Learning Style Identification System: Design and Data Analysis

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Abstract. The article analyzes different approaches to design adaptive educational systems on the basis of students' learning style identification. As a result of the investigation a system to identify the student's learning style with the data analyzing module has been designed and implemented. A data analyzing module is applied for the further adaptation of digital educational content and educational methods to students' learning style. The data background for the module to analyze learning style identification system is the universal e-learn environment users' database, the results of learning style identification due to VARK (visual, audial, read-write, kinesthetic) model or any open external information like psychotype, type of intelligence, etc. Data storage uses the concept of data warehousing to predict special methods for data model design taking into account the integrity of datasets from different sources, object orientation, consistency, data consolidation or multidimensional data architecture to simplify analytical queries. The data analyzing technologies being applied within the system are based on the information retrieval approach using SQL language; OLAP and Data Mining technologies. The results of the system implementation gave an opportunity to fix the correlation of learning styles with other personal characteristics like psychotype, gender, secondary education level, academic achievements, etc. The represented data of data analysis concerning IT major students give reason for the conclusion about the necessity to adapt digital content to multimodal and kinesthetic learning style, to apply learning methods and technologies on the basis of project tasks, group communication and collaboration.

Keywords: Learning Style, Design of the Learning Style Identification System, Technologies of Data Analysis.

1 Introduction

1.1 The Problem Statement

One of the digital educational environment key components is e- learning material including e-learning courses (ELC), e-tutorials, virtual labs, video lectures, multimedia resources, etc. The format to represent the same educational material may be different. For one and the same topic a set of textual materials, a multimedia guide, a training video, a webinar, etc. may be elaborated to differ in the way of perceiving the educational material in audio, visual, kinesthetic or verbal samples. The students often deal with educational content without taking into account their special features of educational content perception, leading to the results of no constant learning style adequacy. At the end it influences on the level of professional competence development and on studying achievements results. Student's learning style is developed due to many factors exampling psychotype, emotional state, physiological and other factors [1]. There are many scientific investigations devoting to the students' learning styles, automated systems of their identification or to adaptive e-learn systems but it is a lack in investigation of the item concerning information systems design to analyze not only students' learning style but the factors influencing on its formation or change.

The purpose of the article is to design and to investigate the ways of data analysis technologies application within the learning styles identification system.

Each student has own individual needs and special features being formed in high school [2]. The most of the systems to control educational content do not take into account these needs namely in adaptive courses providence. The majority of existing LMS systems do not support adaptability of the learning process, so it is necessary to focus on adaptive learning content management systems. In our research we will answer the following questions: How to determine learning style automatically and what technologies of analysis or for what purpose may be applied within the learning style identification system.

1.2 The Theoretical Background

Native and foreign researchers pay considerable attention to the study of students' educational styles. In [3] learning styles are defined as a set of cognitive, emotional, specific and physiological factors to serve as relatively stable indicators of how a student perceives, interacts with learning environment or responds to it. Most of investigations prove that learning style influences students' attitude to studying, satisfaction level and academic achievements within online educational environment [4]. While developing e-learn systems they take into consideration the need in taking into account a student's learning style to be proved by results publication of adequate investigations [5, 6, 7].

There are two the most spread methods to identify learning style: static one on the basis of learning style inventory and dynamic one on the basis of behavior mode while studying. Static method of identification is simply enough though it takes student's time for testing. Dynamic method of identification is based upon different methods application like neural networks, Bayesian networks or rule-based reasoning. In particular, many researchers have confirmed the efficiency of Bayesian network-based automatic style identification. According to Feldman's review [8] Bayesian networks are one of the most widely used methods to identify students' learning style automatically [9, 10, 11, 12].

The models of learning styles are classified and are characterized by the way of educational content receiving and working out. The fundamental aspects of such models are cognitive styles and educational strategies. The most spread and known models of learning styles are VARK, Myers-Briggs, Kolb, Felder-Silverman and 4MAT.

