

## Predicting intraindividual changes in learning strategies: The effects of previous achievement

VESNA BUŠKO and AMELA MUJAGIĆ

Socio-cognitive models of self-regulated learning (e.g., Pintrich, 2000) emphasize contextualized nature of learning process, and within-person variation in learning processes, along with between-person variability in self-regulation. Previous studies about contextual nature of learning strategies have mostly focused on the effects of different contextual factors on interindividual differences in learning strategies utilization. However, less attention was given to the question about contextual effects on within-person variability in learning strategies. In this paper, the following questions were explored: (a) whether students exhibit intraindividual variability in learning strategies between two measurement occasions, or not, and (b) to what degree the observed intraindividual variability in selected learning strategies between two learning episodes can be accounted for by achievement after the first learning episode. The research questions were analyzed under the methodological framework of the latent state-trait theory (Steyer, Ferring, & Schmitt, 1992). The sample consisted of 297 first year university students attending Introduction to Psychology course. Selected learning strategies (organization, elaboration, and critical reasoning) were measured by means of adapted version of the Inventar zur Erfassung von Lernstrategien im Studium (Wild & Schiefele, 1994). Participants filled in the questionnaire before the exams on two occasions with a 7-week time lag. Students' scores on the first exam were obtained from the teacher's record. Results provide the evidence that there are individual differences in students' changes in the frequency of use of learning strategies at the end of semester (compared to the midsemester). Also, students who scored higher at the first exam exhibited less intraindividual variability in learning strategies utilization.

*Key words:* learning strategies, self-regulated learning, contextual effects, intraindividual variability

Cognition, motivation, behavior and context have been identified within Pintrich's socio-cognitive model of self-regulated learning as four areas of learning process that students can actively self-regulate (e.g., Pintrich, 2000). Self-regulated learning is usually defined as "...an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment" (Wolters, Pintrich, & Karabenick, 2003, p. 5). Students' ability to self-regulate all aspects of learning

process is thought to have an impact on their learning and achievement.

Self-regulated learning process is described through planning, monitoring, regulation and reflection phases, but there is no strong assumption that the phases are hierarchically or linearly structured. It is viewed, however, as a dynamic process in which evaluations and reactions on previous experiences are used in subsequent learning activities. Evaluation includes judgments that students make regarding task execution, goal attainment, causes of successes or failures, choice of behavior to be followed in the future, etc. Every learning episode is thus, at least in part, based on evaluations from previous learning episodes. Cognitions (and motivations) relating to a task and learning behaviors used by students to perform the task can therefore vary substantially across tasks. These within-person variations in learning processes, along with between-person variability in self-regulation, suggest the need for a contextualized examination of self-regulated learning processes and its components (Credé & Philips, 2011).

Contextualized nature of learning process is emphasized in models of students' approaches to learning, too (Biggs,

---

Vesna Buško, Department of Psychology, Faculty of Humanities and Social Sciences, University of Zagreb, Croatia. E-mail: vbusko@ffzg.hr;

Amela Mujagić, Faculty of Educational Sciences, University of Bihać, Bosnia and Herzegovina. E-mail: mujagicamela@gmail.com (the address for correspondence).

*Acknowledgements:* The study was conducted as a part of the research project No. 130-1301683-1402 "Measuring latent psychological attributes: Person dispositions and processes" led by the first author of this paper and supported by Ministry of Science, Education, and Sports of the Republic of Croatia.

2001; Ramsden, 2003). This perspective also acknowledges that learning approaches are not stable psychological features, but the result of the interaction between the learner and the learning environment (Renzulli, 2001). Descriptions of self-regulated learning process (e.g., Pintrich, 2004), as well as descriptions of students' approaches to learning (e.g., Ramsden, 2003), include numerous components, such as motivation, emotions, behavior, epistemological beliefs, etc., yet one of the core elements in these theoretical models are learning strategies. Flexible and efficient use of learning strategies is considered to be a critical self-regulatory process that facilitates learning and comprehension. In students' approaches to learning perspective, successful learning is described as deep learning approach, which implies the use of 'deep' learning strategies.

