0.88	8			–	0.44*	0.18*	0.39*	0.35*	0.27*	$0.13^{\dagger}$	$0.15^{\dagger}$	$0.14^{\dagger}$	0.25*
Cognitive strategies																	
4 Elaboration	4.88	0.94	5.00	0.75	6				–	0.60*	0.61*	0.57*	0.51*	0.25*	0.31*	0.27*	0.21*
5 Organisation	4.66	1.17	4.75	0.71	4					–	0.52*	0.49*	0.45*	0.25*	0.28*	0.19*	0.10
6 Metacognition	4.05	0.91	4.00	0.78	9						–	0.48*	0.44*	0.21*	0.24*	0.17*	0.18*
Resource management																	
7 Time management	4.64	1.09	4.80	0.82	8							–	0.69*	0.27*	0.53*	0.29*	0.32*
8 Effort regulation	4.93	1.12	5.00	0.76	4								–	0.31*	0.50*	0.35*	0.38*
Participation																	
9 Lecture attendance	4.69	0.66	5.00	–	1									–	0.30*	0.56*	0.34*
10 Study assignments	4.14	1.08	5.00	–	1										–	0.31*	0.45*
11 Skills training attendance	4.53	0.76	5.00	–	1											–	0.38*
Year 1 performance																	
12 Year 1 GPA	6.00	1.01	–	–	–												–

* $p < 0.01$; † $p < 0.05$
SD = standard deviation; GPA = grade point average

resulted in a model with a good fit ($\chi^2[43, n = 303] = 79.89$, $p = 0.001$; CMIN/d.f. = 1.86, CFI = 0.97, RMSEA = 0.053, ECVI = 0.496). One-at-a-time deletion of the non-significant relationships in this model resulted in a final model that included only significant relationships (Fig. 3). This model also represented a good fit with the data ($\chi^2[49, n = 303] = 87.70$, $p < 0.001$; CMIN/d.f. = 1.79, CFI = 0.97, RMSEA = 0.051). The smaller ECVI value of 0.482 signals that this final, and most parsimonious, model represents the best fit to the data.

Value Beliefs was positively related to Deep Learning, but did not have a statistically significant association with Resource Management or Participation (Fig. 3). Self-Efficacy had a positive direct relationship with Year 1 Performance. Deep Learning was positively associated with Resource Management, but negatively associated with Year 1 Performance. Resource Management was positively related to Participation, but did not have a direct association with Year 1 Performance. Participation was positively associated with Year 1 Performance.

The resulting model explained 50% of the variance in Deep Learning, 59% of the variance in Resource Management, 63% of the variance in Participation and 47% of the variance in Year 1 Performance.

Cross-validation of the model

The stability of the final model was tested in a new, independent sample, the 2009 cohort. Initially conducted *t*-tests revealed only one statistically significant difference between the 2008 and 2009 cohorts: Intrinsic Motivation was slightly higher for the 2009 cohort than for the 2008 cohort ($t[597.6] = -2.08$, $p < 0.05$; mean difference = 0.12, effect size = 0.17).

Table 2 Goodness-of-fit statistics for tests of measurement and structural invariance across the 2008 and 2009 cohorts

Model description	Comparative model	χ^2	d.f.	CMIN/d.f.*	$\Delta\chi^2$	Δd.f.	p-value†	CFI‡	ΔCFI§	RMSEA¶
1 Configural model; no equality constraints imposed	–	254.30	98	2.60	–	–		0.947	–	0.049
2 Measurement model, all factor loadings constrained equal	2 versus 1	263.63	103	2.56	9.32	5	NS	0.945	0.002	0.048
3 Structural model, all factor loadings and structural paths constrained equal	3 versus 1	271.44	109	2.49	17.14	11	NS	0.945	0.002	0.047

* CMIN/d.f. = chi-squared statistic divided by degrees of freedom, which is required to be < 3.0 to indicate a reasonable fit of a hypothetical model

† $\Delta\chi^2$ should be non-significant

‡ CFI: the comparative fit index compares the fit of the particular model under test with a model in which none of the variables are related. A CFI of ≥ 0.95 indicates that the tested model fits the data well

§ ΔCFI should be < 0.01

¶ RMSEA: the root mean square error of approximation represents the root square of the chi-squared statistic divided by the number of degrees of freedom. This value is required to be < 0.06 to be considered acceptable

The configural model, in which no equality constraints are imposed, showed good fit ($\chi^2[98, n = 303] = 254.30$, p = 0.00; CMIN/d.f. = 2.60, CFI = 0.95, RMSEA = 0.049). Testing for measurement and structural invariance indicated that the factor loadings (models 2 and 3) and structural paths (model 3) were the same across the 2008 and 2009 cohorts (Table 2).

DISCUSSION

This study showed that participation and self-efficacy beliefs were positively associated with Year 1 performance. Deep learning strategies were negatively associated with Year 1 performance, but positively related to resource management strategies. Resource management strategies were positively related to participation. Value beliefs were positively related to deep learning strategies only.

