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Personalized E-Learning: Relation Between Felder–Silverman Model and Academic Performance

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Abstract – **The growing demands for the training of students and the need for continuous improvement of the quality of university education make it necessary to find and apply more effective educational technologies and practices based on the correlation of teaching with the student's profile and his/her individual Learning Style. This article discusses the topic of relevance of personalized e-learning. It describes Learning Styles and looks at the Felder–Silverman model in more detail. The article contains the results of student surveys on the basis of which the interrelation between the Index of Learning Styles and academic performance is analysed. The relation between performance and learning styles according to the Felder-Silverman Learning Style Model is shown: in some specialties, students with sequential learning style have higher academic performance than students with global learning style, as well as students with mild learning style preferences on the Activist/Reflector dimension.**

Keywords – **Academic performance, Felder–Silverman model, learning styles, personalized e-learning.**

I. Introduction

Today the innovative vector of the development of society is becoming decisive. In the field of education, the principles of humanization and personal orientation began to prevail. They are reflected in IBM's annual 5 in 5 forecast, which describes the five most interesting potential inventions and innovations for the next 5 years. This forecast is based on market trends and social processes that will help make these innovations real in the next five years. The first place is occupied by the forecast of personalized education, when each student will need an individual approach. Personalized education will help improve the quality of education, develop an individual style of thinking, and also allow people to more successfully and quickly adapt to the environment and the ongoing social changes. We can no longer imagine the educational process without the use of the Internet. Each university, institute has its own website, which contains news, information about departments, electronic library, archive of conferences, database of students, archive of graduates, etc. [1]. The issue of personalization in e-learning has been the subject of many recent research efforts [2]–[4].

Students in the same grade have different knowledge levels and learn at different rates. They are more likely to succeed academically, emotionally, and behaviourally when they are supported as individuals [5].

Relevance of personalized e-learning could be categorized in external and internal factors from a standpoint of an educational organisation. External factors are related to students' different initial level of knowledge; their individual characteristics and the difference in Learning Styles; different motivation. In turn, internal factors for organisation can be divided into marketing and educational factors. Marketing factors include high competitiveness in the educational market; attracting foreign students, including students of distance education; formation of image and brand of the university. Educational factors include training of high-quality specialists, regardless of the initial level of knowledge; the need to use e-learning in the learning process (most of the time – self learning); creating a friendly educational environment using personalized learning.

Technology tools can offer personalized learning environments, in which students collaborate, interact with software, conduct research, create products, and communicate with others outside their schools [6]. In addition, the quality of education and Learning Objects (LO) of the university, in particular, the level of personalization of LO, have a great influence on the promotion and formation of the university brand.

The aim of the present research is to explore the relationship between Learning Style and students' performance and to create recommendations for personalized e-learning taking into account students' individual Learning Style.

The paper is organised as follows. Section II describes Learning Styles and looks at the Felder–Silverman model in more detail. Section III outlines conducted study methodology. Section IV shows results of student survey. Section V explains interrelation between the Index of Learning Styles and academic performance. Section VI discusses the presented results of the study. Section VII concludes the paper by briefly discussing the future direction of research.

II. Learning Styles

A Learning Style is a student's consistent way of responding to and using stimuli in the context of learning. Keefe [7] defines Learning Styles as the "composite of characteristic cognitive, affective, and physiological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment". Stewart and Felicetti [8] define Learning Styles as those "educational conditions under

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which a student is most likely to learn". It could be concluded that Learning Styles are concerned rather with how students prefer to learn than to what they learn. There are many conceptual and operational models of Learning Styles known (Kolb [9]; Felder–Silverman [10]; Myers–Briggs [11]), Honey and Mumford [12], etc.), on the basis of which different conclusions are made and conditions to improve learning are looked for, while studies show a direct relationship between Learning Style, teaching style and the difficulties that students face. These models offer several methods and instruments to categorize students according to their differences.

In this article, the most widely used learning styles of the Felder–Silverman model in the e-learning field will be reviewed in more detail. The Felder–Silverman model (see Fig. 1) was designed in 1988 and published as an article "Learning and Teaching Styles in Engineering Education" in the Journal of Engineering Education.