Adaptive e-learn systems apply learning styles in order to propose valuable recommendations and regulations for students and scholars to optimize educational process [13]. Adaptive e-learn systems are considered to be one of the interesting directions within digitally based educational technologies [14]. The main goal of these systems is to propose the way to percept educational material on the basis of students' preferences, needs, educational experience, learning style, students' age, etc. [15].

[16] has reviewed above 50 investigations concerning integration of learning styles with the adaptive educational system. These investigations involve different aspects: from choice of e-learn environment learning styles theories, learning styles forecasting or learning styles automatic classification up to numerous systems to identify learning styles. Integration of learning styles into the adaptive educational systems is comparatively new trend within e-learn technologies.

The example of the above named systems realization is WELSA being described by [17]. In particular, there were functionality, designing tools, data analysis and WELSA system adaptation on the basis of dynamic content adaptation to the learning style investigated. The possibilities of one more adaptive Manhali educational management system are observed by [18]. The experimental observation of IT students' e-learn studying within the adaptive Manhali educational management system dealt with analysis and evaluation of students' behavior mode on e-learn platform as well as with the identification of their learning styles according to two learning styles theories: Kolb's theory and Felder's theory. The main goal was to study two important interconnections within the e-learn systems: interconnection of students' behavior mode with his academic achievements as well as interconnection of student's gender with his learning style. Paper by [19] reviews the design of adaptive educational system on the basis of several learning styles models exampling VAK (visual, audial, kinesthetic) and Felder. VAK learning styles include visual, auditory and kinesthetic samples while Felder learning styles include global and consistent ones. This system combines learning styles and extends benefits of regular e-learn studying - regardless of auditorium or platform. The research by [20] characterizes individual studying environment on the basis of adaptive taxonomy using learning styles by Felder and Silverman which combines with choice of adequate teaching strategy and adequate IT tools. The students have efficient opportunity to improve educational process with such method. Investigation by [21] observed the system to provide educational content being adequate to students' preferences according to Felder-Silverman's learning styles model. To optimize functionality of this system they applied the method of approximate ant colony optimization (ACO). The represented solution provides adaptive and personalized way of studying.

Many researchers proclaimed that learning style might vary in time and might depend upon task/ studying content [22, 23, 24, 25]. In particular, the goal of investigation by [26] was to identify students' learning style on the basis of identification using data from mining web register concerning student's learning behavior mode. To classify styles, they used Felder-Silverman's model. This investigation proved that learning style is changeable during certain time. Thus, the system must adapt to changes for what the algorithm of artificial neural network for students' style forecasting is applied.

2 Implementation

Learning styles identification system on the basis of VARK model was elaborated within the National University of Life and Environmental Sciences of Ukraine. To analyze data OLAP and Data Mining technologies were proposed. From one side it gave opportunity to analyze learning styles in order to design adaptive content or to apply adequate studying methods and from another side – to analyze factors influencing learning style development and correction. Different students' databases and static method of learning style identification were applied for it.

2.1 The model of learning styles identification system architecture

The designed system is web-oriented, its functions predict authorization with the application of universal e-learn environment users' database, testing to identify learning style due to VARK model, noting additional data for each student to be in need for further analysis, data importing from system (psychotype, IQ), data exporting into analyzing module, formation of the recommended studying resources on the basis of learning style and their evaluating by students, formation of regulations to apply educational methods for scholars.

To identify learning style according to poll results concerning VARK methods they elaborated algorithms to identify predominant learning style basing upon testing students' behavior modes. There were following four learning styles to be identified:

- Visual type: information perception is more efficient if the represented information is underlined or colored; block-schemes are applied; images are demonstrated as well as video fragments, posters or slides; lecturers use gestures, bright facial expressions or figurative language; there are textbook diagrams to illustrate scientific information; curve graphs are applied; digital system to represent information is applied; individual time period for material perception is proposed.
- Audial type: information perception is more efficient while attending group lessons, discussion clubs; discussing scientific problems with other students; discussing scientific problems with scholars; explanation new ideas to other people; using audio recording; memorizing interesting examples, stories, jokes; pictures and other visual images; missing notes place to be filled up further after some details recognizing.
- Read/Write type: information perception is more efficient while it is represented as a list of concepts; in vocabularies, dictionaries in alphabetic order; in the form of glossary; in the form of definitions; in the form of handouts (theses); in textbooks; in the form of notes (reports); by scholars with correctly built speech using much information for every sentence, in the form of essay; in regulations, manuals for practical works.