Learning strategies can be described as specific patterns or combinations of learning activities on cognitive level. Strategies are forms of procedural knowledge that students voluntarily use for acquiring, organizing or transforming information, as well as for reflecting upon and guiding their own learning. These cognitive strategies range from the simple memorizing strategies like repeating information, to sophisticated strategies that individuals use for reading, mathematics, writing, problem solving, and reasoning (Wolters et al., 2003). It is presumed that students who use more complex strategies will learn more and develop more coherent understanding of concepts compared to those who rely on rote memorization. Nevertheless, memorizing information can add to one's knowledge base especially during its early development (Chiu, Chow, & McBride-Chang, 2007).

Questions about contextual nature of learning strategies have been explored extensively in previous research. Comparisons were reported on learning strategies in different learning tasks (e.g., Bråten & Samuelstuen, 2004), different academic disciplines (e.g., VanderStoep, Pintrich, & Fagerlin, 1996; Vermunt, 2005), in traditional and redesigned academic courses (e.g., Segers, Nijhuis, & Gijsselaers, 2006), in relation to different assessment procedures (e.g., Scouller, 1998), before and after specific instruction on learning strategies (e.g., Rozendaal, Minnaert, & Boekaerts, 2005), during the semester (e.g., Zusho, Pintrich, & Goppola, 2003), throughout higher education (e.g., Donche, Coertjens, & Van Petegem, 2010). Yet, the results are inconclusive. While some studies show that students spontaneously change the way they learn (the frequency of learning strategies deployment) during academic year or semester (e.g., Severiens, Ten Dam, & Van Haut Wolters, 2001), others show that students learn in an unchanged manner even if academic courses are redesigned to promote more complex learning strategies (e.g., Vermetten, Vermunt, & Lodewijks, 2002). There might be several reasons for this pattern of results. For example, Vermetten, Lodewijks, and Vermunt (1999) suggest that there might be differences between strategies in "resistance" to situational factors. Moreover, Nijhuis, Segers, and Gijsselaers (2008) suggest that there are

also individual differences in flexibility of learning activities. Though, some methodological issues could also play an important role in these findings, since inferences about (in) consistency in use of learning strategies are mostly based on tests of mean differences between groups or between measurement occasions. Less attention was given to the question on contextual effects on within-person variability in learning strategies.

Studies exploring the relationship between learning strategies and academic performance have also produced ambiguous results. In recent review Senko, Hama, and Belmonte (2012) note that it is commonly acknowledged that academic achievement tends to have a mix of null or negative links with surface learning strategies, and a mix of null or positive links with deep learning strategies. The magnitudes of correlations depend on the level of measurement of learning strategies (as general or subject/task specific strategies) and achievement (GPA or course achievement).

Baeten, Kyndt, Struyven, and Dochy (2010) note that while there are plenty of studies on the relationship between learning strategies employment and learning outcomes, fewer studies addressed the reverse relationship. They assume that students adapt their learning strategies to the perceived assessment requirements. Experience with the assessment might do just the same. In other words, experience with assessment, and feedback information about achievement, might be a predictor of change in learning strategies employment. Several patterns of this relationship might be predicted. For example, if a student concludes that his or her performance was unsatisfactory, he/she might try to replace previously used learning activities with more adaptive ones. On the other hand, if a student perceives his/her performance on the exam as satisfactory, he/she might stick to the same learning pattern, or try to use strategies that he/she perceived as useful more often than in the previous learning session.

This study aims to explore whether previous achievement might serve as a contextual variable predicting inter-individual differences in intraindividual change in learning strategies. To answer this question we designed the study relying on psychometric framework of the latent state-trait theory (LST; Steyer, Ferring, & Schmitt, 1992). Over the last two decades many structural equation models under LST framework for different types of data and research questions have been developed. These models are defined following assumptions about the basic variables of LST theory (see e.g., Steyer et al., 1992, for a full description; Buško, 2010, for an outline; Kulenović & Buško, 2005, and Mujagić & Buško, 2012, for the demonstration of empirical procedures of testing and model comparisons). One class of structural equation models developed under latent state-trait framework includes latent change models (Steyer, Eid, & Schwenkmezger, 1997; Steyer, Partchev, & Shanahan, 2000). These models define the change in true scores on measures between two (or more) occasions of measure-

ment as latent variables. These latent difference variables can serve as endogenous variables to be explained by other latent variables, or as exogenous variables explaining other variables.

Thus, the latent change models appear suitable for testing hypotheses about contextual effects on intraindividual change in learning strategies between occasions of measurement. In this paper, LST methodological framework and latent change models are used to explore the questions (a) to what extent do students exhibit intraindividual variability in learning strategies between two measurement occasions, and (b) to what degree the observed intraindividual variability in selected learning strategies between two learning episodes can be accounted for by achievement after the first learning episode.