One of the most striking outcomes is the finding that, despite a positive indirect relationship, the use of *deep learning strategies* had a negative direct relationship with Year 1 performance. This result suggests that the use of deep learning strategies may lead to academic success, but only if it is combined with good resource management and participation. This finding may explain why in previous studies the association of deep learning with medical school grades was found to be weaker than expected[36] or even absent.[37] The importance of resource management strategies – time management and effort regulation – over the use of deep learning strategies in the explanation of academic performance has also been reported by others.[4,24] An alternative explanation may be that characteristics of the learning environment, such as the examination methods used, influence the degree to which the deep learning strategies affect performance.[4,36] For example, Year 1 examinations, which are mainly machine-marked, may (despite efforts to prevent this) reward the use of memorisation rather than the use of deep learning.

The hypothesis that *resource management* would have a direct positive association with Year 1 performance was also not confirmed, despite the strong correlations found between effort regulation and time management and Year 1 performance. Our findings suggest that the positive effect of effort regulation and time management on medical school performance is mediated by participation. Thus, only if a student's resource management strategies stimulate the student to participate in the variety of learning activities offered will these strategies positively influence the student's grades.

In line with the results of earlier studies among medical and nursing students,[9,38] *participation* was found to be strongly related to Year 1 performance, confirming our hypothesis. There may be several

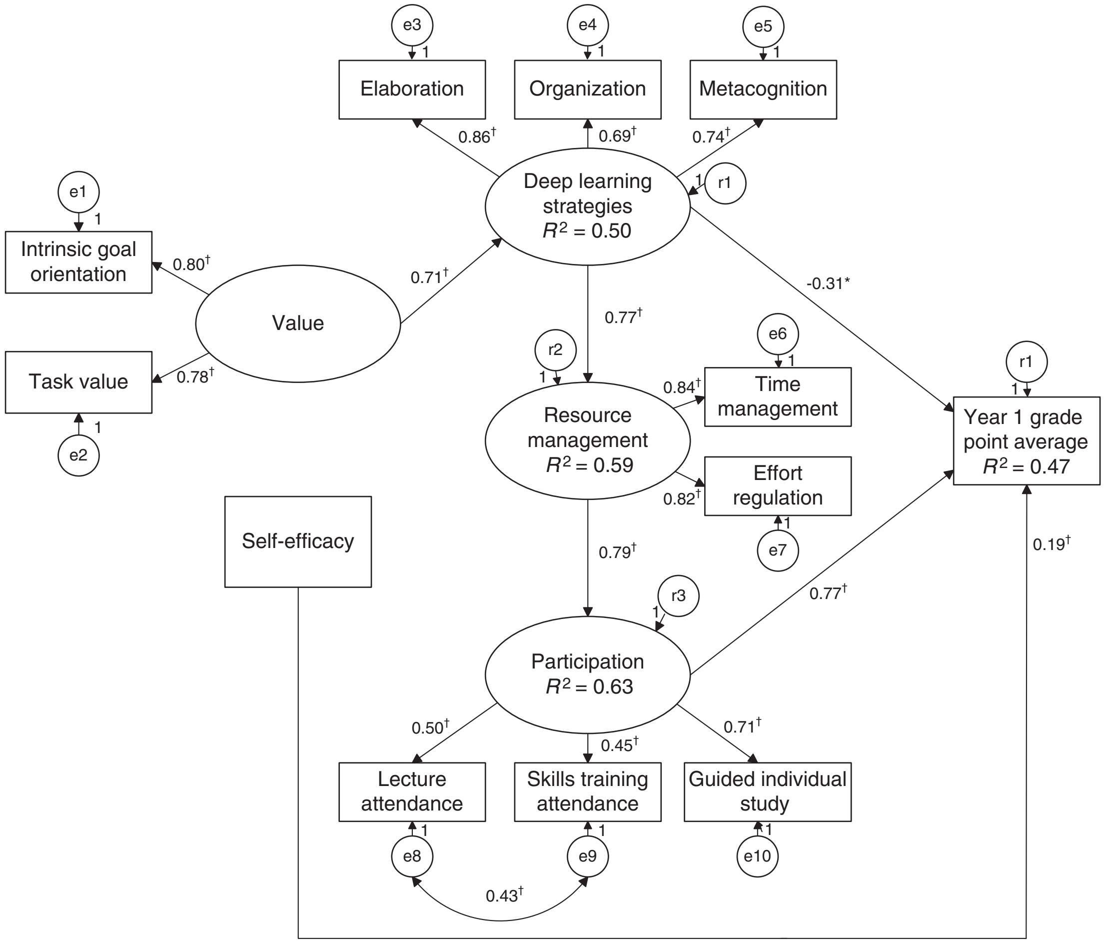

Figure 3 Final model of Year 1 performance (2008 cohort). Reported path values are standardised regression weights. R^2 is the percentage of variance explained for that specific variable. For clarity, correlations among exogenous variables were omitted. e = error (measurement error of observed variables); r = residual (error in the prediction of endogenous factors from exogenous factors); * $p < 0.01$; † $p < 0.001$

explanations for this finding.[8] Firstly, participation in various learning activities may allow students to obtain information that is not contained in the course material. Secondly, regular participation in various learning activities (lectures, skills training and independent study) around the same topic may represent a form of distributed practice (in which study effort is distributed over several study sessions), which is known to have a positive effect on performance. Finally, consistent participation may offer the possibility for the overlearning of material, especially when lectures are combined with tutorials, skills training and (guided) independent study. The importance of a highly structured course and active participation within and outside class has recently been reported with reference to science classes.[39]

