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AN ANALYSIS OF LEARNING BEHAVIOUR AND PATTERNS IN A TECHNOLOGY-ENHANCED LEARNING ENVIRONMENT

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Abstract:

Characterizing, structuring and supplying necessary knowledge for solving complex problems in today's dynamically changing environments is a great challenge. This paper provides an introductory description of the STUDIO learning environment that supports learners in applying and evaluating knowledge and in adapting changes to their own context quickly. The focus of the current study is on analysing learning characteristics and behaviours of undergraduate students of a Management Information System course, who used the STUDIO to facilitate the acquisition of required knowledge. A detailed description of data analysis and the interpretation of results applying cognitive frameworks will be provided.

Keywords: self-assessment, self-adaptation, learning behaviours and patterns, learning characteristics analysis, cognitive reference frame

I. INTRODUCTION

Knowledge plays a vital role in performing and reflecting on day-to-day activities, as well as in solving complex, unique problems in all organizations. At the same time, the relevance of knowledge may change over time and it is also risky to assume that the right knowledge is naturally at the right place and our workers have all the necessary knowledge all the time. Therefore, the need for effective learning and knowledge management tools that enable both individuals and organizations (or even the whole society) to adapt their knowledge quickly to the requirements of social, economic and technological changes is permanently increasing. Besides supporting the creation, application or reuse of knowledge, learning tools should also enable users to gain new insights concerning their knowledge from the data trails of their interaction with information, with other users and with technology, as well. Moreover, feedback – preferably – should be provided on the fly to enable the update and actualizing of knowledge and skills as required by the changing environment. Evidently not only learners but teachers, researchers or even practitioners – all who are involved in the learning process – can benefit from learning analytics. Applying analytics in learning processes embraces “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” [Siemens et al., 2011].

In the wider context of the learning space we can differentiate between formal and informal learning. De-linearized learning - where any person involved in the learning process can adopt any role of the learning process and thus, can be the supplier of the knowledge – occurs mainly in the context of informal learning situations [Abcouwer et al., 2016]. In the narrower environment of formal learning and teaching we focus on blended learning. In blended learning STUDIO is a tool which supports the self-assessment based learning process and the different roles that can be adopted, for example, the role of the student or of the researcher.

In this paper we present lessons learnt from analysing data available about users and their interactions with the STUDIO technology-enhanced learning environment that offers adaptive self-

assessment and personalized learning solutions. Section II provides an overview of the STUDIO learning environment and describes the concept of the applied adaptive self-assessment approaches. In Section III the research background, namely the case study of using STUDIO and learning analytics in a Management Information System course and research methodology are both described. Section IV highlights the results of data analysis detailing clusters identified based on users' behaviors and learning patterns. Section V provides an interpretation of results applying different cognitive frameworks, while conclusions are drawn in Section VI.

II. STUDIO TECHNOLOGY ENHANCED LEARNING ENVIRONMENT

STUDIO is a web based application where users can repeat a computerized adaptive self-assessment test as long as knowledge gaps can be detected. In short, users' learning workflow is the following: (a) students fill the test until the testing stops (b) the result is visualized on a concept map where each concept is associated to one of the questions of the test (c) then, users can check learning materials related to the asked questions. STUDIO is not aimed for examination but to support users' learning process. This system is a supervised self-learning tool, applied in a blended learning environment where users can discover knowledge gaps through an iterative process of testing and learning. Iterations help users to articulate knowledge in an explicit way. An ontology is used to structure the domain knowledge.

STUDIO offers two knowledge assessment methodologies that enables the exploration of a test candidate's knowledge gaps in order to help them in complementing their training or other knowledge deficiencies. The drill-down algorithm starts the examination at the top of the hierarchy, meaning that it tests the most comprehensive concepts first that have no parent concepts in the given domain. When the user gives an incorrect answer there are two possible options a) if there's another question (concept) on the same level testing continues b) if there's no question (concept) on the same level then testing stops. When the student correctly answers a question then the related top level knowledge area will be considered as "passed". In the next step additional questions are asked related to the sub-areas constituting this top level knowledge area. Only if answers given to these questions are correct, will the top level knowledge area be considered as "accepted" (otherwise it's considered as "rejected"). Questioning is recursively repeated until questions are correctly answered and/or all concepts are reached. Drill-down method finds out the depth of the required knowledge as well.

The concept-importance based approach defines the importance of each concept in the domain based on their ontological relations and defines assessment paths that start with concept that has the highest importance [Weber et al, 2016]. Decision concerning which one to choose can be made by taking into account practical considerations as well as the educational philosophy chosen.

Either strategies we choose the result of the testing procedure is a knowledge map, or more precisely, a map of missing knowledge. At the end of the test the learner can see an evaluation form and learn:

- which knowledge elements he or she knows as expected (accepted);
- which knowledge elements are those where questions were correctly answered but still the knowledge element has not been unaccepted. In this case the parent knowledge element has been correctly answered, but questions related to its sub-knowledge areas were incorrectly answered. This means that only a partial knowledge of the given parent concept could be detected (passed but not accepted); and
- which knowledge areas are those where questions were incorrectly answered (as illustrated on Figure 1).