METHOD

Sample

The sample consisted of 297 first year university students of the Faculty of Educational Sciences at the University of Bihać, Bosnia and Herzegovina, attending Introduction to psychology course. Most of the participants were female (244 or 82.2%).

Measures

Adapted version of the Inventar zur Erfassung von Lernstrategien im Studium (Wild & Schiefele, 1994) was used for the measurement of selected learning strategies. The translation and validation of the instrument was done on Croatian sample (Sorić & Palekčić, 2002). Evaluation procedures showed similar, albeit not identical, factor structure to those found in the original questionnaire. For the purposes of this study, translated version of the instrument was used. However, data gathered in this study resembled the factor structure found in the original instrument better than the structure obtained in the validation process (see Mujagić, 2012, for more detailed information on this issue). Hence, three learning strategies scales, identical in content to those defined by Wild and Schiefele (1994), were used: organiza-

tion (8 items, e.g., “I draw diagrams, graphs or tables so to make lecture material better structured”), elaboration (eight items, e.g., „I try to link new concepts and theories with the concepts and theories I know already“), and critical reasoning (eight items, e.g., „I think of alternatives for the statements or conclusions expressed in the texts I learn“). Subjects were asked to respond on a 4-point Likert-type scale, ranging from 1 (*almost never*) to 4 (*almost always*), how often they behaved in a described manner while learning for the exam. Scores on each scale were computed as sum of scores on items of respective scales.

Performance on the first exam was taken from the teacher’s record. The first written exam consisted of 20 questions (multiple choice, true/false, matching, and fill-in questions), which are scored with total of 35 points.

Procedure

Participants filled in the questionnaire on two occasions with a 7-week time lag. In both occasions testing took place prior to written exams in Introduction to psychology. The two written exams were formally very similar (when it comes to the type of exam questions, and examination procedures, as well), but related to different topics. In order to set the context for answering the questionnaire items, students were instructed to answer to the items with regard to their behavior while learning for the exam they are about to write.

Results and Discussion

Descriptive statistics for the three learning strategies scales based on the data of the first and second measurement occasion, and for the exam results are given in Table 1. Cronbach’s alpha internal consistency coefficients were somewhat higher at the second measurement occasion for all three learning strategies scales, and similar to those reported by Wild and Schiefele (1994) except for organization scale.

Mean scores on the learning strategies scales at the first and second measurement occasion reveal that students re-

Table 1  
Descriptive statistics of the three learning strategies scales on two measurement occasions and the exam results

Scale	<i>k</i>	<i>M</i> <sub>1</sub>	<i>M</i> <sub>2</sub>	<i>SD</i> <sub>1</sub>	<i>SD</i> <sub>2</sub>	<i>S</i> <sub>1</sub>	<i>S</i> <sub>2</sub>	<i>K</i> <sub>1</sub>	<i>K</i> <sub>2</sub>	$\alpha$ <sub>1</sub>	$\alpha$ <sub>2</sub>	$\alpha^a$
Organization	8	22.42	22.36	4.37	4.38	-0.57	-0.46	0.14	0.39	.69	.74	.82
Elaboration	8	21.73	22.34	4.69	4.79	-0.29	-0.54	-0.04	0.23	.73	.80	.72
Critical reasoning	8	17.97	18.07	4.49	4.31	-0.01	0.01	-0.38	-0.29	.74	.77	.77
Exam scores	20	15.76		10.23		-0.02		-1.32				

Note. *S* = skewness; *K* = kurtosis;  $\alpha$  = Cronbach’s alpha internal consistency coefficient; subscripts 1 and 2 stand for the first and second measurement point, respectively.

<sup>a</sup> (Wild & Schiefele, 1994).

*Table 2*  
Correlations among the three learning strategies scales on two measurement occasions and the exam scores

	Org 2	Ela 1	Ela 2	CR1	CR2	Exam scores
Organization 1	.490*	.518*	.310*	.439*	.181*	.209*
Organization 2		.224*	.559*	.222*	.481*	.036
Elaboration 1			.513*	.573*	.241*	.339*
Elaboration 2				.291*	.599*	.157*
Critical reasoning 1					.524*	.024
Critical reasoning 2						-.100

\* $p < .01$ .

ported rather similar frequency of the learning strategies deployment in the middle and at the end of semester. Although the results of statistical tests are not given here, there were no changes on average in the use of learning strategies as a function of time point.