However, an alternative explanation is that students with better rates of participation achieve higher grades not because they comprehend the material better, but because explicit or implicit cues to the content of examinations are given during class.[8,38] There is also the possibility that participation is a marker for individual differences between students that have not been measured. However, Credé *et al.*[8] reported only weak relationships between participation and student characteristics such as conscientiousness and cognitive ability. One theory that appears promising in explaining voluntary participation is Higgin's regulatory focus theory.[40,41] According to this theory, students may participate in learning activities either because they 'want to' (promotion focus) or because they feel they 'have to' (prevention focus).

The finding that the relationship of *academic self-efficacy* with Year 1 performance was direct and not mediated by learning strategies contradicts our hypothesis. A possible explanation for this direct relationship is that students with high levels of self-efficacy do not always need to participate to a great degree in order to be successful. Several studies have revealed the existence of a group of better or more confident students who are less likely to attend classes on a regular basis.[8,27,38] However, whether these students are more confident because they have performed well in early examinations or whether their higher initial self-efficacy results in better performance at the end of the year is a matter of debate.[21] The impact of self-efficacy on medical school performance may be an interesting area for further research, especially because self-efficacy may be used as a factor to aid in the early identification of students who are at risk for poor performance at medical school. In addition, self-efficacy can relatively easily be influenced by medical educators.[42]

There are some limitations to our study. Firstly, it is not possible to infer causality on the basis of correlational data, despite the fairly robust associations among the study variables that were suggested by our findings and the longitudinal nature of this study. The ascertaining of definitive causal pathways requires more controlled experimental studies. Secondly, it should be noted that structural models are only approximations of reality.[43] Therefore, it is likely that our model omits some relevant variables and associated relationships. For example, a confounding variable is suggested by the added error covariance between Lecture Attendance and Skills Training Attendance. It may well be that students participate in both activities because of their tendencies towards conformity or compliance.[44] Nevertheless, the proposed model was grounded in theory, modified taking theory into account, and cross-validated with an independent sample from the same population. Thirdly, the present study relied heavily on student self-reports of strategies and participation. However, as the questionnaire was used to provide students with an overview of the strengths and weaknesses of their study approaches, we expect the risk for social desirability bias to be low. Finally, this study was performed within one medical school. Although two cohorts of students were used, future replication studies are needed to establish whether the present results can be generalised to other populations. We would like to encourage others to test our model in settings in which learning is more active, such as in problem-based learning (PBL) curricula.

A first practical implication of this study is that medical schools should stimulate students to participate in learning activities. Although it might be tempting to make participation mandatory, it is questionable whether this is necessary[8] or even desirable. Medical schools should, rather, aim to stimulate participation by enhancing students' value beliefs. A recent review suggests that intrinsic motivation may be enhanced by measures such as PBL, small-group work and early contact with patients.[45] Participation that extends beyond physical presence and includes intensive practice – via active-learning exercises – is likely to be most beneficial for all students.[39] Secondly, medical schools should aim to facilitate the maintenance or growth of self-efficacy levels. The most powerful source of self-efficacy beliefs is past performance, but student self-efficacy is also influenced by vicarious experiences (observing others perform), encouragement by others and students' own feelings.[46] To increase self-efficacy, medical schools should help students to monitor their own progress and build their confidence in their ability to learn. Possible strategies are to focus feedback on the competencies mastered rather than on those that have not yet been mastered, to provide students with authentic tasks that fit their skill development level, and to create 'safe' learning environments.[42] Thirdly, our results suggest that the collection of data on SRL and on participation may help medical schools to identify students who are at risk for poor performance early in their training. In addition, these data enable the identification of areas for improvement and consequently can be used to offer proactive and targeted types of support.

In conclusion, we tested and cross-validated an integrated model of motivation, learning strategies, participation and Year 1 medical student performance. Our study suggests that participation mediates the relationships between motivation and learning strategies, and medical school performance. In other words, value beliefs, deep learning strategies and resource management were only indirectly related to performance through participation. However, participation and self-efficacy beliefs also made unique contributions towards performance. Encouraging participation and strengthening self-efficacy may help to enhance medical student performance.

Contributors: all authors substantially contributed to the conception and design of the study. KMS-J collected and analysed the data. All authors contributed to the interpretation of the data. KMS-J wrote the first draft of the article and all authors revised it critically for important intellectual content. All authors approved the final manuscript for submission.

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