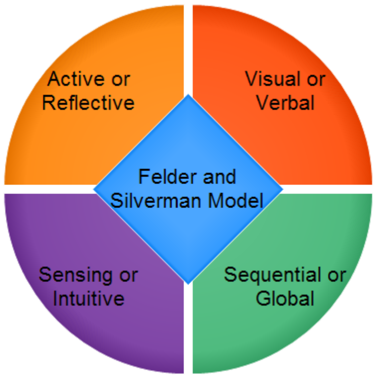

Fig. 1. Felder–Silverman model.

The purpose of this model was to capture the learning style differences among engineering students, and to provide a good foundation for engineering instructors to design a teaching approach that would address the learning needs of all students. The Felder–Silverman model ILSQ (Index of Learning Style Questionnaire) denotes four areas of personality that contribute to learning. This questionnaire consists of 44 questions. The model creates four dimensions (types of learners) of learning styles. These dimensions can be viewed as a continuum with one learning preference on the far left and the other on the far right. They are active or reflective, sensing or intuitive, visual or verbal, and sequential or global. A combination of these styles makes up the individual's learning preferences.

Features of personality style characteristics in the Felder–Silverman Learning Style Model (FSLSM) are presented in Table I.

The Felder–Silverman study focuses on the thesis according to which learners who have expressed strong preferences for a specific learning style may encounter serious difficulties during the learning process if the teaching style does not match their learning style or it cannot be fully integrated into an educational environment.

TABLE I
FEATURES OF PERSONALITY STYLE CHARACTERISTICS IN FSLSM
(SOURCE: [13])

Learning Style	**Style definition**	**Characteristics**
Visual	Determines how a learner prefers information to be presented.	Preference to use graphic and figurative information in the processes of information processing.
Verbal		Better assimilation of educational material when using words in written and oral form, pronouncing and writing down educational material.
Active	Determines how a learner prefers to process information.	Assimilation through active experimentation and practice, preference to do and then to evaluate the result.
Reflective		Preference of learning new information in a calm environment; working alone, thinking about each step.
Sensing	Determines how a learner prefers to perceive or take in information.	Work with facts and details, conducting experiments; accuracy, attentiveness, good memory.
Intuitive		Preference to work with abstract ideas, theories; non-standard practice and innovative approaches; powerful imagination.
Sequential	Determines how learner prefers to organise and progress toward an understanding of information.	The perception of information is gradual and continuous, step-by-step and using logic, linear reasoning and analysis; gradual forming of the full picture.
Global		Learning at a rapid pace, irregular; preference to solve complex problems by non-standard methods. Understanding of the full picture, integrating and synthesizing individual knowledge.

To build an e-learning recommender system that takes into account the individual characteristics of students, first of all, it is necessary to identify factors that, on the one hand, can significantly affect students' learning, and, on the other hand, can be adapted to the individual characteristics of the student. One of the essential indicators of student learning success is their academic performance.

The Felder–Silverman model has been chosen, as many studies have described its use for determining the student's learning style in distance education [14], [15], [16], [17] and the form, in which educational materials can be represented in e-learning systems (see Table II).

TABLE II
PREFERRED LEARNING CHARACTERISTICS MATCHING WITH ELECTRONIC MEDIA OF FSLSM (SOURCE: [3])

Learning group	**Characteristics**	**Electronic Media**
Active	Simulation, problem-solving, discussion group, brainstorming, experiment, questions and answers	Forum, wiki, learning, weblog, chat, e-mail
Reflective	Presentation, case study	E-book, written text
Sensing	Presentation, reading, problem-solving, simulation games, questions and answers	Forum, weblog, wiki, animation, graphic, picture
Intuitive	Discussion group, simulation, role games, case study, reading	Internet research engine, QCM
Visual	Simulation, presentation, reading	Forum, wiki, animation, graphic, picture, simulation, video
Verbal	Discussion group, brainstorming, questions and answers, problem-solving	Audio recording, podcast
Sequential	Presentation, questions and answers	E-book, audio
Global	Role games, brainstorming, case study	Weblog, wiki, chat, e-mail

The literature shows that student's performance may depend on the compliance of the student's learning style with the teaching style. Therefore, in order to create personalized learning objects for a particular course, first of all, it is necessary to find out if there is a correlation between academic performance and the learning style, in the presence of such a correlation, it is necessary to establish learning styles that help the students become more or less successful in this course. This will allow revealing the weaknesses of learning methods and making corrections of LO for personalized e-learning in accordance with the learning styles. Therefore, at the first stage of the research, which is aimed at developing the personalized e-learning system, the tasks have been set, first, to determine whether there is a relationship between performance and FSLSM learning style, and, second, to identify which learning styles are suitable for the existing educational system and which are not. In this case, three hypotheses have been formulated.