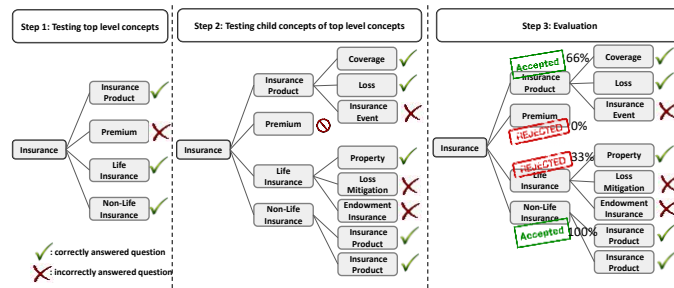


Figure 1: Illustration of the drill-down adaptive testing methodology in STUDIO

In the evaluation form a graph of the tested (sub)domain is also provided. By clicking on any of the concepts in the graph the user can see content related to the given concept (learning material).

III. APPLYING STUDIO IN MANAGEMENT INFORMATION SYSTEMS EDUCATION.

Research questions and measures

The main goal of our research is to identify characteristics and patterns of students' learning curves not only to understand better the learning process but to help developing more dynamic and flexible learning solutions. Student's learning curves should be extracted to find out if there is an improvement through the repetitive process over time. Once the learning curves have been extracted they will be processed in order to determine similarities and differences between students. To explore the reasons behind learning curve differences, various factors including social background and cognitive characteristics have to be taken into account. The starting point of our research is the assumption that different cognitive styles can influence students' learning curves.

Three selected measures capture students' performance each time they take a test. The first one - defined as the rate of accepted concepts per all concepts (nodes) - measures how large proportion of the domain the test taker mastered. The second one - defined as the rate of the number of concepts tested compared to the number of all concepts in the given domain - measures how large proportion of the domain was covered during a given test. The last one - defined as the rate of the number of accepted concepts per the number of concepts tested (that is the product of the first two measures) - determines how large proportion of the domain covered in the given test a student mastered. The first measure is capturing the individuals final performance at the end of each test while the second and third one show the understanding of the whole domain and tested domain part respectively. Since the first one is the most important concerning performance, this particular measurement will be used in the following analysis.

Background of the research

We collected empirical data from undergraduate Hungarian students of Business Administration major (at Corvinus University of Budapest), enrolled in the Management Information Systems course. The introductory Management Information Systems course for Business Administration students was designed to give a high level overview of the basic concepts of ICT including the very general and emerging new technologies. The goal of course is to highlight strong connections between ICT applications and enterprise management.

In our experiment students filled in a self-assessment questionnaire first, concerning their cognitive styles, then they got access to the STUDIO system, where students were free to fill in the adaptive self-assessment test as many times as they needed in order to get prepared for their final exam of the Management Information Systems course. The purpose of the questionnaire was to determine the Myers-Briggs Type Indicator of Corvinus University students to enhance

their course performance appearing in STUDIO. The questionnaire had been created with Google forms and contained forced choice questions aiming to assess students' MBTI types on the following variable pairs: Intuition/Sensing, Introversion/Extroversion, Thinking/Feeling, Judging/Perceiving [Quenk, 2009, Briggs-Myers et al. 1998]. In total 238 students filled the questionnaire, the vast majority of them were aged between 20 and 23. During the data cleaning process we eliminated 35 cases. In the next step the ten Management Information Systems seminar groups were split into two groups (group A and group B) containing in almost equal proportion all of the sixteen MBTI types. As it was mentioned in Section II, in STUDIO two kinds of algorithms are used for testing: the concept-importance based algorithm assigned to group A and the drill-down algorithm to group B.

Both the self-assessment test in STUDIO and final exam of the course were made up of multiple choice questions (but only the 10% of the test items were identical in the two test item repository). Out of the 203 students, 109 tested by the concept-importance based algorithm and 94 by the drill-down method. However, students were not aware of the fact which algorithm was running during their tests.

Research methods and tools used

A pre-test – post-test method is applied picking up the first and last trial of the students to compare and measure the degree of change in performance, self-learning behaviours, learning paths, patterns and characteristics as a result of repeating the computerized test over time. The aim of the analysis is to provide a representation of students' learning curve. In order to identify which factors may contribute to high performance, the circumstances of that round where students reached the highest scores were analyzed.

Descriptive statistics are used to extract learning curves. However, there was a hidden structure on learning curves preventing us from deducing safe inferences. In order to uncover the hidden structure, Self-Organizing Maps (SOM) were used to monitor and discover patterns throughout the population applying an unsupervised learning training for the first, last and best rounds of testing. In practice, SOM visualizes high-dimensional data sets in two-dimensional representations. A 6x6 SOM grid was chosen to train the SOM for 100 iterations. In order to investigate the SOM in detail, a unique *heatmap* has been created for each important feature. Finally, a Monte Carlo [Milligan and Cooper, 1985] evaluation of 30 indices is conducted on SOM to determine the optimal number of clusters for each round. After defining the best number of clusters, a hierarchical clustering is performed on the SOM nodes to isolate groups of students with similar metrics.

For the data analyses the STUDIO statistical functionality provided details on students, their level of use and access of resources, information on testing and learning activities.

IV. ANALYZING USER BEHAVIOUR AND PATTERNS

Figure 2 shows individual learning curves of students taking part in the experiment. The majority of students show an improving performance over time. However, it is not clear yet what the students' rate of learning improvement is, how many of them are improving over trials, and how the other features like time needed, number of repetitions, and views on the learning material change over the learning curve.

