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Predicting Academic Achievement With Students' Learning Diary and Epistemic Beliefs

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Abstract

Epistemic cognition has been found to positively predict academic achievement. However, measuring epistemic cognition has proved to be problematic. In the last decade, learning analytics has emerged as a field of study and practice with new means to collect data on different types of psychological constructs.

This study focuses on a learning analytics tool, a structured learning diary, and its connections with self-reported epistemic beliefs. Connections between these and academic achievement are investigated at four temporal measurement points. The first aim was to test which measures of the diary tool correlated with academic achievement. The second aim was to test epistemic beliefs' correlation with academic achievement. Models of linear regression were then designed and tested at different times.

The results show that we should collect student-originated behaviour data for the best predictive power and connect that with independent psychological measures.

1 Introduction

Factors contributing to academic performance have been studied for at least a century (Hellas et al., 2018). In their systematic literature review of 565 scientific articles since 2010, Hellas et al. (2018) found that the most used predictive values were course grades (or ranges), exam scores, programme or module graduation, or retention. Grade point average (GPA, or range of GPA) was also one of the most predicted measures. The features most often used for predicting academic performance ranged from pre-course and course performance to different demographic (gender, age, family) features to personality, self-regulation, and engagement measures. Behavioural data (log data) was one of the features mentioned in the study (2018). However, epistemic cognition was not mentioned.

The usefulness of academic performance, or *academic achievement* (AA), depends on how these measures, such as course grades or module graduation, are operationalised in the institution. In the context of this study, the participating university awards the highest grade for every student who fully

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(or almost) meets all the predefined learning outcomes. The university is rewarded in funding based on the number of degrees finished in normative time. Therefore, it can be argued that GPA and the number of courses (or ECTS credits) completed are relevant student outcomes.

As mentioned before, epistemic cognition was not one of the features found in the systematic literature review (2018). Nevertheless, epistemic cognition, i.e. "how people acquire understand, justify, change, and use knowledge in formal and informal contexts" (Greene et al., 2016, p. 1), has been studied quite extensively concerning AA (Greene et al., 2018). Still, there is much to learn from this mostly positive connection between the psychological epistemic construct and performance. This study explores the connections between behavioural data (learning process data). Epistemic beliefs (self-report questionnaires) and academic performance.

1.1 Related literature

Structured learning diaries have been typically designed to foster reflective learning. These differ from regular learning diaries in utilising standardised questions that students answer repeatedly over a period of time. Structured learning diaries and more traditional learning diaries have been successfully used as intervention tools and instruments of measurement (Broadbent et al., 2020; Kawalkar & Vijapurkar, 2015; Schmitz & Perels, 2011; Schmitz & Wiese, 2006). The main focus of these studies has been on self-regulated learning. Further, structured learning diaries have been argued to be the third wave in measurement (SRL), as they combine log data with students' self-report data (Panadero et al., 2016). Much less attention has been given to the connection between these diaries and epistemic cognition.

Epistemic cognition has been seen as an essential psychological construct related to other metacognitive constructs. As Pieschl, Stahl, and Bromme (2013, p. 61) summarise studies in the field: "[--] these studies show superior SRL [self-regulated learning] processes and outcomes for learners with sophisticated epistemic beliefs, namely, main effects of epistemic beliefs." These types of connections are essential. However, as Hofer (2016, p. 31) points out, epistemic cognition has been mainly studied as one construct related to other constructs, "seldom used by others as an additional explanatory variable in broader studies."

In their meta-analysis of 132 nonexperimental studies, Greene, Cartiff, and Duke (Greene et al., 2018) found epistemic cognition correlating positively with AA. The correlation was rather small ($r = .162$, $p < .001$), but an important one (2018). They found varying effect sizes over different measures used to capture epistemic cognition. These measures are typically self-report questionnaires, which have been criticised on the reliability and validity of the measures, response bias, and the fact that students may encounter the terminology used for the first time in the questionnaire they are being measured by (Hofer & Sinatra, 2010), and that epistemic cognition might not be enacted at the time of the measure (Kelly, 2016). Despite the critique, self-report measures are still commonly used in the research literature, and, as Sandoval, Greene, and Bråten (2016, p. 483) point out, "people can self-report best about thoughts and attitudes that are explicit in their minds and that require little construction in the moment".

