RIGA TECHNICAL UNIVERSITY

Iveta Daugule

KNOWLEDGE FLOW RESEARCH IN E-LEARNING ENVIRONMENT

Summary of the Doctoral Thesis

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RIGA TECHNICAL UNIVERSITY
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DOCTORAL THESIS PROPOSED TO RIGA TECHNICAL UNIVERSITY FOR THE PROMOTION TO THE SCIENTIFIC DEGREE OF DOCTOR OF SCIENCE

To be granted the scientific degree of Doctor of Science (Ph. D.), the present Doctoral Thesis has been submitted for defence at the open meeting of RTU Promotion Council on 19 December 2022 at 12:30 at the Faculty of E-Learning Technologies and Humanities of Riga Technical University, 1 Kronvalda Blvd., Room 200.

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DECLARATION OF ACADEMIC INTEGRITY

I hereby declare that the Doctoral Thesis submitted for the review to Riga Technical University for promotion to the scientific degree of Doctor of Science (Ph. D.) is my own. I confirm that this Doctoral Thesis had not been submitted to any other university for promotion to a scientific degree.

Iveta Daugule ……………………………. (signature)
Date: ……………………….

The Doctoral Thesis has been written in Latvian. It consists of an Introduction, 3 chapters, Conclusions, 87 images, 16 tables, and 3 appendices; the total number of pages is 162 not including appendices. The Bibliography contains 156 titles.

CONTENTS

1. GENERAL REVIEW OF THE DOCTORAL THESIS

1.1. Subject topicality

Improving education systems through better data analysis and forecasting is the third priority of the European Union Action Plan. The European Union is now moving from a one-size-fits-all approach to a more personalized approach and solutions, with digitalization and learning analytics playing a key role in this process. The role of learning analytics in learning processes is growing and will grow more and more (Vlies van der, 2020). To achieve the set learning goals and realize the successful transfer of knowledge, it is essential to consider the characteristics of knowledge. By understanding how to identify and analyse the characteristics of the knowledge being acquired, the results obtained can be further used to improve the transfer of relevant knowledge. It is necessary to take advantage of all opportunities to teach faster and/or more in a certain period, providing adapted learning content for the student's needs and form of motivation. To achieve this, it is necessary to have an easy-to-understand and easy-to-use learning analytics tool that allows the tutor to get an idea of the characteristics of the knowledge in the course and the suitability of the course for the student. Data on students' activities are already accumulated in digital learning management systems, and it is important to find solutions to make the most of the data generated during the learning period. Course design should consider the transfer properties of the knowledge embodied in the course.

It is impossible to transfer all knowledge equally quickly and equally efficiently. Identifying the knowledge that flows easily and unwieldy is essential to plan and shape the flow of knowledge (Nissen, 2005). Higher efficiency can be achieved if the characteristics of knowledge are identified and the way knowledge is transferred is adapted and managed accordingly. Using technology for knowledge transfer is easier when the knowledge embodied in the course is explicit, while the transfer of tacit knowledge is more difficult (Squier, 2006). By applying knowledge management solutions, it is possible to turn tacit knowledge into explicit knowledge (Becerra-Fernandez & Sabherwal, 2014).

The pandemic has had a significant impact on higher education institutions. Historically, higher education has been face-to-face and distance solutions have been viewed with great caution. In the case of distance learning, universities have had to work diligently on quality assurance procedures to ensure public trust and recognition. With the onset of the pandemic, changes in the education sector were very rapid, which contributed to the distance learning process becoming part of the daily life of universities (Zuhairi et al., 2020). The desire for distance learning is determined by objective restrictions on moving comfortably to the educational institution, finding the chosen educational institution in a geographically remote place, and other personal circumstances, such as work schedules. In recent years, the transition to fully distance learning has been directly related to the need to reduce epidemiological risks, however, the need for knowledge to be acquired in the digital environment will increase, especially in the environment of universities and enterprises. Educational institutions see an opportunity to expand their student base in this way, while entrepreneurs see more efficient use of the time spent on learning and a reduction in the associated costs.

The time of the pandemic has made it possible to better identify and understand the possibilities of e-learning as well as created the prerequisites for their development also in a situation where the movement and gathering of persons are no longer restricted (Aremu et al., 2022). The development of e-learning will continue to play an important role in the post-pandemic period. At the same time, several significant challenges have been identified that must be considered when developing e-learning (Adzovie et al., 2022). A study conducted in Indonesia on e-learning during the Covid-19 pandemic found that 60 % of tutors indicate lack of self-discipline as a problem, however, only 37 % of students admit it (Dewanti et al., 2022). In turn, a study conducted for the same period in Ukraine concluded that insufficient attention to the development of cooperation and communication functions on e-learning platforms negatively affects the quality of distance learning (Zhenchenko et al., 2022).