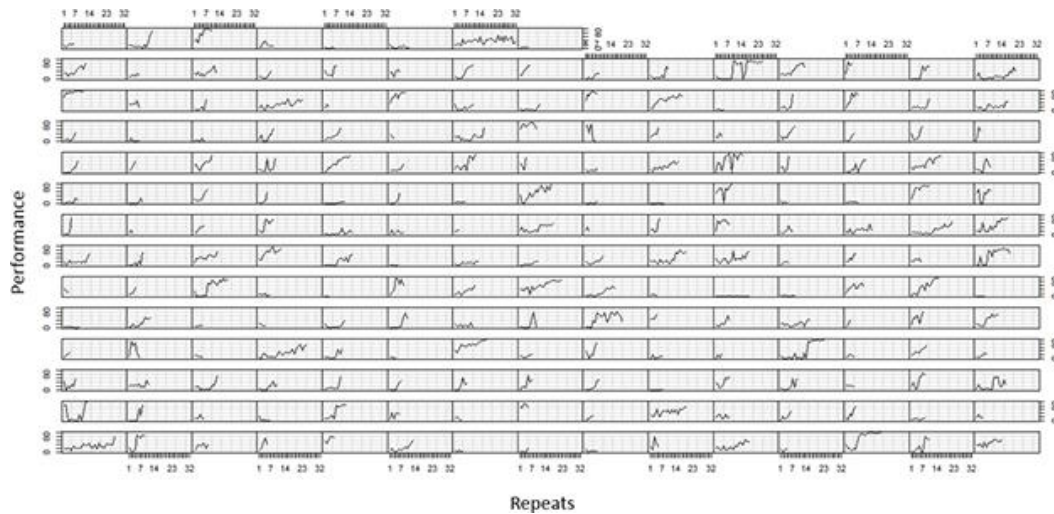


Figure 2: Individual students' learning curves

Looking for the most important factors in the first round which drive to higher performance we found that there is a positive correlation between the average time students needed to respond to a question and the performance ($r = .5, p < .01$). In the best round time to give an answer is not anymore a significant factor of achieving higher performance. However, two other important factors contribute to the improvement of the students. The number of times students repeat the test ($r = .4, p < .01$) and the number of views on the learning material ($r = .3, p < .01$) before the best round happened, are positively correlated with the performance, as well. A completely similar behaviour is observed in the last round which on average occurred one round after the best one, very close to the final exam of the course.

Based on the above outcome a heatmap is produced for each important feature. A descriptive analysis on the heatmaps of the first round of testing (Figure 3) reveals that the majority of the students (70%) achieved a poor performance, lower than 20%. In general, the average time needed for a student to respond to a question is 15.9 seconds (SD = 12.8 seconds). Only the 2% of them reach a score higher than 50%. Actually, these students achieve a performance around 65.7% (SD = 11.6%) just spending more time to respond to a question (M = 33.5, SD = 8.4 seconds). As a rule, students spending more time to give an answer tend to have a higher performance, in the first round. At the end of the first round, students covered on average 37.6% (SD = 19.4%) of the domain.

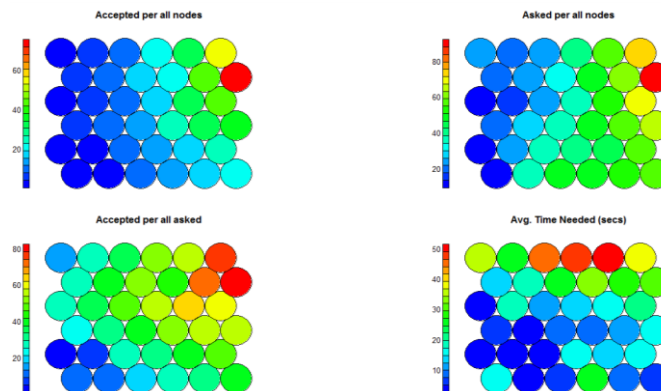


Figure 3: Heatmaps after the first round of testing

A drastically different learning behaviour was observed in the best round (Figure 4) since 57.6% of the students achieved higher performance (more than 50%), and they spent more time to give an answer ($M = 20.5$, $SD = 11.8$ seconds) than in the first round. The analyses also showed that, students repeated the test 8 times on average ($SD = 5$) and had more than 25 views ($SD = 41$) on learning materials before the best round happened. Students who gained a performance greater than 50%, repeated the test ($M = 9$, $SD = 5$) and checked learning materials ($M = 36$, $SD = 46$) more times than those students who achieved a performance lower than 50% repeating the test ($M = 5$, $SD = 3$) and checking the learning materials ($M = 12$, $SD = 27$) fewer times. At the end of the best round, students covered a larger proportion of the domain ($M = 72.5\%$, $SD = 21.9\%$) compared to that one of the first round.

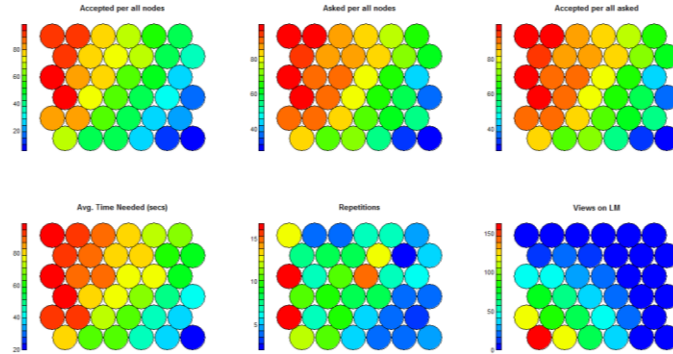


Figure 4: Heatmaps after the best round of testing

We can detect similar patterns during the last round of testing (Figure 5). Students achieved a much higher performance ($M = 46.6\%$, $SD = 29.7\%$) compared to that one of the first round ($M = 16.9\%$, $SD = 15.6\%$), but a bit lower in comparison to best one ($M = 55\%$, $SD = 28.1\%$). Students had more views on the learning materials ($M = 33$, $SD = 46$) than in the best round ($M=25$, $SD = 41$) checking the results at the end of the best round. Finally, in the last round, they respond to a question in a shorter amount of time ($M = 18.1$, $SD = 14.4$ seconds).