The epistemic belief scales used in this study were developed on the scales developed by Schommer (Schommer, 1990, 1993). In the Greene et al. (Greene et al., 2018), the closest comparable scales were Schommer/Schommer-Aikins scales that were found to deliver a statistically significant effect size of .144 ($p < .001$) in predicting AA. Further, the specific scale of certain knowledge had .136 effect size ($p < .001$) and general epistemic cognition, where authors had summed sub-scales into one measure, had an effect size of .266 ($p < .01$).

Emotions, especially positive emotions, have been found to be connected with AA (Oriol-Granado et al., 2017; Rodríguez-Muñoz et al., 2021). Factors like experiencing challenges, confusion, or difficulties can make students more resilient and thus become better learners. On the other hand, experiencing too many or too severe difficulties can make students more passive towards their studies.

Nevertheless, an experience of difficulty has been seen as a relevant factor close to affect (emotions) (Lodge et al., 2018) and an area of interest in this study.

This study corroborates the self-report questionnaires with behavioural data collected with structured learning diaries. The validity and reliability of the measures used with regard to what they were initially intended to measure is not the primary concern in this study. This study is more interested in exploring the use of these measures and their effect on AA. This study aims to increase our understanding of designing or developing tools for collecting relevant data to predict student achievement, which we will discuss further in the next section.

1.2 Present study

In this study, the author examines the connection between learning process data (structured learning diary) and epistemic beliefs (questionnaires) to AA (register data). The diary data was further defined to include the structured item scales (competence, difficulty, and feeling) that are most suitable for the quantitative explorative purposes of this study. The diaries are rich in data, with topic-level comments and student-drawn relations between courses and topics. These aspects of the data require qualitative approaches, which is not the focus of this study.

Based on the literature and prior research with the structured learning diary, the following research questions (RQ) and hypotheses (H) were formulated:

RQ1: Are the structured item entries in the diaries connected with academic achievement?

H1: Literature suggests a connection (possibly through self-regulation), but the connection is weak or non-existent.

RQ2: Are students' epistemic beliefs connected with academic achievement?

H2: Literature suggests a weak connection that varies between different belief measures.

RQ3: How does a theory-based model perform compared to a statistical regression model?

H3: Predictive power (effect size) is better when diary data is combined with epistemic beliefs. The statistical model will outperform the theory-based model. Possible connection diminishes over time due to the dynamic nature of the student's learning patterns.

2 Methods

2.1 Participants and procedure

This study is based on a cohort (N=104) of new master's degree students in a large European research university. At its first stage, the study was designed to accommodate a randomised controlled trial to measure structured learning diary tool use and the diaries' effect on self-regulated learning and engagement (Pesonen et al., 2020). The experiment group (n=70) used the tool in the first semester, in autumn, and the control group (n=34) used the tool in the spring. This study focuses on the experiment group and their longitudinal data for temporal coherence.

The participants answered the first questionnaire (pre-test) at the start of the academic year. Students answered the same questionnaire again at the end of the autumn semester (post-test).

2.2 Instruments

Kivimäki et al. (2019) designed the structured learning diary tool used in this study. This study focuses on the competence, emotion, and difficulty scales explained in Figure 1. Data were collected during the first semester (autumn). Students' weekly submissions were summarised at an individual level depicting, e.g., the overall count of course topics for which students had selected the emotion *excited*.