– Kinesthetic type: information perception is more efficient while: all sensory organs are involved: visual, tactile, taste, auditory; studying takes place in labs; field trips and excursions are held while studying; action of any rule or principle (law) is demonstrated; scholar teaches material using real life examples; information is visual; there are approaches to allow percepting knowledge on practice; the method of attempts and mistakes is applied; collecting visual material is practiced exampling samples of stones, plants, shells, etc.; exhibitions are organized, objects samples under observation are demonstrated as well as photo images of different scientific phenomena; the ways and tools to solve studying tasks are described, last year examination tasks are exampled.

According to the proposed algorithm a multimodal style is distinguished in the case when no predominant style is identified.

To get other statistic data according to such factors as: gender; previous educational establishment (school, college); age; what is the child in family; psychotype (Myers-Briggs Type Indicator (MBTI) technique) [2], they performed data importing from other sources (Learning Management System "University", potok.ua site). To realize IT providence they chose MySQL database where the data are stored in separate tables, due to what the speed and flexibility for work with data is achieved. The tables are connected each with other due to interconnection thanking to what the possibility to connect data from some tables while request executing is achieved. Physical data model is represented on fig. 1.

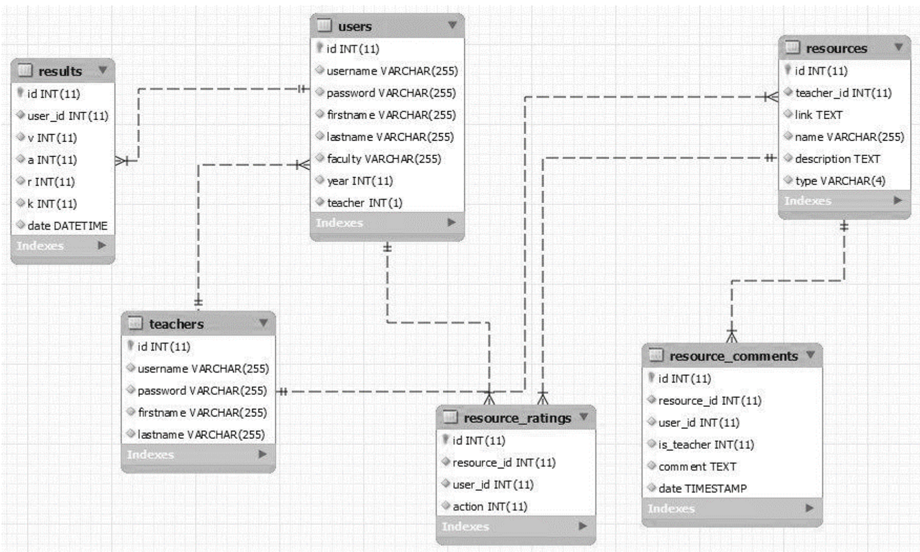

Fig. 1. The data model of learning styles identification system

General system architecture is represented on fig. 2. The scheme represents learning styles identification system – as one of modules within e-learning environment. Web interface for static identification of learning style transfers data toward server for the further storage and analysis. Database of learning styles and other students' characteristics is stored within the system and is available for analyzing module. Interface for analyzing module gives opportunity to apply different methods of static analysis and intellectual analysis of data in order to determine the factors which mostly affect the learning style. Learning Portal includes CLMS, e-learn courses which obtain educational resources to take into account predominant students' learning styles using Adaptive Content Manager.