Hypothesis 1: There is a predominant FSLSM learning style among students.

Hypothesis 2: Students' performance is correlated with their individual FSM learning style.

Hypothesis 3: RTU students' academic performance in a course depends on whether students have mild or moderate & strong preferences in the FSM learning style.

III. METHODOLOGY

The studies were conducted on the basis of data of the Faculty of Computer Science and Information Technology at Riga Technical University in 2019. The course "Algorithmization and Programming of Solutions" is delivered to the first-year students of the study programmes "Computer Systems (CS)", "Automation and Computer Engineering (A&CE)", "Information Technology (IT)", "Financial Engineering (FI)" and "Intelligent Robotic Systems (IRS)". The study course provides the basic knowledge of the principles of computational process algorithmization and software creation technology using Java programming language. The study course "Algorithmization and Programming of Solutions" is based on the following learning methods: lecture presentations, practical tasks, eight practical home assignments and seven laboratory assignments, where the students have to develop a software program [18].

As indicators of student progress, the overall rating is used, which takes into account students' activity during the semester. This indicator includes the marks for four home assignments, two laboratory works, three tests and bonus points (for completing the work on time).

To determine the Index of Learning Style (ILS), the Learning Style Questionnaire (ILSQ) proposed by the Felder–Silverman model (ILSQ) was used. In this questionnaire, there are 11 questions for evaluating each of the four dichotomous dimensions, so for assessing students' preferences 44 questions were used in total [19]. There are 2 variants of answers for each question, each of which corresponds to one pole of 4 dichotomous dimensions: Visual – Verbal, Active – Reflective, Sensing – Intuitive, Sequential – Global. As a result, students' preference for each of the 8 styles is determined, as well as the strength of these preferences: a mild preference, a moderate preference, a strong preference. For the students' survey, the Learning Style Questionnaire was posted on Google Docs Forms and the students were asked to answer it via the ORTUS e-learning system. Of the 384 students who completed the course "Algorithmization and Programming of Solutions", 201 (52.3 %) students answered the questionnaire (Table III).

To test the null hypothesis that there are no differences between the total rating levels (points in total) in groups, Independent Sample Student's *t*-test and ANOVA were used with the post-hoc Duncan's new multiple range test. ANOVA was applied after testing for homogeneity of group dispersions using Leuven's test, with $p > 0.05$ [20]. Total rating levels in different groups are presented as mean values (M) ± standard deviation (SD).

TABLE III
THE QUANTITATIVE DESCRIPTION OF THE GROUPS OF STUDENTS WHO RESPONDED TO THE LEARNING STYLE QUESTIONNAIRE

Sex	Specializations by group					Total
	IT	CS	A&CE	FI	IRS	
M	85.7 % (54)	83.9 % (47)	94.3 % (33)	41.7 % (10)	82.6 % (19)	81.1 % (163)
F	14.3 % (9)	16.1 % (9)	5.7 % (2)	58.3 % (14)	17.4 % (4)	18.9 % (38)
All groups	100 % (63)	100 % (56)	100 % (35)	100 % (24)	100 % (23)	100 % (201)

Frequency data are presented as relative (%) and (n) absolute numbers of respondents and 95 % confidence intervals (CI). 95 % confidence intervals for frequencies were determined using the Wilson method [21].

All analyses were performed using the Statistica 8.0 software package. The threshold level of statistical significance was taken when the criterion value was $p < 0.05$.

IV. Survey Results

To build a recommender system model for personalized e-learning, first, it is necessary to determine which learning style profiles are most common among students, and which profiles are rarer. Table IV presents the learning style profiles of the interviewed students. Attention is devoted to the uneven distribution of students according to the preferences of all dichotomous dimensions, except Sequential/Global.

Thus, 68.7 % (138) of all the students surveyed were classified as "Activist", 84.1 % (169) as "Sensing" and 86.1 % (173) as "Visual". Only a small number of students showed themselves as "Reflector" 31.3 % (63), "Intuitive" 15.9 % (32) and "Verbal" 13.9 % (28). Students were distributed between Sequential and Global classes more evenly: the difference in a number of students who preferred sequential perception of information (Sequential, 59.7 % (120)) was not statistically significant from the number of students for whom a holistic approach was preferable (Global 40.3 % (81)). At the same time, it should be noted that there were no differences in the learning style preferences for men and women.