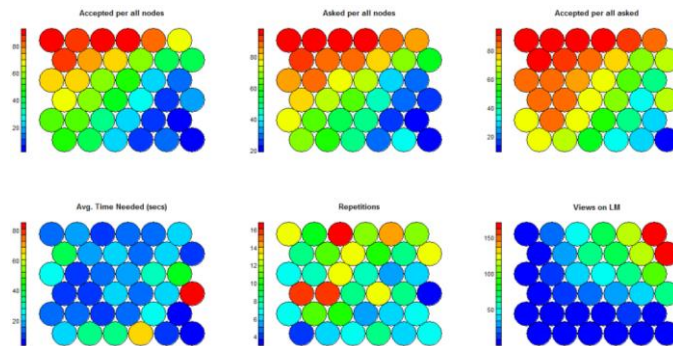


Figure 5: Heatmaps after the last round of testing

Using the Monte Carlo procedure evaluation of 30 indices shows that the majority of methods propose 2 as the best number of clusters for the first, and 3 for the last and best round. In the **first round of testing**, the majority of students (76.4%) belongs to the cluster of poor performers (blue – where performance is lower than 11% ($SD = 7.3\%$) on average) without spending much time ($M = 13.4$, $SD = 10.6$ seconds) to respond to a question (Figure 6). There is another cluster (orange – where performance is between 19.4% and 75.8%) with fewer students (23.6%) who spend more

time to give an answer ($M = 29.2$, $SD = 13.5$ seconds) achieving a fair performance ($M = 39.5$, $SD = 16.5$).

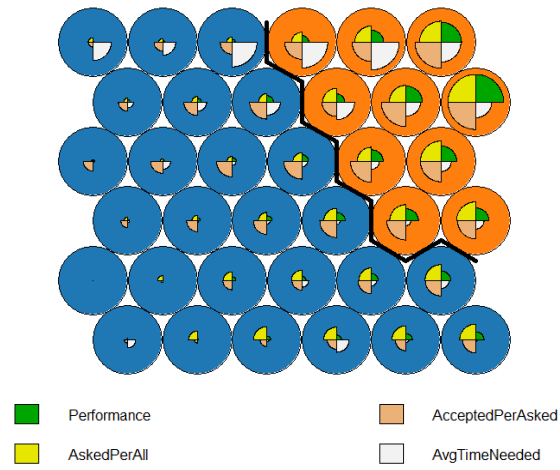


Figure 6: Clusters after the first round of testing

A different pattern is shaped on the SOM in case of the **best round of testing** (Figure 7). Most of the students migrate to the clusters of good or high performers. The majority (58% of the students) belongs to the good-performer cluster (orange – where performance is 66.9% on average, $SD = 17.3\%$) repeating the computerized test 8 times on average ($SD = 4$) and spending more time to respond to a question ($M = 21.4$, $SD = 8$ seconds). A smaller cluster in size (12.4% of the students) of high-performers (blue - where performance is between 44.5% and 94.1%) has quite similar learning behaviour patterns. The main difference is that these students have more views on learning material ($M = 111$, $SD = 33$) repeating the test a bit more times ($M = 11$, $SD = 3$). Only a small amount of students (20.7%) remained in the poor-performers cluster (green – where performance is between 4.9% and 32.7%) without being active at all.

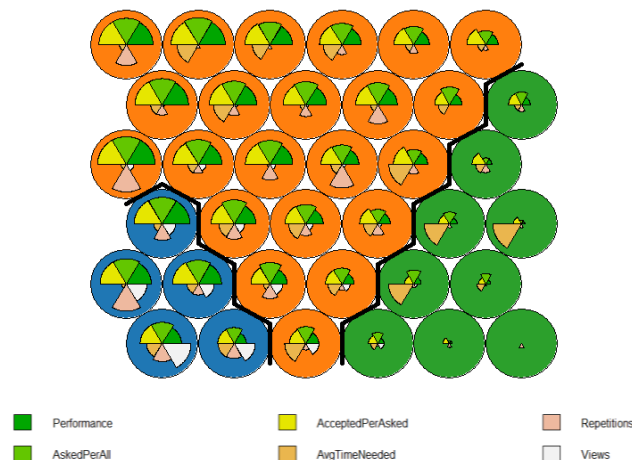


Figure 7: Clusters after the best round of testing

A slightly different behavior pattern is discovered in the last round of testing (Figure 8). In particular, most of the students (46%) fit to the good-performers cluster (blue - where performance is between 38.4% and 91.8%) having some additional views on the learning material than the best round as it was mentioned above, when describing the distribution of the heatmaps. Students belonging to this cluster in the best round but without achieving a quite strong performance (lower than 45%) move to the poor-performers cluster (orange) in the last round. Finally, students who remained in the high-performers cluster (green – where the performance is between 40% and 91%) are the ones that explored the learning material more times ($M = 127$, $SD = 39$).