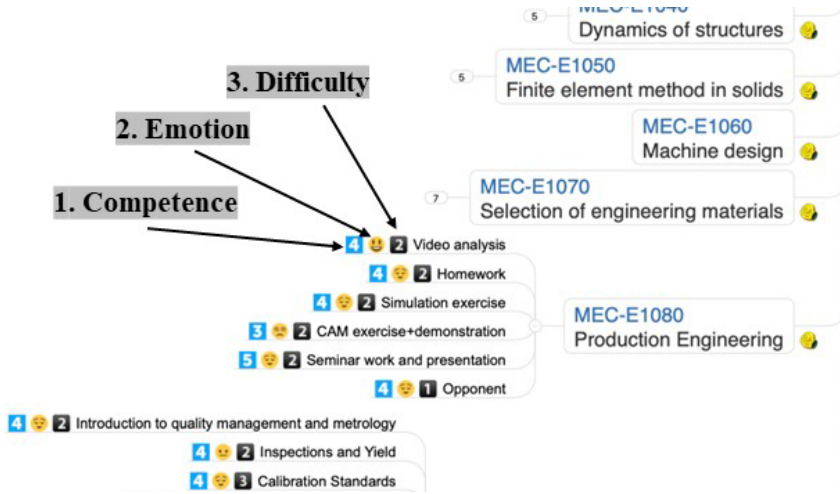

Fig. 1 Excerpt from a learning diary with all main diary elements: 1. Competence (selectable scale from 1, low, to 5, high), 2. Emotion (student selects between excited, relaxed, neutral, bored, and anxious), 3. Difficulty (selectable scale from 1, easy, to 5 hard)

Epistemic beliefs were measured using a set of scales from the MED NORD questionnaire (Lonka et al., 2008). All students in the master's programme were asked to participate in the pre-test (pre-t) and post-test (post-t). The scales' reliability was measured with McDonald's Omega (McDonald, 1999). All scales were acceptable apart from the post-test *valuing metacognition* (ω = .57).

Scale	No. of items	No. of students: pre-t, post-t	Example item	ωt: t1, t2
Certain knowledge	4	105, 88	Scientific knowledge is absolutely certain in nature.	.62, .63
Collaborative knowledge building	4	105, 88	In my opinion, it is essential that the issues being studied are discussed together by the teacher and students.	.80, .76
Practical value	2	105, 88	A theory is useful only if it can be applied to real life.	.62, .74
Reflective learning	3	105, 88	As I study a new topic, I often think about new questions, which I try to answer myself.	.81, .78
Valuing metacognition	2	105, 88	Knowing one's own thinking is the major contributor to successful learning.	.76, .57

Table 1 Questionnaire scales, participants in each questionnaire time, and McDonald's Omega

The student registry was used to measure AA. This study used two measures: grade point average (GPA) and the number of ECTS credits (CR).

2.3 Statistical analyses

Pearson correlation was used to calculate the correlation between the dependent (AA) and independent variables (diary data, epistemic belief scales). Multiple linear regression was used to model the relationship between AA and the diary and epistemic belief variables. This study uses forward selection and stepwise selection methods, i.e., statistical regression (Tabachnick & Fidell, 2014), to find the variable that best predicts the dependent variable (GPA and CR).

A mixed approach was designed to increase the validity and reliability of this study. First, two competing models were built. One model was built based on literature, combining variables from the diary tool with epistemic beliefs. The second model was built stepwise in SPSS software to find the best predictive model between all the variants. Second, the models were tested to predict AA at three different times for the GPA and CR dependent variables, i.e., 12 tests were performed.

3 Results

3.1 Correlation coefficients: diary scales

None of the single emotion items correlated statistically significantly with GPA or CR (Table 2). Still, the number of total emotion selections correlated positively with the first autumn GPA, $r(60)=.284$, $p=.025$. Students who assessed their competence at the medium high level (Table 3), resulted in positive correlation with the autumn GPA, $r(58) = .314$, $p = .015$. The total number of competence selections correlated positively with GPA, $r(60) = .283$, $p= .026$. Average difficulty (Table 4), i.e,. a number 3 selection on the 1–5 scale, had statistically significant positive correlation with GPA, $r(60) = .281$, $p=.027$. Like in other scales, the total number of difficulty selections had a statistically significant positive correlation with GPA, $r(60) = .283$, $p = .026$. Hard difficulty experiences resulted in a significant positive correlation with CR, $r(34) = .373$, $p = .025$.