At both measurement occasions, critical reasoning was the least frequently used strategy, whereas the remaining two strategies were used to the similar extent. Intercorrelations of the learning strategies (Table 2) ranged from .44 to .57 and from .48 to .60 in the first and second time point, respectively. While the inspection of means showed no differences in the average deployment of learning strategies between the two measurement occasions, test-retest correlation coefficients point to modest or fairly low stability of individual differences. These results seem worth emphasizing also in view of previously noted internal consistency indices of all scales. If there were no differential intraindividual change, the retest correlations and the reliability estimates should be about the same. Hence, the question why do some students change the use of learning strategies more than others is meaningful in this context, although there is no change in the average use of learning strategies variables. Exam scores are significantly correlated with organization and elaboration scales, but not with critical reasoning.

To test theoretical assumptions on the existence of intraindividual variability in use of learning strategies, four structural equation models based on different assumptions were formulated and tested for each of the three learning strategies. The first model (latent trait model - LT) assumes that all the systematic variance of the observed variables (learning strategies scales) can be attributed to underlying latent trait. In other words, it is assumed that learning strategies scales measure just stable interindividual differences in learning strategies deployment. In the second model (LTm), additional assumption is made that there might exist another systematic source of variance for the observed variables (scale parcels) representing measurement method factor in the model. Method factor is uncorrelated with the latent trait variable and loads on one of the two scales for each occasion of measurement. Introducing the method factor

into model was based on the assumption that the two scale parcels are not perfectly parallel in the sense of classical test theory (Lord & Novick, 1968; see e.g., Eid, 2000, for the background for this kind of modeling method factors). The third model (latent change model - LCH) assumes that observed variables (scale parcels) on both measurement occasions measure a common latent state variable. At the same time, observed variables at the second measurement occasion are set as indicators of the latent change variable, that is, the difference in true scores between the two occasions of measurement. Finally, in the fourth model the assumption on the existence of method factor is added to the previous, LCH model. Again, method factor is uncorrelated with the latent state and latent change variables and loads on one of the two subscales measured at each occasion of measurement.

For factor identification, each of the three learning strategies scales was split into two subscales or parcels (test-halves) based on random assignment of items to parcels. Tests of univariate and multivariate normality for indicators were conducted using a  $\chi^2$  procedure of the PRELIS 2 software (Jöreskog & Sörbom, 2004). Although the test indicated statistically significant departure from multivariate normality, skewness and kurtosis values of all individual indicators were relatively small (all values  $< 1.00$ ), so the ML-procedure of LISREL 8.71 program (Jöreskog & Sörbom, 2004) was used. Fit statistics for the tested models are presented in Table 3.

Comparisons of fit of the alternative models revealed that latent change model with method factor in its non-restrictive version (LCHm<sub>nr</sub>) provided for the best account of data for organization and elaboration, while the restrictive version of the latent change model (LCH) was the best fitting model for critical reasoning strategy. In all three cases, however, latent change models described data better than latent trait models. These results indicate that there is a significant situational component influencing measurement of learning strategies in the two occasions. In other words, there is obviously some degree of intraindividual variability in the use of each learning strategy over occasions. Hence, the obtained results provide evidence that some students changed the frequency of use of learning strategies at the end of semester (compared to the mid semester) more than others.

These findings support the idea that there are individual differences in flexibility of learning activities implied by self-regulated learning models. As already stated, socio-cognitive models of self-regulated learning explicitly state that cognitive activities relating to a task and learning behaviors used by students to perform the task can vary substantially across tasks (e.g., Pintrich, 2000). Previous studies have explored this assumption by comparing learning activities in different learning tasks in within-subjects (e.g., Samuelstuen, Bråten, & Valås, 2007), and between-subjects designs (e.g., Vermetten et al., 2002). Data analyses in these

*Table 3*  
Main fit indices and related statistics for LST models comparisons for the three learning strategies