TABLE IV
Student Distribution by Learning Style Preferences

Dimension	Totals, % (*n*) [95 % CI]	M, % (*n*) [95 % CI]	F, % (*n*) [95 % CI]
Activist	68.7 % (138) [65.3 – 71.8 %]	66.3 % (108) [62.4 – 69.8 %]	78.9 % (30) [70.9 – 84.0 %]
Reflector	31.3 % (63) [28.2 – 34.7 %]	33.7 % (55) [30.2 – 37.6 %]	21.1 % (8) [16.0 – 29.1 %]
Total	100 % (201)	100 % (163)	100 % (38)
Sensing	84.1 % (169) [81.2 – 86.3 %]	84.0 % (137) [80.7 – 86.5 %]	84.2 % (32) [76.6 – 88.4 %]
Intuitive	15.9 % (32) [13.7 – 18.8 %]	16.0 % (26) [13.5 – 19.3 %]	15.8 % (6) [11.6 – 23.4 %]
Total	100 % (201)	100 % (163)	100 % (38)
Visual	86.1 % (173) [83.3 – 88.2 %]	87.7 % (143) [84.7 – 89.8 %]	78.9 % (30) [70.9 – 84.0 %]
Verbal	13.9 % (28) [11.8 – 16.7 %]	12.3 % (20) [10.2 – 15.3 %]	21.1 % (8) [16.0 – 29.1 %]
Total	100 % (201)	100 % (163)	100 % (38)
Sequential	59.7 % (120) [56.2 – 63.0 %]	60.1 % (98) [56.2 – 63.8 %]	57.9 % (22) [49.7 – 65.3 %]
Global	40.3 % (81) [37.0 – 43.8 %]	39.9 % (65) [36.2 – 43.8 %]	42.1 % (16) [34.7 – 50.3 %]
Total	100 % (201)	100 % (163)	100 % (38)

Table V shows that students with mild preferences are more on the dimension of Activist/Reflector 58.2 % (117) and Sequential/Global 66.7 % (134). However, according to dimension Sensing/Intuitive and Visual/Verbal, moderate & strong preferences are observed towards Sensing 57.7 % (116) and Visual 53.7 % (108).

The obtained data on the distribution by categories of strengths of preferences match with the literature data published by Felder and Spurlin [22], who summarised the bachelor students' learning style profiles from 29 studies. In most of the survey results of technical specialty students, Activist, Sensing, Visual styles also predominate. 60 % and more visual students are shown in all articles, in 22 articles 60% and more are sensing students and in 17 articles 60 % and more are activist students. Only in 13 articles, 60 % or more are sequential students.

TABLE V
Strengths of Preferences: Classes Mild, Moderate & Strong

Dimension	Strengths of preferences, % (*n*) [95% CI, %]			
	Mod-Str	Mild		Mod-Str
Activist/ Reflector	Activist		Reflector	
	33.8 % (68) [30.7 – 37.3 %]	34.8 % (70) [31.6 – 8.3 %]	23.4 % (47) [20.7 – 26.6 %]	8.0 % (16) [6.4 –0.3 %]
Sensing/ Intuitive	Sensing		Intuitive	
	57.7 % (116) [54.2 – 61.1 %]	26.4 % (53) [23.5 – 29.7 %]	11.9 % (24) [10.0 – 14.6 %]	4.0 % (8) [3.0 –5.8 %]
Visual/ Verbal	Visual		Verbal	
	53.7 % (108) [50.2 – 57.2 %]	32.3 % (65) [29.2 – 35.8 %]	11.9 % (24) [10.0 – 14.6 %]	2.0 % (4) [1.4 –3.5 %]
Sequential/ Global	Sequential		Global	
	19.9 % (40) [17.4 – 23.0 %]	39.8 % (80) [36.5 – 43.3 %]	26.9 % (54) [24.0 – 30.2 %]	13.4 % (27) [11.4 – 16.2 %]

Moderate or strong preferences of certain learning styles can interfere with the switching of the perception of information that is served in an "inconvenient" form. Conversely, students with mild preferences are more likely to switch easily between categories, rather than constantly demonstrating behaviour associated with a particular learning style. If the method and type of presentation of educational material do not meet the student's style requirements, this may affect both his/her academic performance and the motivation to acquire knowledge and skills. The lecturer does not always have the opportunity to organise the educational process optimally for all styles, but this can be done with the help of e-learning. In order to check the need for the presentation of educational material to students in different forms according to the Felder–Silverman model, the hypothesis about the interrelation of the learning style and student performance was tested.