Emotions variable	GPA 1st Autumn	CR 1st Autumn
Anxious	-0.017	.132
Bored	-0.049	.291
Neutral	.251	.019
Relaxed	.182	.130
Excited	.251	.198
Emotions total	.284*	.222

*. Correlation is significant at the .05 level (2-tailed)

Table 2: Pearson correlation between AA and (diary) emotions

Competence variable	GPA 1st Autumn	CR 1st Autumn
Low	.006	.173
Medium low	.123	.222
Medium	.220	.129
Medium high	.314*	.021
High	.136	.119
Competence total	.283*	.220

*. Correlation is significant at the .05 level (2-tailed)

Table 3: Pearson correlation between AA and (diary) competence

Difficulty variable	GPA 1st Autumn	CR 1st Autumn
Easy	-0.070	-0.098
Easier than average	.100	.147
Average	.281*	.195
Harder than average	.207	.178
Hard	.066	.373*
Difficulty total	.283*	.220

*. Correlation is significant at the .05 level (2-tailed)

Table 4: Pearson correlation between AA and (diary) difficulty

3.2 Correlation covariances: epistemic beliefs

The pre-test epistemic beliefs did not reach statistically significant correlation with GPA. However, all the post-test epistemic belief scales positively correlated with GPA: reflective learning $r(64) = .363$, $p = .003$; collaborative knowledge building $r(62)=.335$, $p=.007$, valuing metacognition $r(62) = .350$, $p = .005$; certain knowledge $r(62) = .388$, $p = .002$; and practical value $r(62)=.290$, $p=.020$. Certain knowledge and practical value scales in the pre-test positively correlated with CR: $r(62) = .347$, $p =.005$; $r(62) = .324$, $p = .009$, respectively. All post-test epistemic belief scales in the post-test questionnaire reached statistically significant correlation with CR: reflective learning $r(62) = .324$, $p = 009$, collaborative knowledge building $r(62) = .270$, $p = .031$; valuing metacognition $r(62) = .281$, $p = .025$; certain knowledge $r(62) = .430$, $p < .001$, practical value $r(62) = .334$, $p = .007$.

Time of measure	Independent variable	GPA 1st Autumn	CR 1st Autumn
Pre-test	Certain knowledge	.230	.347**
Pre-test	Collaborative knowledge building	.095	.066
Pre-test	Practical value	.065	.299*
Pre-test	Reflective learning	.147	.205
Pre-test	Valuing metacognition	.187	.057
Post-test	Certain knowledge	.350**	.430***
Post-test	Collaborative knowledge building	.335**	.270*
Post-test	Practical value	.290*	.334**
Post-test	Valuing metacognition	.350**	.281*
Post-test	Reflective learning	.363**	.324**

*. Correlation is significant at the .05 level (2-tailed), **. Correlation is significant at the .01 level (2-tailed), ***. Correlation is significant at the .001 level (2-tailed).

Table 5: Pearson correlation between AA and epistemic beliefs

3.3 Model 1: Theoretical model

Theoretical linear regression models were designed for GPA and CR based on the literature and correlation coefficients. The first model consisted of medium-high competence, average difficulty, excitement (even though it did not reach statistical significance), and all post-test epistemic beliefs for GPA. Another model consisting of excited emotion, hard difficulty, certain knowledge (pre- and post-test), and practical value (post-test) was designed for CR. The positive emotions were strong candidates based on the literature. These were dropped from the model due to low correlation covariances. Observations further than two standard deviations from the predicted values were handled as outliers. The GPA model did not reach statistical significance. For the CR model, a significant regression equation was found ($F(4, 31) = 5.612$, $p = .002$), with an R^2 of .420. Participants' predicted CR is equal to -5.937 – 0.317 (practical value) + 5.484 (post-test certain knowledge) + 3.819 (pre-test certain knowledge) + 0.242 (hard difficulty). The number of CR increased 0.242 ECTS credits for each hard difficulty selected, increased by a higher certain knowledge measure, and decreased when students believed more in bringing theory into practice. None of the independent variables in the model reached statistical significance. Based on this finding, the pre-test certain knowledge ($p = .224$) and practical value ($p = .889$) were removed from the model.