	$\chi^2(df) p$	RMSEA (90% int) $p$	GFI	CFI	SRMR
<b>Organization</b>					
LT	72.38 (8) .000	.165 (.13-.20) .00	.89	.80	.140
LTm	73.13 (7) .000	.179 (.14-.22) .00	.89	.81	.110
LCH	46.88 (6) .000	.152 (.11-.19) .00	.93	.89	.120
LCHm	11.76 (5) .038	.068 (.02-.12) .23	.98	.98	.044
LCHmnr <sup>a</sup>	2.39 (4) .664	.000 (.00-.07) .87	1.00	1.00	.030
$\Delta\chi^2(\text{LCHm} - \text{LCHmnr}) = 9.37, df = 1, p < .01$					
<b>Elaboration</b>					
LT	72.69 (8) .000	.165 (.13-.20) .00	.89	.82	.087
LTm	73.21 (7) .000	.179 (.14-.22) .00	.89	.81	.086
LCH	37.48 (6) .000	.133 (.09-.18) .00	.94	.92	.054
LCHm	20.25 (5) .001	.102 (.06-.15) .03	.97	.96	.076
LCHmnr <sup>b</sup>	3.02 (3) .389	.004 (.00-.10) .66	.99	1.00	.025
$\Delta\chi^2(\text{LCHm} - \text{LCHmnr}) = 17.22, df = 2, p < .01$					
<b>Critical reasoning</b>					
LT	74.49 (8) .000	.168 (.13-.20) .00	.89	.86	.085
LTm	62.49 (7) .000	.164 (.13-.20) .00	.90	.87	.087
LCH	6.95 (6) .325	.023 (.00-.08) .71	.99	1.00	.023
LCHm	4.36 (5) .498	.000 (.00-.08) .81	.99	1.00	.032
$\Delta\chi^2(\text{LCH} - \text{LCHm}) = 2.59, df = 1, p > .05$					

Note. LT = latent trait model; LTm = latent trait model with method factor; LCH = latent change model; LCHm = latent change model with method factor; LCHmnr = latent change model with method factor and nonequal residuals within the time point.

<sup>a</sup> ( $\epsilon_{11} = \epsilon_{12}$ )  $\neq$  ( $\epsilon_{21} = \epsilon_{22}$ ). <sup>b</sup> ( $\epsilon_{11} = \epsilon_{12}$ )  $\neq$  ( $\epsilon_{21} = \epsilon_{22}$ );  $\lambda_{21} = \lambda_{22} \neq 1$ .

studies were mostly limited to inspection of group means. Lack of significant differences between group means is then interpreted as indication of stability of learning strategies, and significant differences are interpreted as indicators of variability in learning activities (e.g., Nijhuis, Segers, & Gijssels, 2005). In general, studies comparing students in different learning environments produced mixed results triggering “trait vs. state” debate regarding students’ learning. However, previous studies have rarely explored the question about within-person variability in learning activities across tasks. Nijhuis et al. (2008) took another approach to answer the question about consistency and variability in students’ learning by focusing on groups of students with different levels of variability (defined as standard deviation of learning strategies scores across three courses) in

learning activities. They identified two clusters of students regarding variability in learning across different courses – variable and restricted group. In our study, intraindividual variability in learning was treated as individual differences variable. Results of this study suggest that students exhibit intraindividual variability in learning activities even when learning activities are measured in two very similar learning tasks. It should be emphasized that participants in this study were first year university students who did not have previous experiences with psychology courses at university level. These sample characteristics might have had an impact on the magnitude of within-person variability in learning. It might be expected that more experienced students in learning specific academic domains would exhibit more stable learning patterns.

*Table 4*  
Main fit indices and related statistics for structural equation models with exam scores as predictors of latent states and changes in learning strategies

	$\chi^2(df) p$	RMSEA (90% int) $p$	GFI	CFI	SRMR
Organization	7.15 (6) .307	.025 (.00-.08) .69	.99	1.00	.034
Elaboration	4.16 (5) .526	.000 (.00-.07) .82	.99	1.00	.024
Critical reasoning	9.44 (8) .307	.025 (.00-.08) .74	.99	1.00	.023

The next question we put in this paper was whether these interindividual differences in intraindividual change can be explained by previous experience with regard to achievement in the same subject after the first learning episode. In the next step, exam scores (as observed predictor variable) were added to the latent change models. Main fit indices are presented in Table 4.

Given the acceptable overall model fit for all three learning strategies, models' parameters were analyzed. Exam scores were significantly related to the latent state variables of organization (Figure 1) and elaboration (Figure 2) strategies indicating that students who used these strategies more often throughout semester performed better at the first exam (note that one way directed structural arrows in path diagram do not imply causation). The use of critical reasoning was not related to the exam scores (Figure 3).