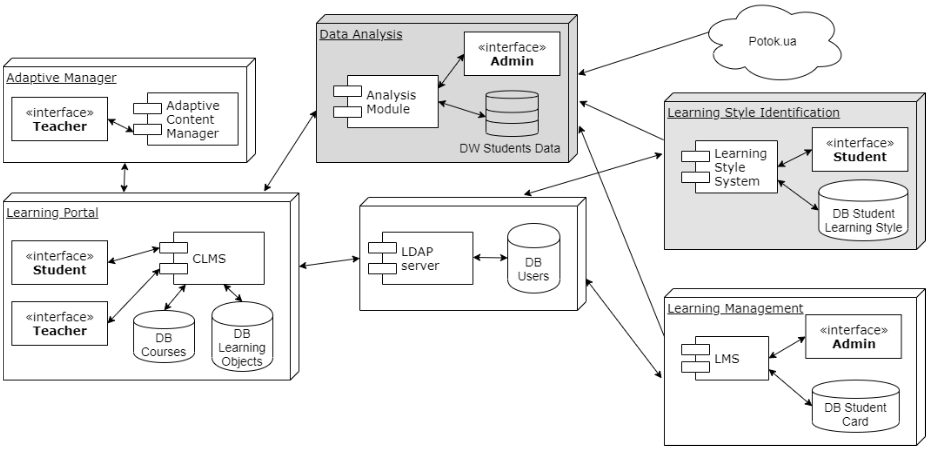

Fig. 2. Learning Styles Identification System and Analysis Module as part of e-learning environment

2.2 Data Analysis Module: data source, storage, analysis technologies

In order to design subsystem of analysis concerning learning styles identification system it is necessary to adopt decision about the data sources, data storage method and to choose technology for data analysis [27].

Data source. Data source involves operative systems of data proceeding exampling the universal educational environment users' database and the results of testing to determine learning style according to VARK model. Such data are received from the internal environment of system. In addition, the data source for subsystem analyzing may be any external information system (for example, student assessment data is from the LMS "University". All data sources for analysis module are presented in fig. 2.

Data storage method. To store data being in need for analysis in order to identify learning style the *data warehouse* concept (DW) is used. The usage of DW concept predicts special methods to design data model involving such moments as integration of datasets from different sources; object orientation, data consistence and consolidation; multidimensional data architecture to provide simplification of analytical requests performance.

The essence of multidimensional data representation is that most of real business processes is described involving large amount of metrics, properties, attributes, etc. So, for solving the task to identify learning style they need information about gender, previous educational establishment (school, college), age, what child in family or psychotype. If to select whole this information into two scaled table, it will appear to be complicated for visual analysis and comprehension. Moreover, it may be over norm if to take into consideration separate linkages like “psychotype-learning style”, “gender-learning style”, etc. All this complicates the extraction of useful information from such table. The mentioned problems arise due to only one common reason: two-scaled table stores multidimensional data

The background of multidimensional data representation is their division into two groups – *measurements and facts*. Measurements are categorical attributes, objects titles and properties being engaged into certain business process. Measurements qualitatively describe the observing business process; they are discrete by nature. Facts are the data to describe business process in a quantitative way, continuous by nature, that is why they may take infinite number of values.

Fig. 3 represents DW architecture, being designed for learning styles identification system.

The designed data warehouse consists of on facts table and eight measurements tables. The measurement “psychotype_dim” includes the list of psychotypes being observed within system; measurement “result_dim” deals with the list of the possible learning styles. The rest of measurements represents information which will allow specifying students’ data: gender, faculty, specialty, previous education, child in family. Measurement “year_dim” will allow to connect the received facts with year. It gives opportunity to determine student’s age (studying course at university).

The facts table “student_fact” includes information about concrete student. It obtains unique complicated key to combine primary keys for measurements tables. Besides these attributes facts table contains personal students’ data (identification number, surname, name and patronymic name, date of birth, year of entering University, average mark concerning the concrete period), attribute “value_domin” means the quantity of students’ questionnaire answers being adequate to one or another learning style after percentage transfer.