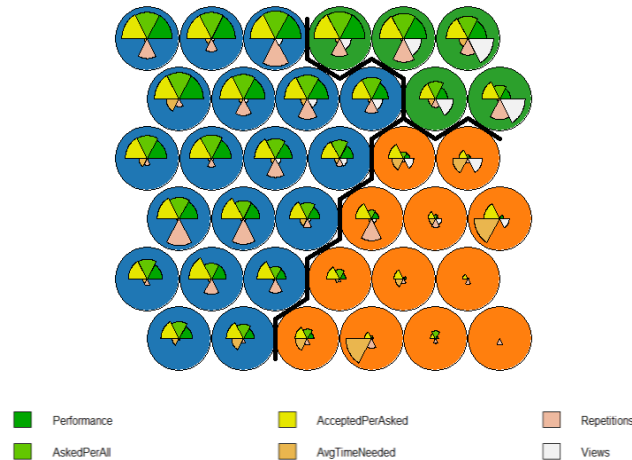


Figure 8: Clusters after the best round of testing

A bunch of chord diagrams were also implemented to visualize simultaneously the relative size of estimated flows of the students from one round of testing to another, splitting them into four groups according to their performance at the end of each round. The next diagram (Figure 9) displays the bilateral migration flow of the students between the first and best round. The majority of students moves to the good- or excellent-performers groups. 47.3% percent of students migrate to the groups of good- (between 50% and 75%), and excellent- performers (greater than 75%) while 36% of them migrate to the group of fair-performers (between 25% and 50%). Students having a considerably low performance (lower than 24.1%) in the first round remain in the same group in the best round, however, they achieve a higher performance (arrow 1 on Figure 8). On the other hand, the greater the performance is in the first round, the higher it is in the best round.

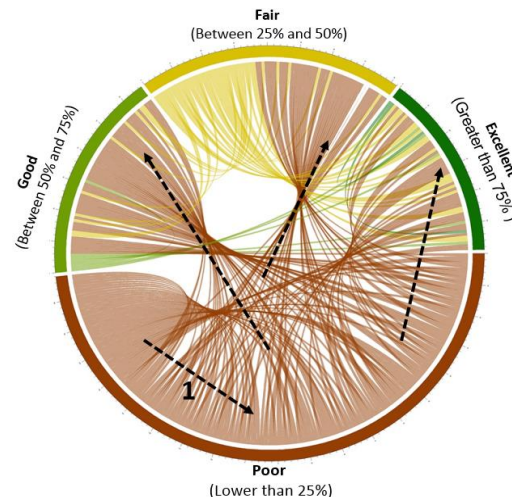


Figure 9: Bilateral migration flow of the students between the first and best round

At the end of the experiment we found that the final exam grade weakly correlates with the number of times students repeated the computerized self-assessment test ($r = .12, p < .001$). This phenomenon needs further investigation.

V. INTERPRETATION OF RESULTS IN A COGNITIVE REFERENCE FRAME

In this section a detailed interpretation of the learning curves' analysis - *described* in the previous sections – will be provided. The research follows an approach based on cognitive style and personality theory amongst others. Therefore, we shortly outline the main features of the selected approach and then apply them to the actual results of the experiment.

Many models were proposed to describe human learning behavior. Some theorists [Entwistle, 1995; Vermunt, 1994; Sternberg, 1991] claim that cognitive or learning styles are in reality strategies influenced by the environment and therefore, they can change over time. Other models [Honey and Mumford, 2004; Kolb, 1984; Herrmann, 1989; Myers-Briggs, 1962] view learning styles as flexibly stable or stable characteristics of the learner while a few authors, including Gregorc [1982] state that they are rooted in fixed genetic traits [Coffield, 2004]. Although learning or cognitive styles are widely researched topics there is still no universally accepted theory.

The two terms causing the most confusion in the literature describing human learning behavior are learning and cognitive style. Various researchers use the terms interchangeably. In this study we differentiate between learning and cognitive styles taking Keefe's definition of **learning styles** as "... *characteristic **cognitive, affective, and physiological behaviours** that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment.*" [Keefe, 1982]. In this approach cognitive style, among various factors, is a constitutive of learning style. **Cognitive style** – concurring with Triantafillou et al. [2004]– "*is usually described as a **personality dimension** that influences attitudes, values and social interaction. It refers to the preferred way an individual processes information.*" In other words, learning styles include relatively stable cognitive characteristics but also more easily changing learning tactics and psychological factors such as mood or motivational level. Cognitive styles focus exclusively on the individuals' preferred way of information gathering and information processing. A similar distinction can be observed in Curry's onion model of research approaches where the cognitive personality style constitutes the core, information processing the middle layer, and instructional preferences the outermost part of the "learning personality" [1983].

The aim of the current research is to find out whether students' learning curves are influenced by cognitive styles or not. The selection of the cognitive style model which would fit best to the goal of the study was based on 1) Coffield's classificatory overview [2004] of 13 learning styles analyzing strength and weaknesses of each style and the external evaluation of tests' statistical structure,

reliability and validity 2) the existence of any kind of neurophysiological evidence supporting the theories 3) the models' level of complexity, number of dimensions 4) the previous year's study results of the Felder-Silvermann questionnaire. Considering all the factors mentioned above, Myers-Briggs Type Indicator and Gregorc Style Delineator were selected because both models 1) have acceptable test reliability and validity 2) are supported by neurophysiological evidence 3) take into account information gathering **and** processing 4) focus on the core element of the learning personality.