The obtained results support a reasonable expectation that students who organize new information using outlines, schemes, tables, and try to establish internal connections between information, as well as connections between new information and existing knowledge and/or personal experiences, perform better on the exams. Lack of correlation between critical reasoning strategy and exam performance can be attributed to at least two possible reasons. First, critical reasoning, defined here in terms of evaluating new ideas and applying them to novel situations, is a complex strategy that can hardly be used appropriately during early development of one's knowledge base. Second, it can be assumed that the exam questions did not require critical elaboration of the information and ideas presented in learning materials.

However, students who performed better at the first exam exhibited less change in the critical reasoning strategy (Figure 3). The same applies for the organization (Figure 1) and elaboration strategies (Figure 2). Stated reversely, students who changed the frequency of learning strategies

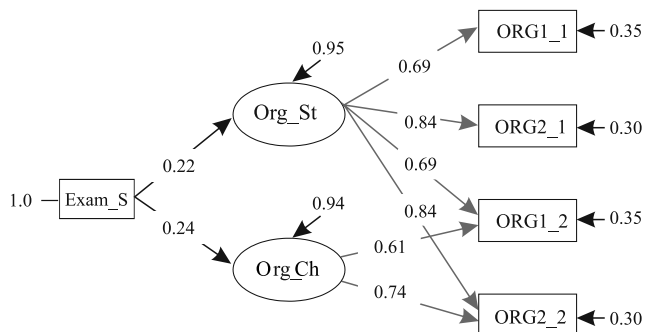


Figure 1. Predictive model for organization strategy (Org): Standardized path coefficients. Method factor loadings of ORG1\_1 and ORG1\_2, and correlation between latent state and change variables omitted for the clarity of path diagram. All path coefficients significant at  $p < .01$ . St = latent state; Ch = latent change.

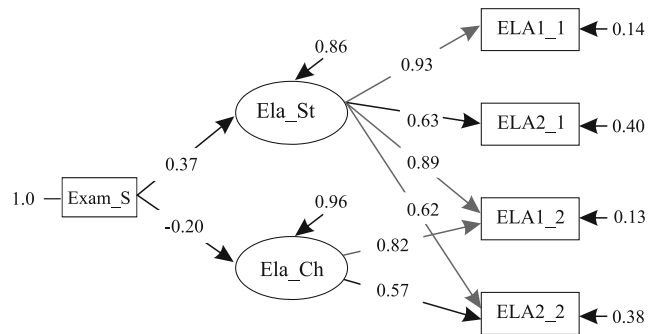


Figure 2. Predictive model for elaboration strategy: Standardized path coefficients. Method factor loadings of ELA2\_1 and ELA2\_2, and correlation between latent state and change variables omitted for the clarity of path diagram. All path coefficients significant at  $p < .01$ . St = latent state; Ch = latent change.

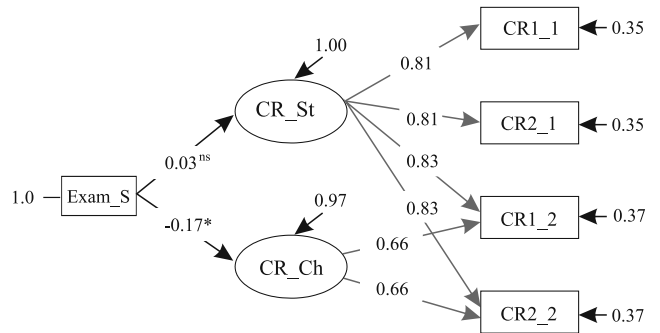


Figure 3. Predictive model for critical reasoning (CR) strategy: Standardized path coefficients. Correlation between latent state and change variables omitted for the clarity of path diagram. St = latent state; Ch = latent change.

\*  $p < .05$ . ns = not significant. All other path coefficients significant at  $p < .01$ .

utilization more were those whose performance at the first exam was lower. This finding supports our hypothesis that students with lower exam performance would try to change previously used learning activities. It also supports the general idea formulated in Pintrich's model (e.g., Pintrich, 2000) of self-regulated learning that evaluations of previous learning are used for subsequent learning. Nevertheless, it should be noted that, based on the design of this study, we cannot know whether the observed intraindividual variability in learning strategies was adaptive.