The represented multidimensional structure allows to track down the correlation of learning style with student’s psychotype, gender, age, etc. Such correlation may be represented either in series “learning style – psychotype”, “learning style– gender”, “learning style – age” or more complicated dependencies to take into account influencing of several attributes on learning style at once.

The data are delivered to DW from the operative sources through the OLE DB provider. OLE DB is a set of COM-interfaces allowing appendices to work with the data from different information sources and repositories. OLE DB separates data repository from the program which must have access to it through the set of abstractions including data source (DataSource), session (Session), command (Command) and a set of rows (Rowset).

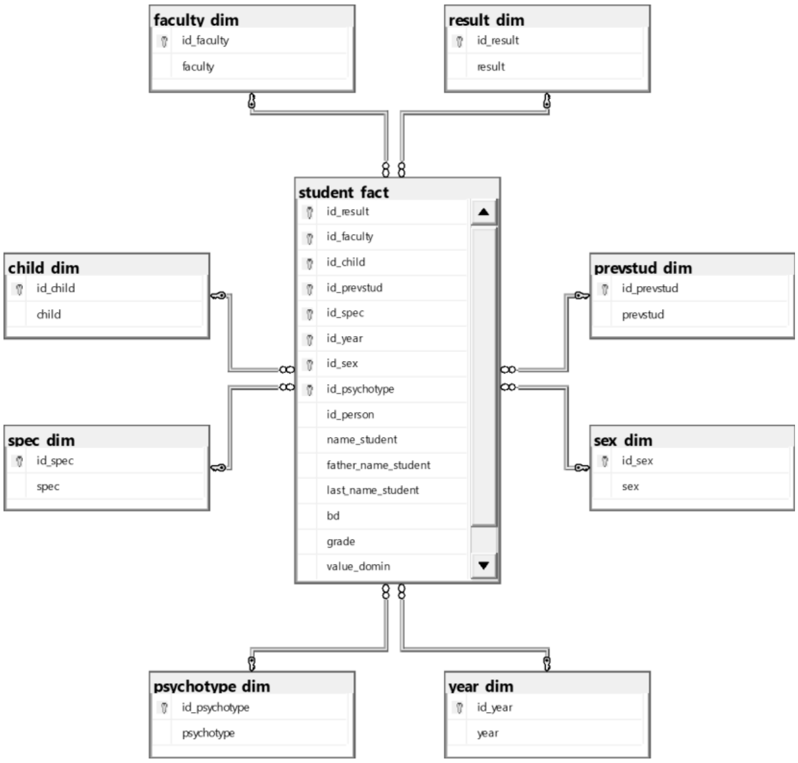

Fig. 3. Structure of data warehouse

The technologies to analyze data. The analyzing subsystem as a component of learning styles identification system is based upon information retrieval approach using SQL; operative data analysis (OLAP-technology); intellectual data analysis (Data Mining technology).