Myers-Briggs Type Indicator (MBTI) is a four axis sixteen styles classification that shows two types of abilities, information gathering (perception) and processing (ordering). Therefore, it can be considered as a cognitive style classification. The MBTI model states that there are differences in the ways we perceive and judge information. The model has its origins in Carl Jung's psychological types that inspired Katherine Briggs and her daughter, Isabel Myers to design a questionnaire able to measure cognitive types [Quenk, 2009; Briggs-Myers et. al. 1998]. Type indicator means that MBTI is a self-assessment personality test with no right or wrong answers nor right or wrong types. It reflects only what the person told to the test. While the Myers-Briggs questionnaire is widely used in educational and business environments it also attracted a lot of criticism over the years. In his article "*Measuring the MBTI... And Coming Up Short*" Pittenger [1993] examines the test's statistical structure, reliability and validity. Howes and Carskadon [1979] in their studies come to the conclusion that the standard error of measurement for each of the four dimensions is fairly large. However, other analysis of reliability across 210 studies found that MBTI has acceptable score of reliability when reliability data is available but the reliability of every instrument is "dependent on sample characteristics and testing conditions" [Capraro and Capraro, 2002].

An American researcher, Dario Nardi conducted EEG experiments in the labs of UCLA to prove the neurological validity of the Jungian model of the mind. When examining volunteers' brain during various tasks Nardi detected consistent patterns of activity characteristic to each type: "Each of the Jungian/Myers-Briggs personality types shows a unique global pattern. The patterns strongly influence how people handle all kinds of situations as well as how people adapt, learn and grow." Nardi's brain map shows the key regions of the neocortex and the associated cognitive skills. The regions were also given numbers to make the areas easier to recall [Nardi, 2011]: The MBTI classification differs from other learning styles' classification in the confirmed neuroscientific validity of its types.

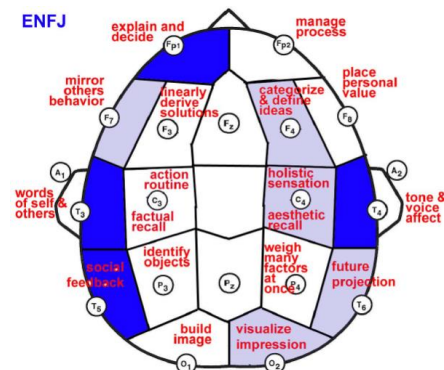


Figure 9: Example of brain map of an MBTI type (in this case, ENFJ)

Pre-test Activities

For the interpretation of the above detailed testing results we selected the Gregorc Styles Delineator and Myers-Briggs Type Indicator from the wide range of cognitive styles. Besides the selection reasons mentioned earlier both models have a self-assessment questionnaire which is the optimal method to determine students' learning styles in an organized manner and with

minimal time needed. We collected empirical data from 238 students of Business Administration major enrolled in the Management Information Systems course. A descriptive statistical analysis was carried out to find correlation between Gregorc styles, MBTI types and the number of test repetitions and performance in the first, best and last rounds of testing. Gregorc Style Delineator showed no significant correlation with performance at all. In the following paragraphs MBTI results will be discussed.

Connection of MBTI with knowledge assessment

Students with very different background start their studies in higher education each year where they also have to cope with emerging new technologies and instructional media used to optimize information delivery. In today's educational environment uniform instruction methods are considered less and less effective: there's an increasing need for tailor-made and personalized solutions in the design and delivery of the course content. Mismatches between teaching and learning or cognitive style may be real drawbacks for students but instruction modalities based on styles can offer a solution for this problem.

The effect of personality types on the academic performance has been analyzed. From the three performance indicators mentioned above (See Section II, Background of the research) the first one is the most important which measures how large proportion of the domain is mastered by the test taker calculated as accepted concepts per all concepts of the domain.

According to the cluster analysis presented in Section IV students' performance influenced by various factors. These explanatory variables are a) number of repetitions of the test b) time spent on the test (includes time spent on answering the questions and also time spent on checking learning material) c) the testing algorithm.

Analyzing User Behaviours and Identifying Patterns

Many previous studies have examined the relationship between higher education students' performance and Myers–Briggs personality types in the fields of macroeconomics and microeconomics. Borg and Shapiro [1996] examined the influence of MBTI personality dimensions on academic success on Macroeconomics courses. They found that ISTJs (the most frequently occurring personality among the students and the second most frequent in our research) had outperformed other types on the course. Other introverted types also had a greater chance of getting a good grade.

Ziegert [2000] found that on the Microeconomics course ISTJs performed significantly better than the other types in terms of grades. In her study she examined how students' performance on the post-TUCE test (Test of Understanding College Economics after the completion of the course) was correlated with MBTI types. Ziegert found that ISTJ type students outperformed significantly ESFP, ENFP, INFJ, ENFJ, ESFJ, INFP, ISFJ and ESTJ students (predominantly extraverted and feeling types). INTJ students achieved the best results.

In Hungary a similar study had been carried out at the University of Debrecen. Study results show that on Business Administration and Management major INTJ, ESTJ, and ESFJ students had better performance than other types while among the Business Informatics students the ENFJ type had a significantly better grade mean [Kapitány-Kiss-Kun, 2014].

First and best round of testing

In the following paragraphs results found in the first and best round will be discussed.

Based on the results of the first round students preferring introversion and judging had slightly better results than extroverted and perceiver students. There's only a minimal difference between sensing/intuitive or thinking/feeling type students.

The results of the best round show us the same slight difference between introverted (59,4%) and judging (57,7%) type students compared to extroverted (53,75%) and perceiving ones (52,5%). Sensing-intuition seem to play a less important role in the performance of students in the best round than introversion/extroversion or judging/perceiving. Thinking type students' performance

(59,35,% on average) is 10% better than the result of persons preferring feeling over thinking (48,9% on average). This is the strongest indicator of performance in the best round of testing.