After this statistical iteration, the new model consisted of hard difficulty and post-test certain knowledge, which reached statistical significant regression equation as ($F(2, 33) = 10.530$, $p < .001$), with an R^2 of .353. Participants' predicted CR is equal to 4.647 + 0.262 (hard difficulty) + 6.155 (certain knowledge). Participants' CR number increases 0.262 for every hard difficulty selection and 6.155 for those who believe in certain knowledge.

3.4 Model 2: Statistical regression model

The model predicting GPA was formulated with the forward and stepwise procedures, which produced the same result, a model consisting of three independent variables: medium-high competence, neutral emotion, and hard difficulty. A significant regression equation was found ($F(3,12) = 9.239$, $p = .002$), with an R^2 of .698. Participants' predicted GPA is equal to 2.115 - 0.020 (hard difficulty) + 0.016 (neutral emotion) + 0.008 (medium-high competence). GPA increased .008 for each medium-high selection, .016 for the neutral emotion selection, and the GPA was .020 better for those who expressed less hard difficulty in their diary. Medium-high competence, neutral emotion, and hard difficulty were significant predictors of GPA.

The second model was formulated following the same procedure to predict CR. The best model consisted of the post-test certain knowledge scale and neutral emotion. A significant regression equation was found ($F(2, 13) = 13.508$, $p < .001$), with an R^2 of .675. Participants' predicted CR equals -41.347 + 0.220 (neutral emotion) + 13,969 (certain knowledge), where neutral emotion is measured as a number of times selected in a student's diary, and certain knowledge is measured as a summarised Likert-scale multiple-item variable from 1 to 6. CR increased 13.969 for each number of certain knowledge measures, and neutral emotion selection increased CR by 0.220 credits. Both certain knowledge and neutral emotion were significant predictors of CR.

3.5 Model testing

The regression equation models formulated by theory and statistical selection were tested with a forced (enter) method at three times of measure (autumn, 1st year, 2nd year). Each model's related effect size (R square) was calculated, and the independence of the independent variables for all statistically significant models was tested for collinearity (condition index less than 10 in SPSS collinearity diagnostics). A linear relationship, residual normality, and homoscedasticity were visually reviewed from scatter plots and histograms. Autocorrelation was analysed with the Durbin-Watson test, which showed no problems in autocorrelation in the models used (d close to 2).

Four multiple linear regression models were tested with the autumn data as forced (enter procedure in SPSS) models. The theoretical model for GPA prediction consisted of the medium-high competence, average difficulty, excited emotion, and all post-test epistemic belief independent variables. Theoretical CR models consisted of hard difficulty and post-test certain knowledge. The statistical model predicting GPA consisted of medium-high competence, neutral emotion, and hard difficulty. The statistical CR model was based on a post-test certain knowledge scale and neutral emotion.

Time of measure	Theoretical models' R^2	Statistical models' R^2
GPA 1st autumn	.146	.129
CR 1st autumn	.390***	.208***
GPA first academic year	.302*	.073
CR first academic year	.451***	.228***
GPA second academic year	.234	.103
CR second academic year	.170*	.033

*. Correlation is significant at the .05 level (2-tailed), **. Correlation is significant at the .01 level (2-tailed), ***. Correlation is significant at the .001 level (2-tailed).

Table 6: R squares of the linear multiple regression models used to predict the first autumn, first academic year, and second academic year GPA and CR

4 Discussion and conclusions

The first research question asked whether the structured items in the diaries were connected with AA. The hypothesis was that there was a connection. All the dimensions were statistically significantly positively correlated with GPA regarding the total number of selections (Table 2, Table 3, Table 4). This suggests that the correlation was mainly higher activity-based since more active (engaged) students were also achieving more in their studies. Still, medium-high competence as a single variable correlated the most (.314) with the best GPA. This, along with the positive average difficulty correlation (.281), suggests that in addition to the overall activity, there is a more profound content-based correlation between the scales used and student GPA. Students who had expressed more hard difficulty in their autumn studies resulted in them completing more ECTS, or at least there was a significant correlation.

The second research question and hypothesis concerned possible connections between epistemic beliefs and AA. Interestingly, none of the pre-test beliefs correlated statistically significantly with GPA (Table 5). In contrast, all the post-test beliefs correlated positively with GPA. Similarly, all the post-test beliefs correlated with CR. In addition, certain knowledge and practical value reached a statistically significant positive correlation with CR. Findings align with the literature (Greene et al., 2018), where the general epistemic belief scales and certain knowledge as a single scale correlated positively with AA.