Information retrieval approach allows receiving data from DW tables by performance of requests, written in SQL. In such requests the data may be derived from the different DW tables according to different criteria and may be filtered under some conditions. For example, the request, represented on fig. 4 allows calculating the quantity of "Read-Write" style students who study at the Faculty of Information Technologies, questionnaire was held in 2018.

```
select count from student_fact inner join result_dim on student_fact.id_result=result_dim.id_result inner join faculty_dim on student_fact.id_faculty=faculty_dim.id_faculty inner join year_dim on student_fact.id_year=year_dim.id_yearwhere result_dim.result='Read-Write' and faculty_dim.faculty='Факультет інформаційних технологій' and year_dim.year=2018
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Fig. 4. The students' quantity request

The received results may be represented in the form of tables, charts or graphs etc. Operational data analysis (OLAP-technology) involves DW as hypercube allowing to perform special actions with it: *residual review* (formed as subset of multidimensional data array being adequate to the universal value of one or several measurements elements being out of this subset); *rotation* (the change of measurements location in report); *consolidation and detailing* (identify upper transfer from the detailed data representation to the generalized one and respectively vice versa). Such operations allow receiving information about value correlation from one or several measurements, rearranging rows and columns, retrieving generalized data and tracking what detailed data they are derived from.

OLAP-technology may be regarded as a set of services mentioning one of them to allow concluding reports on the basis of DW data, representing them in the form of tables, graphs, histograms. It simplifies data analysis and allows confirming or refuting certain hypothesis, for example, concerning the correlation of gender with learning style (fig. 5).

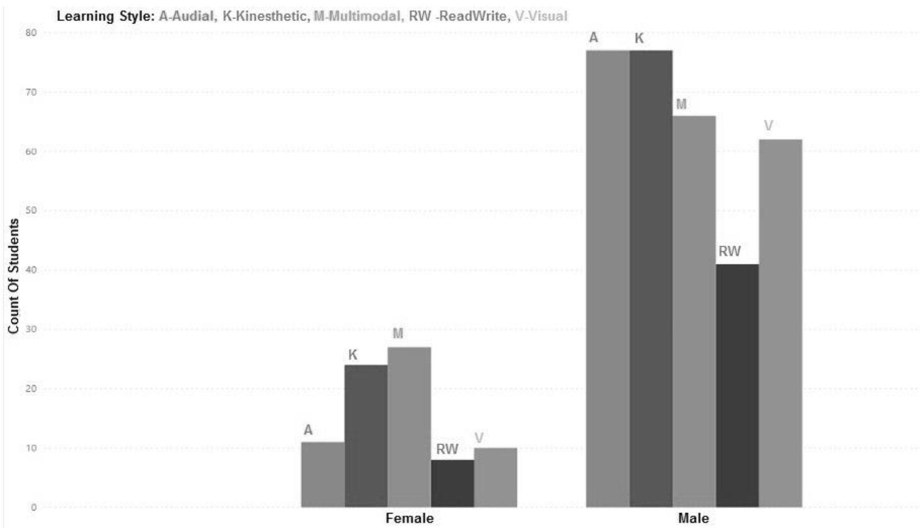

Fig. 5. Correlation of gender with learning style

Intellectual analysis, being based upon Data Mining technology, allow finding new regularizes between data, that is to obtain new hypothesis (new hypotheses) concerning the correlation between measurements and fact. To solve Data Mining tasks, they apply different methods and algorithms. To identify learning style, they propose to apply Apriori algorithm as an algorithm to search associative rules (the rules allowing finding patterns between related events).

Within the system under consideration it will allow assessing the degree of influence of different factors on learning style.

3 The Results of Experimental Work