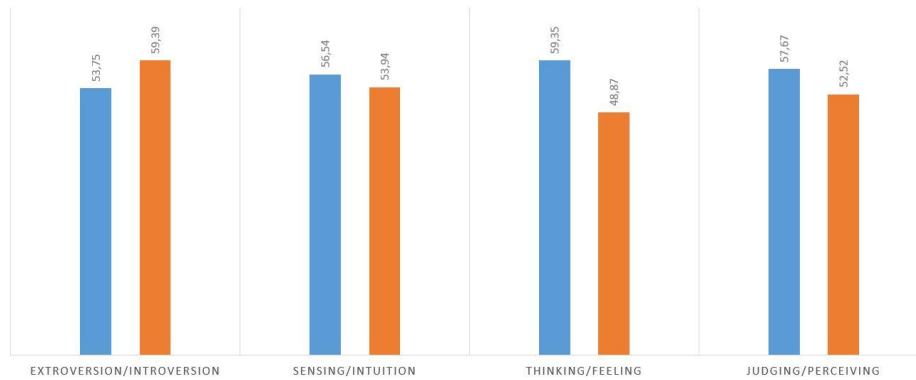


Figure 10: Students' best round performance and MBTI dimensions

Learning dynamics

Comparing the first and the best round results, students whose performance improved the most are ISTPs, INTJs, ISFPs, INFPs, ENTJs. These types' best round performance was more than four times better than the first round performance (ISTP: 4.7; INTJ: 4.68; ISFP: 4.56; ENTJ: 4.37; INFP: 4.03). Students whose performance improved the less from the first to the best round are INFJ, ENFJ, ISFJ, ENTP, ESTP, ISTJ, ESFJ, ENFP. Their best performance was only two to three times better than their average or below average first round performance. INFJs and ENFJs performance improved the less they performed only 1.53 and 2.15 times better respectively. We can conclude that thinking preference may be a weak indicator of greater performance improvement as thinking types' best performance is 3.38 times better than their first round performance while this indicator for feeling types is only 3.07.

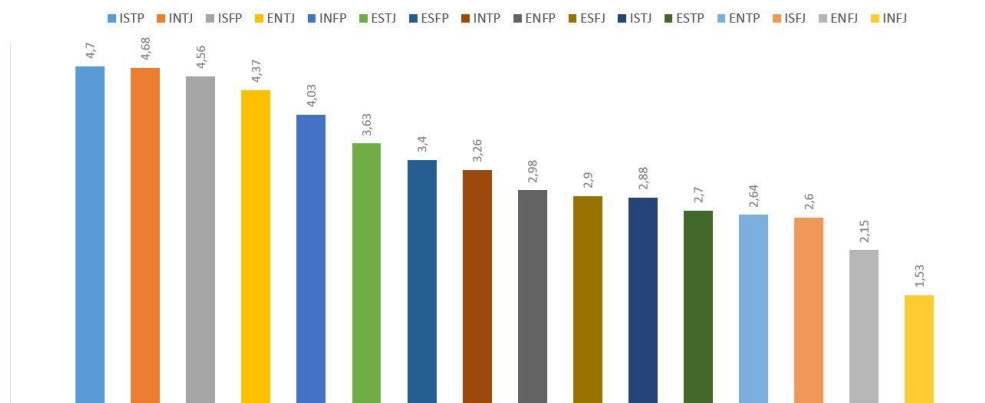


Figure 11: Performance improvement of MBTI types

Performance

Although differences were far not sharp, we may assume the more introverted, sensing, thinker, judger the student is, the better the performance. In our experiment thinking type students achieved a result 6% better than feelers. Being an introvert and a judger also increases the chance to perform better in Studio: the average difference between introverted and extraverted

students' result is 5% while judgers perform 4% better than perceivers. Sensing/intuition seem to have no effect on performance at all in the sample observed.

This finding may confirm results that on economic fields ISTJs or INTJs tend to outperform other cognitive types. Students who prefer introversion over extroversion tend to be more reflective and deal better with theory; as thinking and judging types they evaluate this information immediately and objectively what makes them very well suited for economics related careers.

VI. CONCLUSION

One of the major challenges in today's education is the different ways agents approach the learning process. Teachers have a previously defined objective as a starting point. Based on this goal the expected learning outcome is defined and a suitable educational process leading to the desired result is designed. Finally, in the evaluation phase the results of the ongoing or completed activities are analyzed.

In contrast to the above mentioned process students are often presented first with the evaluation criteria and the related tasks they have to accomplish. After facing the requirements they start the learning process and get grades according to test results. This way the emphasis falls on meeting the requirements and the evaluation criteria while the main focus should be on achieving the goal previously defined.

Moreover, as Abcouwer et al. [2016] describe *"aside from the traditional linear learning approaches there is a growing need for more flexibility in the partially informal learning process... Skilled people have to work together on solving problems in a dynamic context where the outcome of this cooperation will be emergent and – thus – in many cases unpredictable"*. The aim of our study was to identify such characteristics and patterns of learning that enables a better understanding of the learning process and the development of such learning solutions which enables the supply of knowledge relevant for divergent problems of today's dynamic social and economic context.