It would be interesting to explore the question if the observed intraindividual variability in learning strategies was adaptive when subsequent achievement is considered as an outcome variable. Also, having in mind the magnitude of the effects of previous performance on interindividual differences in intraindividual change obtained in this study, it

seems reasonable to believe that some other contextual variables, e.g., characteristics of teaching methods, level of difficulty, or workload, as well as individual differences variables, e.g., personality traits, motivation, intellectual ability, and emotions, could be important correlates of within-person variability in learning.

Finally, it is worth mentioning that all the structural equation models in this study were done treating each learning strategy separately. This was done so for methodological reasons and restrictions related to model complexity, available sample size and resulting degrees of freedom. Having in mind the observed correlations among the learning strategies, their simultaneous treatment in the modeling procedures might produce more illuminating findings.

In conclusion, results of this study add up to the large body of research about students' learning indicating that (a) the use of selected learning strategies—organization, elaboration, and critical reasoning—is significantly shaped by situational factors, even in two very similar learning episodes, and that (b) intraindividual variability in learning strategies is, at least modestly, correlated with previous achievement. Both of these findings are in line with theoretical assumptions of Pintrich's model of self-regulated learning. Moreover, it is our belief that this study can serve as an example of the importance and viability of psychometric theory, and the latent state-trait theory in particular, by offering a formal framework for answering essential questions about the nature of learning process, such as questions about antecedents and outcomes of stable and intra-individually variable components of this process.

## REFERENCES

- Baeten, M., Kyndt, E., Struyven, K., & Dochy, F. (2010). Using student-centred learning environments to stimulate deep approaches to learning: Factors encouraging or discouraging their effectiveness. *Educational Research Review*, 5, 243-260.
- Biggs, J. (2001). Enhancing learning: A matter of style or approach? In R. J. Sternberg & L. Zhang (Eds.), *Perspectives on thinking, learning and cognitive styles* (pp. 73-102). Mahwah, NJ: Lawrence Erlbaum Associates.
- Bråten, I., & Samuelstuen, M. S. (2004). Does the influence of reading purpose on reports of strategic text processing depend on students' topic knowledge? *Journal of Educational Psychology*, 96, 324-336.
- Buško, V. (2010). Measuring individual differences in psychological attributes: A psychometric view of contextual effects. *Review of Psychology*, 17(1), 43-46.
- Chiu, M. M., Chow, B. W., & McBride-Chang, C. (2007). Universals and specifics in learning strategies: Explaining adolescent mathematics, science, and reading achievement across 34 countries. *Learning and Individual Differences*, 17, 344-365.
- Credé, M., & Phillips, L. A. (2011). A meta-analytic review of the Motivated Strategies for Learning Questionnaire. *Learning and Individual Differences*, 21, 337-346.
- Donche, V., Coertjens, L., & Van Petegem, P. (2010). Learning pattern development throughout higher education: A longitudinal study. *Learning and Individual Differences*, 20, 256-259.
- Eid, M. (2000). A multitrait-multimethod model with minimal assumptions. *Psychometrika*, 65(2), 241-261.
- Jöreskog, K., & Sörbom, D. (2004). LISREL 8.71. Scientific Software International.
- Kulenović, A., & Buško, V. (2005). Latentne osobine i stanja: O jednoj generalizaciji klasične teorije testova [Latent traits and states: On a generalization of the classical test theory]. *Suvremena psihologija*, 8(2), 133-146.
- Lord, F. C., & Novick, M. R. (1968). *Statistical theories of mental test scores*. Massachusetts: Addison-Wesley Publishing Company.
- Mujagić, A., & Buško, V. (2012). Situational (in)consistency in learning strategies. *Proceedings in Advanced Research in Scientific Areas*, 1, 943-947.
- Mujagić, A. (2012). *Konzistentnost i situacijska uvjetovanost kognitivnih i motivacijskih komponenata učenja* [Consistency and situational specificity of cognitive and motivational components of learning] (Unpublished doctoral thesis). University of Zagreb, Croatia.
- Nijhuis, J., Segers, M., & Gijsselaers, W. (2005). Influence of redesigning a learning environment on student perceptions and learning strategies. *Learning Environments Research*, 8, 67-93.
- Nijhuis, J., Segers, M., & Gijsselaers, W. (2008). The extent of variability in learning strategies and students perceptions of the learning environment. *Learning and Instruction*, 18, 121-134.
- Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 451-502). Burlington, MA: Elsevier Academic Press.
- Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review*, 16, 385-407.
- Ramsden, P. (2003). *Learning to teach in higher education* (2nd ed.). London: Routledge Falmer.
- Renzulli, J. S. (2001). Abilities, interests, and styles as aptitudes for learning: A person-situation interaction perspective. In R. J. Sternberg & L. Zhang (Eds.), *Perspectives on thinking, learning and cognitive styles* (pp. 23-47). Mahwah, NJ: Lawrence Erlbaum Associates.
- Rozendaal, J. S., Minnaert, A., & Boekaerts, M. (2005). The influence of teacher perceived administration of self-regulated learning on students' motivation and information processing. *Learning and Instruction*, 15, 141-160.