V. Interrelation Between the Index of Learning Styles (ILS) and Academic Performance

Three out of four dichotomous dimensions (Sensing/Intuitive, Activist/Reflector and Sequential/Global) have been associated with performance.

The distribution of the total rating values did not differ from the normal distribution, so ANOVA was used for Sensing/Intuitive and Activist/Reflector, since for them the homogeneity of dispersions was confirmed by the Leuven test (p(Sensing/Intuitive) = 0.57, p(Activist/Reflector) = 0.94).

According to dimensions Sensing/Intuitive, moderate and strong intuitive students (Table VI) had the worst total rating. Apparently, the subject and relevant educational materials did not provide conceptual, innovative theoretical information that was necessary for students with a pronounced intuitive character.

TABLE VI
ANOVA (POST-HOC DUNCAN'S NEW MULTIPLE RANGE TEST): MEANS (M) AND STANDARD DEVIATION (SD) OF TOTAL STUDENT'S RATING WITH MILD AND MODERATE & STRONG STRENGTHS OF PREFERENCE DIMENSION SENSING/INTUITIVE

	Mod-Str Sensing n = 65	Mild n = 89	Mod-Str Intuitive n = 5
$M \pm SD$	37.08 ± 12.51	37.66 ± 11.15	25.18 ± 15.33
Mod-Str Sensing		n/s	0.009
Mild	n/s		0.010
Mod-Str Intuitive	0.010	0.009	

Differences in Activist/Reflector performance were revealed only in the combined group of students studying CS Computer Systems) and FI (Financial Engineering). For IT, A&CE and IRS students, performance was not related to dimensions Activist/Reflector. In this case, the performance of students with a moderate & strong activist was statistically significant (p = 0.007) lower (35.94 ± 8.33) than for students of mild activist (44.57 ± 8.45) as Table VII shows. Moderate & strong activist students prefer to work in a group, manipulate objects, conduct experiments, and learn. There are no experiments and manipulations with objects in the study course "Algorithmization and Programming of Solutions", but such a learning activity is not difficult to implement in electronic form. The results showed that, first, some students might have poor academic performance due to methodological reasons, and, second, the ways these reasons could be neutralized.

TABLE VII
ANOVA (POST-HOC FISHER'S LEAST SIGNIFICANT DIFFERENCE (LSD) TEST): MEANS (M) AND STANDARD DEVIATION (SD) OF TOTAL STUDENT'S RATING WITH MILD AND MODERATE & STRONG STRENGTHS OF PREFERENCE DIMENSION ACTIVIST/REFLECTOR

	Mod-Str Activist n = 16	Mild Activist n = 17	Mild Reflector n = 18	Mod-Str Reflector n = 4
$M \pm SD$	35.94 ± 8.33	44.57 ± 8.45	41.37 ± 9.62	41.18 ± 7.84
Mod-Str Activist		0.007	n/s	n/s
Mild Activist	0.007		n/s	n/s
Mild Reflector	n/s	n/s		n/s
Mod-Str Reflector	n/s	n/s	n/s	

ANOVA could not be used to analyse the relationship of performance with Sequential/Global, since the Levene's test revealed the inhomogeneity of dispersions (p = 0.03), so Independent Sample Student's t-test was used. In this case, differences were also found only in students of CS, FI (Table VIII). The global students had a lower total rating (37.91 ± 7.91) than the sequential ones (42.84 ± 9.60) (p = 0.048). In other words, students who preferred a holistic approach studied worse, that is, they first saw the big picture and then filled it with details.

TABLE VIII
MEANS (M) AND STANDARD DEVIATION (SD) OF TOTAL STUDENT'S RATING WITH STRENGTHS OF PREFERENCES SEQUENTIAL AND GLOBAL

Learning groups	Sequential		Global		t-value	df	p
	$M \pm SD$	N	$M \pm SD$	N			
IT, A&CE, IRS	35.12 ± 14.70	48	34.93 ± 8.60	23	−0.07	102	0.94
CS, FI	42.84 ± 9.60	32	37.91 ± 7.91	23	2.02	53	0.048

The specificity of the study course "Algorithmization and Programming of Solutions" is such that in order to show the overall picture, first, the details should be explained. Such a presentation of information makes it difficult for these students to perceive the material. In this case, in the e-learning system for such students, a special course could be prepared, where a brief general overview of all the material will be given with a demonstration of the result, which they can eventually obtain.