The learning styles identification system obtains interface for students' and scholars' authorization, however it applies the authorization data within universal e-learn University environment; basic testing to identify learning style (fig. 6) and additional testing and questionnaires to get different facts being adequate for students and being in need for further analyzing.

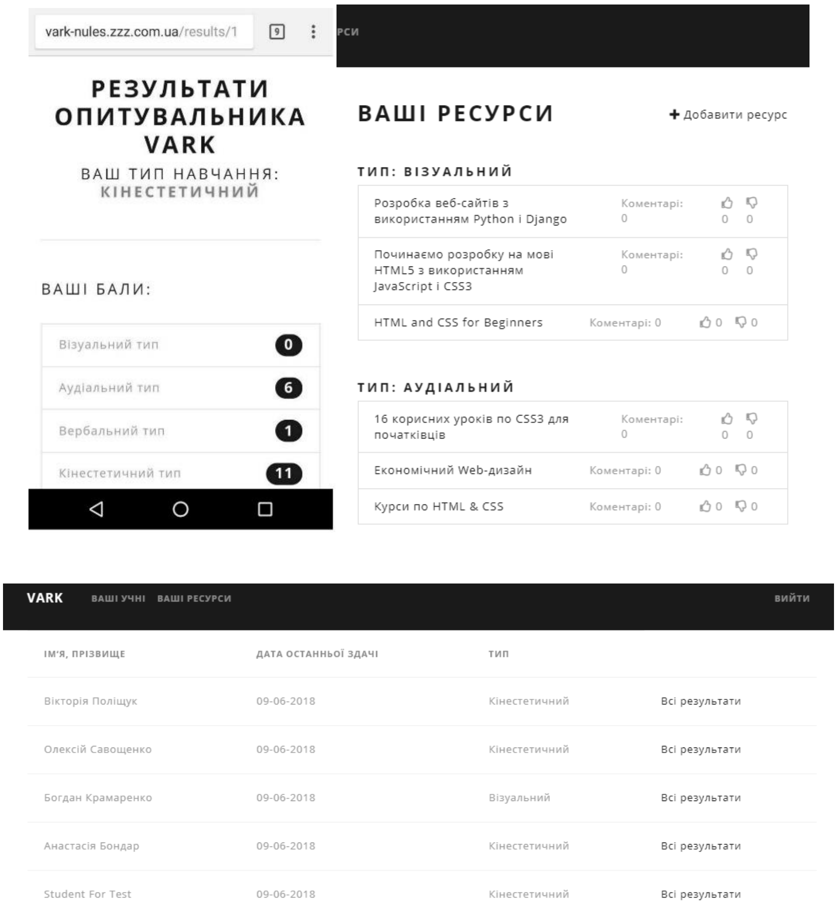

Fig. 6. Resulting page

Statistical analysis according to the results of academic achievements for the second year students majoring in specialty "Computer Sciences" and their adequate learning styles allows paying attention on such fact that "Read /Write" style students obtain more significant studying achievements (average mark – 82) comparatively to the students with other learning styles (fig. 7).

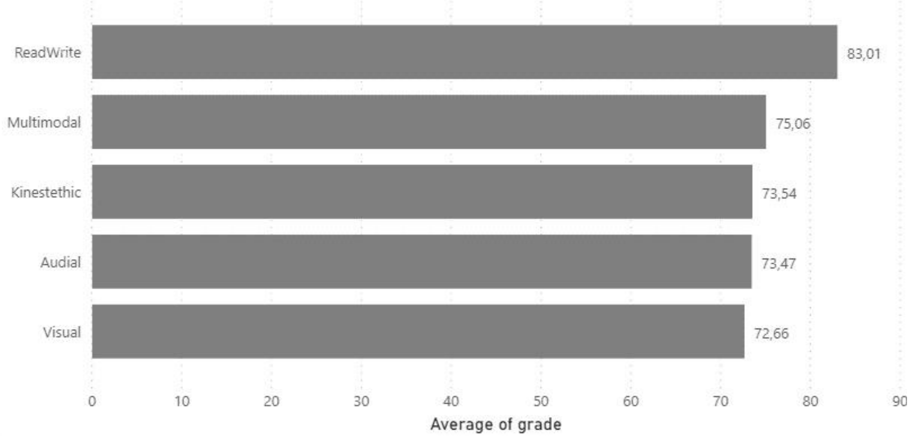

Fig. 7. Average mark of students with different learning styles

Having analyzed the educational content to be proposed to students within e-learn courses it was found out that e-learn courses mostly included educational resources with textual structural materials (48%), presentations – 36%, video resources – 12%. Such resources were the most favorable for the students with “Read /Write” learning style. At the same time, the percentage of the second year students majoring in specialty “Computer Sciences” (total of 78 people) with “Read /Write” learning style. was only 13 %. Thus, the educational content might be adapted to the students with kinesthetic and visual learning style. After it the second term of studying demonstrated the best academic achievements for students with multimodal learning style (82 marks), kinesthetic style (79 marks) and visual style (80 marks).

Basing upon the fact that the majority of that year students belonged to kinesthetic learning style (65%) the analyzing module gave opportunity to identify the most predominant psychotypes for that learning style (fig. 8).

One third of all students with this learning style belong to three out of twelve psychotypes obtaining the following psychological features:

Logic-sensory extrovert. He likes leadership and represents leader’s features, is rather responsible, has a developed sense of obligation, follows plan, does not accept deviations from the planned actions, is sincere, conscientious, holistic nature, does not like innovations

Sensory-logic extrovert. He has inexhaustible energy, likes to take risk, builds relationship with people easily, is able to control quite diverse team, is pragmatic and is efficient at constant risk, can find solution concerning extraordinary situations, is friendly with everyone and is always on his own.

Sensory-ethical extrovert. He is easy to contact, is efficient in group work, is ill tolerate loneliness, tries to find pleasure in life, avoids unpleasant situations, is prone to depressions because of long-lasting problems, communicates well in team, in not prone to deal with science.

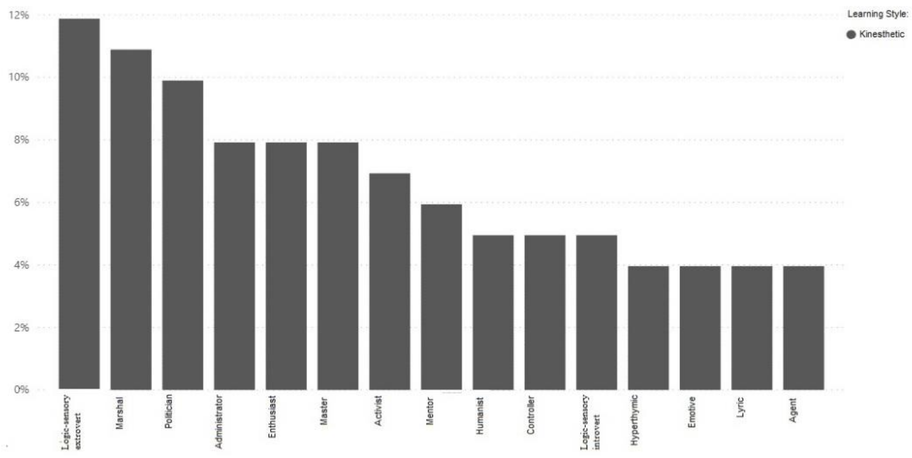

Fig. 8. Number correlation of kinesthetic style students with different psychotypes