- Samuelstuen, M. S., Bråten, I., & Valås, H. (2007). Context effects in Norwegian 10<sup>th</sup> grade students' reports on learning strategies using the cross-curricular competencies instrument. *Scandinavian Journal of Educational Research*, 51(5), 511-529.
- Scouller, K. (1998). The influence of assessment method on students' learning approaches: Multiple choice question examination versus assignment essay. *Higher Education*, 35, 453-472.
- Segers, M., Nijhuis, J., & Gijsselaers, W. (2006). Redesigning a learning and assessment environment: The influence on students' perceptions of assessment demands and their learning strategies. *Studies in Educational Evaluation*, 32, 223-242.
- Senko, C., Hama, H., & Belmonte, K. (2013). Achievement goals, study strategies, and achievement. A test of the "learning agenda" framework. *Learning and Individual Differences*, 24, 1-10.
- Severiens, S., Ten Dam, G., & Van Haut Wolters, B. (2001). Stability of processing and regulation strategies: Two longitudinal studies on student learning. *Higher Education*, 42, 437-453.
- Sorić, I., & Palekčić, M. (2002). Adaptacija i validacija LIST-upitnika za ispitivanje strategija učenja kod studenata [Adaptation and validation of the LIST - learning strategies questionnaire in students]. *Suvremena psihologija*, 5, 253-270.
- Steyer, R., Eid, M., & Schwenkmezger, P. (1997). Modeling true intraindividual change: True change as a latent variable. *Methods of Psychological Research Online*, 2(1), 21-33.
- Steyer, R., Ferring, D., & Schmitt, M. J. (1992). States and traits in psychological assessment. *European Journal of Psychological Assessment*, 8(2), 79-98.
- Steyer, R., Partchev, I., & Shanahan, M. J. (2000). Modeling true intraindividual change in structural equation models: The case of poverty and children's psychosocial adjustment. In T. D. Little, K. U. Schnabel, & J. Baumert (Eds.), *Modeling longitudinal and multilevel data: Practical issues, applied approaches, and specific examples* (pp. 109-126). London: Lawrence Erlbaum Associates.
- VanderStoep, S. W., Pintrich, P. R., & Fagerlin, A. (1996). Disciplinary differences in self-regulated learning in college students. *Contemporary Educational Psychology*, 21, 345-362.
- Vermetten, Y. J., Lodewijks, H. G., & Vermunt, J. D. (1999). Consistency and variability of learning strategies in different university courses. *Higher Education*, 37, 1-21.
- Vermetten, Y. J., Vermunt, J. D., & Lodewijks, H. G. (2002). Powerful learning environments? How university students differ in their response to instructional measures. *Learning and Instruction*, 12, 263-284.
- Vermunt, J. D. (2005). Relations between student learning patterns and personal and contextual factors and academic performance. *Higher Education*, 49, 205-234.
- Wild, P. K., & Schiefele, U. (1994). Lernstrategien im Studium: Ergebnisse zur Faktorenstruktur und Reliabilität eines neuen Fragebogens [Learning strategies in studying: Factor structure and reliability of a new questionnaire]. *Zeitschrift für Differentielle und Diagnostische Psychologie*, 15, 185-200.
- Wolters, C. A., Pintrich, P. R., & Karabenick, S. A. (March, 2003). *Assessing academic self-regulated learning*. Paper presented at Conference on indicators of positive development: definitions, measures, and prospective validity, Washington, DC.
- Zusho, A., Pintrich, P. R., & Goppola, B. (2003). Skill and will: The role of motivation and cognition in the learning of college chemistry. *International Journal of Science Education*, 25, 1081-1094.