Students' behaviour in STUDIO are reflecting the two contradictory approaches mentioned above. The two most important performance indicators by which students' performance can be measured in STUDIO are Accepted Per All Concepts (of the domain) and Accepted Per Asked Concepts. The first one shows us the final result as the ratio of the total number of concepts which were accepted and the total number of concepts, while the second one is the ratio of the total number of concepts which were accepted and the total number of concepts tested during the self-assessment. Best round clustering analysis divides the students into three main groups a) students with poor performance b) students with relatively good performance putting emphasis on the test questions and the related results but not checking the learning material and repeating the test as many times as the best performing cluster does c) students with very good performance where the focus of learning behaviour is on seeing the big picture by checking the learning material thoroughly. A learning behaviour focusing on the long term goals increase the most effectively the performance measured by Accepted Per All.

Although no strong relation was found between MBTI type and performance nor between MBTI types and groups defined by the clustering analysis the exercise provided ample evidence to expand research related to the connection of cognitive (and learning) traits and academic performance. Myers-Briggs Type Indicator seems to be a possible/promising method.

Possible reasons for the lack of strong relations could be the following: a) domain is narrow: collecting data from other courses may provide more detailed understanding b) data was collected only in one semester, a longitudinal study may provide more information c) Management Information Systems course is not a core course for BAM students thus motivation levels are lower d) self-assessment questionnaires' reliability and validity are questionable: false positive and false negative problems cannot be handled e) indicators used for clustering students and creating groups have no relation with personality types characteristics.

Future research therefore might extend our examination to other courses which would provide more ample and diverse sample to observe. Control environment of monitored population should be more sensitive and selective giving students more exact instructions about how to fill self-assessment questionnaires. Introduction of control groups and inclusion of master and post-graduate students would be highly beneficial. Study results must be interpreted and explained in detail for instructors to make them able to act upon the information received. At this point we don't detail the technical preconditions (which are many) but we intend to fine-tune the identification of the students' individual cognitive style.

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VIII. REFERENCES

- Abcouwer T., B. Smit, and E. Takács. (2016) "De-linearizing learning". *Proceedings of the Special Interest Group for Education (SIGED) 2016*. Dublin, Ireland.
- Abel, G. J. and Sander, N. (2014) "Quantifying global international migration flows". *Science*, (6178)343, pp. 1520-1522.
- Borg, M.O. and Shapiro, S.L. (1996) "Personality Type and Student Performance in Principles of Economics". *The Journal of Economic Education*, (27)1, pp. 3–25.
- Capraro, R. M. and Capraro M.M. (2002) "Myers-Briggs Type Indicator Score Reliability Across Studies: A Meta-Analytic Reliability Generalization Study." *Educational and Psychological Measurement*. (4) 62, pp. 590-602.
- Coffield, F. et al. (2004) *Learning styles and Pedagogy in Post-16 Learning: A Systematic and Critical Review*. Learning and Skills Research Centre. London. Retrieved from <http://www.voced.edu.au/content/ngv13692>
- Curry, L. (1983) "An organization of learning styles theory and constructs. " Paper presented at the Annual Meeting of the American Educational Research Association, Montreal, Quebec. Retrieved from <http://files.eric.ed.gov/fulltext/ED235185.pdf>
- Howes, R. J. and Carskadon, T. G. (1979) "Test-Retest Reliabilities of the Myers-Briggs Type Indicator as a Function of Mood Changes." *Research in Psychological Type*, (2) 1, pp. 67-72.
- Kapitány A., M. Kiss and A.I. Kun. (2014) How Do Student Personality Types Contribute to the Academic Success in the Hungarian Business Higher Education? Retrieved from: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2514050
- Keefe, J. W. (1982) Assessing Student Learning Styles: An Overview. In Keefe, J.W. (ed) *Student Learning Styles and Brain Behavior*. Reston, VA: National Association of Secondary School Principals
- Milligan, G. W. and Cooper, M. C. (1985) "An examination of procedures for determining the number of clusters in a data set". *Psychometrika*, 50(2), pp. 159-179.
- Nardi, D. (2001) *Neuroscience of Personality: Brain Savvy Insights for All Types of People*. Radiance House. Los Angeles, CA.
- Pittenger, J. (1993) "Measuring the MBTI... And Coming Up Short". *Journal of Career Planning and Employment*, (54)1 pp. 48-52. Retrieved from: <http://indiana.edu/~jobtalk/Articles/develop/mbti.pdf>
- Quenk, N. L. (2009) *Essentials of Myers-Briggs Type Indicator® Assessment*. Second Edition, John Wiley and Sons, Hoboken, NJ.
- Triantafillou, E. et al. (2004). "The value of adaptivity based on cognitive style: an empirical study." *British Journal of Educational Technology*, 35(1), pp. 95–106. Retrieved from: <http://doi.org/10.1111/j.1467-8535.2004.00371.x>
- Van Hulle, M. M. (2012) Self-organizing maps. In: *Handbook of Natural Computing*, pp. 585-622. Springer Berlin Heidelberg.
- Vesanto, J. and Alhoniemi, E. (2000) "Clustering of the self-organizing map". *IEEE transactions on neural networks*, (3)11, pp. 586-600.
- Weber C., G. Neusch, and R. Vas. (2016) STUDIO: "A Domain Ontology Based Solution for Knowledge Discovery in Learning and Assessment". *Proceedings of the Special Interest Group for Education (SIGED) 2016*. Dublin, Ireland.
- Ziegert, A.J., (2000) "The Role of Personality Temperament and Student Learning in Principles of Economics: Further Evidence". *The Journal of Economic Education* (31)4 pp. 3–14 retrieved from: <http://www.montana.edu/stock/ecns305/ziegert.pdf>

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