VI. DISCUSSION

Presented results of the study confirmed the interconnection of the Index of Learning Style and student performance. It has been shown that a lower total rating is found in students with an emphasis on Intuitive, Activist and Global learning style. One of the reasons for this situation may be the lack of conformity of the educational process and methodological materials with the student's learning styles. Or by defining a problem in a more general sense, it can be stated that the Learning Objects for personalized learning should be oriented at least towards the student's individual styles. Thus, for Learning Objects we accept the definition of Gibbons, Nelson, & Richards, where LO are related to an architecture for model-centred instructional products "that can be independently drawn into a momentary assembly in order to create an instructional event" and "can include problem environments, interactive models, instructional problems or problem sets, instructional function modules, modular routines for instructional augmentation (coaching, feedback, etc.), instructional message elements, modular routines for representation of information, or logic modules related to instructional purposes (management, recording, selecting, etc.)" [23].

Based on the specified requirements, LO should not only contain training materials optimized for individual learning style, but also instantly be customized for a specific situation and needs of a particular student.

Focusing on the Felder–Silverman model, we can conclude that stationary and interactive multimedia materials should be included in the LO kits in the e-learning system, which will differ in:

- types of submission: audio, video, typed texts, games, intellectual quests, etc.;
- graphic representation: drawings, diagrams, tables;
- degree of interactivity, that is, the ability to experiment with duration objects;
- individual and group work opportunities;
- the level of theoretical and practical information, as well as degrees of abstraction and practical orientation;
- availability of generalized and specific information;
- strategies for presenting educational material from general to specific or from particular to general;
- possibilities of deepening and expanding information on the issues being studied;
- level of conceptual and innovative information etc.

To implement such an e-learning model, an intelligent system is needed, which, based on the results of the primary data and data obtained during the training process, will adapt to the individual needs of the student, will recommend certain materials and a learning strategy, as well as produce LO elements in an optimal form and in a temporary mode.

In addition to the factors of learning style, which are taken into account in the Felder–Silverman model, there are other characteristics that can be significant for the learning process and which can be taken into account when forming the learning object in e-learning systems. The research by Essalmi et al. [4] provides a rather broad list of personalization parameters, such as the learner's level, learning goals, Honey–Mumford learning style, La Garanderie learning style, participation balance, cognitive traits and others. With personalized e-learning, it may be necessary to take into account and identify behavioural characteristics, personal, cognitive and other relevant characteristics. Thus, the personalized e-learning system should be constantly trained and improved, focusing on the data of dynamic observations.

At the same time, it is necessary to take into account that the improvement of the system is not possible without taking into account the quality, which can be assessed both according to the level of knowledge and competencies, and according to the perceived quality from both students and lecturers. At the same time, perceived quality is understood as quality dependent on the consumer's opinion [24].

VII. Conclusion and Future Work

The issues related to personalization in the learning process have been widely discussed in the recent years and remain in the focus of many researchers today. The growing demands for the training of students and the need for continuous improvement of the quality of university education make it necessary to find and apply more effective educational technologies and practices based on the correlation of teaching with the learner's profile and his/her individual learning style.

This study confirmed Hypothesis 1: among the surveyed students there were more activist type students than of reflector type, more sensing than intuitive students, more visual than verbal and more sequential than global students. At the same time, the number of students on the Sequential/Global dimension was not significantly different.

Hypothesis 2 was partially confirmed: first, the Visual/Verbal dimension did not show a relation with academic performance, and second, differences in academic performance on the Sensing/Intuitive and Sequential/Global learning style dimensions were observed only among students majoring in Computer Systems and Financial Engineering.

Hypothesis 3 was also partially confirmed: differences in performance among students with mild preferences and moderate & strong preferences were observed only on the dimension of Activist/Reflector. At the same time, the performance was higher among students with mild preferences.

The purpose of further research will be to identify and assess other factors that are significant for the effective personalization of the e-learning system in general and for the individual learning objects in particular. At the next stage, the influence of student's learning styles on the assessment and perception of existing learning objects will be investigated. In accordance with the recommendations by Bourkoukou, Bachari and Adnani [3], different types of LO will be prepared and researched. These studies are necessary for the development of personalized e-learning at Riga Technical University.

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