Summarizing the data about predominant psychotypes we can consider kinesthetic style students the students to obtain such psychological features as tending to the group(team) activity, planned actions and responsibility. Such analyzing results give reason to determine the most efficient methods to teach students exampling collective design method, fulfillment of practice-oriented tasks in small and medium groups, problematic studying. Just these methods to allow own knowledge on practice. With it digital educational content and digital educational tools may be also oriented on team work, task planning, reporting and responsibility for the qualitatively performed work, working out theoretical materials on practice.

Data analyzing module may be also applied for observing interconnections and correlations concerning such measurement as intelligence. Among 7 types of intelligence according to Gardner's theory (Linguistic intelligence, Logical-mathematical intelligence, Spatial intelligence, Bodily-Kinesthetic intelligence, Musical intelligence, Interpersonal intelligence, Intrapersonal intelligence, Naturalist intelligence) concerning our investigation the first and foremost task is to study deeply the features of students majoring in specialty "Computer Sciences" and obtaining such type as Logical-mathematical intelligence.

4 Conclusions

Thus, the data analyzing module within learning styles identification system is one of the most important components to organize adaptive system for students' studying. The proposed OLAP and Data Mining technologies simplify operations with multidimensional data structures aiming on the designed system. Besides, students' special features may be imported into data warehouse to identify fact correlation on one or several measurements.

The results being gained during the experimental work with system and analytical module gave opportunity not only to identify learning style of students majoring in IT specialties, but also to fix correlation between academic achievements, learning style, digital educational content and their psychotype. These results gave the reason to adjust studying methods, to improve digital educational content and to change format for its representation within e-learn courses.

The further investigations will focus on different aspects of educational material representation for the students with different learning styles; developing different type content; developing recommendations concerning educational methods for students with different learning styles.

Besides, for further investigation it is important to take into account special features of social intelligence, because the development of social skills and social intelligence is a relevant problem for modern higher school. After all, the skills of efficient communication and cooperation within global society determines human success.

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