The hypothesis suggested that the statistical model would outperform the theoretical model to the third research question. Results are dichotomous. The statistical regression model suggested that over 65% of the AA variance was explainable with our independent variables. However, when the model was tested over time and fitted as a forced model, compared with the theoretical model, the statistical model hardly delivered any reasonable predictive power. The statistical step-by-step procedures (likewise forward and backward procedures) have been criticised for failing to deliver reproducible results (Austin & Tu, 2004). The result of this study is in line with the criticism.

Moreover, the R square rapidly lost statistical significance when the model was tested with students' later AA. In turn, the theoretical CR model succeeded in predicting over 45% ($p < .001$) of the first year's CR variance and maintained statistically significant predictive power over the second-year CR as well (Table 6). However, the connection with the second-year CR is likely better linked with the first-year CR. This relation was not controlled in this study.

A statistically significant correlation was found between both the diary entries and the epistemic beliefs. A linear regression model based on statistical step-by-step procedures promised a high R square but failed to deliver meaningful predictive power against the theory-based model. The theoretical model combining epistemic belief and diary content delivered a meaningful R^2. Results suggest that predictions related to CR should consider mixing different types of independent variables, e.g., learning diary data and questionnaires related to a psychological construct. The predictive power seems to diminish over time. This can be due to the dynamic nature of students and their learning experiences. One solution is to predict using measures that students update periodically. Implementing a structured learning diary as part of the study path is another suitable method to consider.

5 References / Citations

Austin, P. C., & Tu, J. V. (2004). Automated variable selection methods for logistic regression produced unstable models for predicting acute myocardial infarction mortality. *Journal of clinical epidemiology*, *57*(11), 1138-1146. https://doi.org/10.1016/j.jclinepi.2004.04.003

Broadbent, J., Panadero, E., & Fuller-Tyszkiewicz, M. (2020). Effects of mobile-app learning diaries vs online training on specific self-regulated learning components. *Educational Technology Research and Development*, *68*(5), 2351-2372. https://doi.org/10.1007/s11423-020-09781-6

Greene, J. A., Cartiff, B. M., & Duke, R. F. (2018). A meta-analytic review of the relationship between epistemic cognition and academic achievement. *J. Educ. Psychol.*, *110*(8), 1084-1111. https://doi.org/10.1037/edu0000263

Greene, J. A., Sandoval, W. A., & Bråten, I. (2016). Handbook of Epistemic Cognition. https://doi.org/10.4324/9781315795225

Hellas, A., Ihantola, P., Petersen, A., Ajanovski, V. V., Gutica, M., Hynninen, T., Knutas, A., Leinonen, J., Messom, C., & Liao, S. N. (2018, 2018-07-02). Predicting academic performance: a systematic literature review. Proceedings Companion of the 23rd Annual ACM Conference on Innovation and Technology in Computer Science Education,

Hofer, B. K. (2016). Epistemic cognition as a psychological construct. In J. A. Greene, W. A. Sandoval, & I. Bråten (Eds.), *Handbook of epistemic cognition* (pp. 31-50). Routledge. https://doi.org/10.4324/9781315795225

Hofer, B. K., & Sinatra, G. M. (2010). Epistemology, metacognition, and self-regulation: musings on an emerging field. *Metacognition and Learning*, *5*(1), 113-120. https://doi.org/10.1007/s11409-009-9051-7

Kawalkar, A., & Vijapurkar, J. (2015). Aspects of Teaching and Learning Science: What students' diaries reveal about inquiry and traditional modes. *International Journal of Science Education*, *37*(13), 2113-2146. https://doi.org/10.1080/09500693.2015.1067933

Kelly, G. J. (2016). Methodological considerations for the study of epistemic cognition in practice. In *Handbook of epistemic cognition*. Routledge. https://doi.org/10.4324/9781315795225.ch24

Kivimäki, V., Pesonen, J., Romanoff, J., Remes, H., & Ihantola, P. (2019). Curricular Concept Maps as Structured Learning Diaries: Collecting Data on Self-Regulated Learning and Conceptual Thinking for Learning Analytics Applications. *Journal of Learning Analytics*, *6*(3), 106-121. https://doi.org/10.18608/jla.2019.63.13

Lodge, J. M., Kennedy, G., Lockyer, L., Arguel, A., & Pachman, M. (2018). Understanding Difficulties and Resulting Confusion in Learning : An Integrative Review. *Frontiers in education (Lausanne)*, *3*(June 2018). https://doi.org/10.3389/feduc.2018.00049

Lonka, K., Sharafi, P., Karlgren, K., Masiello, I., Nieminen, J., BirgegÅrd, G., & Josephson, A. (2008). MED NORD-A tool for measuring medical students' well-being and study orientations. *Medical teacher*, *30*(1), 72-79. https://doi.org/10.1080/01421590701769555

McDonald, R. P. (1999). *Test Theory: A Unified Treathment (1st ed.)*. Psychology Press. https://doi.org/10.4324/9781410601087

Oriol-Granado, X., Mendoza-Lira, M., Covarrubias-Apablaza, C.-G., & Molina-López, V.-M. (2017). Positive Emotions, Autonomy Support and Academic Performance of University Students: The Mediating Role of Academic Engagement and Self-efficacy. *Revista de Psicodidáctica (English ed.)*, *22*(1), 45-53. https://doi.org/10.1387/RevPsicodidact.14280

Panadero, E., Klug, J., & Järvelä, S. (2016). Third wave of measurement in the self-regulated learning field: when measurement and intervention come hand in hand. *Scandinavian Journal of Educational Research*, *60*(6), 723-735. https://doi.org/10.1080/00313831.2015.1066436

Pesonen, J. A., Ketonen, E. E., Kivimäki, V., & Ihantola, P. (2020). Does Using Structured Learning Diaries Affect Self-regulation or Study Engagement? : An Experimental Study in Engineering Education. https://doi.org/10.1109/FIE44824.2020.9274163

Pieschl, S., Stahl, E., & Bromme, R. (2013). Adaptation to Context as Core Component of Self-Regulated Learning: The Example of Complexity and Epistemic Beliefs. In *International Handbook of Metacognition and Learning Technologies* (pp. 53-65). Springer New York. https://doi.org/10.1007/978-1-4419-5546-3_4

Rodríguez-Muñoz, A., Antino, M., Ruiz-Zorrilla, P., & Ortega, E. (2021). Positive emotions, engagement, and objective academic performance: A weekly diary study. *Learning and individual differences*, *92*, 102087. https://doi.org/10.1016/j.lindif.2021.102087

Sandoval, W. A., Greene, J. A., & Bråten, I. (2016). Understanding and Promoting Thinking About Knowledge: Origins, Issues, and Future Directions of Research on Epistemic Cognition. *Review of Research in Education*, *40*(1), 457-496. https://doi.org/10.3102/0091732X16669319

Schmitz, B., & Perels, F. (2011). Self-monitoring of self-regulation during math homework behaviour using standardized diaries. *Metacognition and Learning*, *6*(3), 255-273. https://doi.org/10.1007/s11409-011-9076-6

Schmitz, B., & Wiese, B. S. (2006). New perspectives for the evaluation of training sessions in self-regulated learning: Time-series analyses of diary data. *Contemporary educational psychology*, *31*(1), 64-96. https://doi.org/10.1016/j.cedpsych.2005.02.002

Schommer, M. (1990). Effects of Beliefs About the Nature of Knowledge on Comprehension. *Journal of educational psychology*, *82*(3), 498-504. https://doi.org/10.1037/0022-0663.82.3.498

Schommer, M. (1993). Comparisons of Beliefs about the Nature of Knowledge and Learning among Postsecondary Students. *Research in higher education*, *34*(3), 355-370. https://doi.org/10.1007/BF00991849

Tabachnick, B. G., & Fidell, L. S. (2014). *Using multivariate statistics* (6. , Pearson new international edition. ed.). Pearson.

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