An appropriate topic of learning management is not enough to ensure an attractive learning process, it is also necessary to supplement it with a student-centred learning strategy, including an evaluation of what has been learned before (Yamani et al., 2022). It must be considered that the needs and desires of students regarding learning activities and pedagogical techniques have a significant impact on the involvement of the student in the learning process (Khan et al., 2022). One of the most serious challenges in the e-learning environment is the appropriate assessment of the quality of learning materials. Given that it is influenced by many factors, the assessment requires decision-making methods that take these criteria into account. To deal with it, mathematical methods are proposed (Grigoryan et al., 2022). The assessment of the needs of tutors and students in the preparation of learning content plays a fundamental role in the readiness to participate in e-learning (Polat et al., 2022), as does the behaviour during e-learning (Husin et al., 2022). Blended learning also suggests a flipped classroom approach when e-learning is followed by face-to-face classes (Li et.al., 2022). In learning management systems such as edX, Sakai, and Moodle, students generate large amounts of data which are valuable for in-depth analysis. Learning management systems offer their own tools and a way for course tutors to get acquainted with the situation in the course they teach. At the same time, not always the proposed solutions are in accordance with the needs of the tutors. The data offered by the systems usually reflects the current situation, while the assessment of the knowledge acquired by the students or the relevance of the learning content to the needs of the students is not available to the tutor. Considering the large amount of data that is accumulated in learning management systems, it is necessary to understand which of the data to analyse and for what purpose.

The course of training is based on the decisions made by the tutor and the systematicity of the training design and the planning of the training. It is necessary to focus the design of training on supporting individualities (Gagne, R. M., et al., 1992). Along with the rapid transition to distance learning, new risks related to student behaviour during distance learning appeared. They were observed in situations where students were not sufficiently involved in the learning process, imitation of presence occurs, was silenced if the offered learning content is too complex, or the learning content is too simple and thus not all opportunities are used to achieve excellent learning results. The tutors found it difficult to spot these situations on time (Kapenieks et al., 2021).

Learning design implies the form and direction in which the course is planned to be directed. It is essential that the course objectives are set according to the results to be achieved that are expected of the students and that all the activities, tasks and evaluations are consistent with these results (Mo, 2010). An important advantage in the educational process is the awareness of the diversity of students, considering the different strengths, needs and learning styles of students in the learning process. The aim is to adapt education to every student, accepting the diversity of students as the norm (Whitby, 2013). The progress of online courses largely depends on student involvement. At the same time, it is necessary to determine what involvement is expected of students (Mo, 2010). Feedback is very important for student learning progress. If the training is managed online and implemented at the pace of the student's own choice, feedback is not always sufficient. It is important that the tutor receives information about students' progress and builds an appropriate interaction aimed at filling in the gaps in the student's knowledge. The tutor should be able to intervene promptly if the student has encountered difficulties in the learning process and stopped (Yan, 2020).

The learning analytics tool must be student-centred, and the correct interpretation of its visual elements is essential for making learning activities meaningful. The reflection of learning analytics data should be easy to perceive and interpret (Pozdniakov et al., 2021)). When selecting data for analysis, it is necessary to make sure that the analysis achieves the set goal. It is not helpful to track a student' clicks in the system unless they are viewed in conjunction with some other data. The student's write-in and discharge data only show the fact of connection and the time spent on the course and do not provide more information. Only with the context, it becomes possible to notice the moment when the student has lost focus and moved from active participation in the training course to imitation of presence (Robinson & Cook, 2018).

1.2. The objective of the Doctoral Thesis

The research aims to study and analyse the properties of the knowledge being acquired and to further use the results obtained to improve the transfer of the relevant knowledge, creating an online learning tool that allows the tutor to use all the possibilities to teach faster and/or more in a certain period, providing the most suitable learning content and form of motivation for the needs of the student.

The work puts forward the following hypothesis: The learning content includes both explicit and tacit knowledge. It is possible to recognize and characterize the properties of knowledge and by acting in a timely and thoughtful manner, adjust the learning content, accordingly, thus facilitating the acquisition of tacit knowledge and improving the involvement of students in the learning process. It is possible to find a method and develop a technology for the timely recognition of knowledge properties, thus finding opportunities to adapt the content during the learning process to promote a more successful acquisition of knowledge.

Research questions:

1. How to describe the properties of knowledge – is knowledge explicit or tacit?
2. How to assess a student's motivation and involvement in the study process?

3. How to determine if the offered course material is suitable and engaging for the student?
4. How to provide the tutor with the necessary information about the involvement of students in the study process?
5. How to provide the tutor with the necessary information about the suitability of the learning content for a group of students?

To find answers to the research questions, the following work tasks have been carried out:

1. Study the characteristics of the knowledge flow, including descriptors, which make it possible to assess whether knowledge transfer is easy or difficult.
2. Study the current e-learning solutions, among them – learning management systems, models, and approaches.
3. Explore solutions to identify and assess student motivation as well as the impact of student motivation on learning progress.
4. Explore solutions to assess students' initial knowledge and knowledge growth during the course.
5. Study the volumes of predictable groups of students and find techniques for learning analytics appropriate to the size of the groups.
6. Develop a method to identify the tacit knowledge contained in the course and to allow assessment of the involvement of students in the course.
7. Develop metrics to measure knowledge transfer.
8. Develop a technology that supports the identification of knowledge transfer properties and the assessment of student engagement.

1.3. Subject and object of study

Subject of study: Online learning and the possibilities of using the data created in the learning process in the improvement of knowledge transfer. The object of study is the properties of knowledge and its transfer in the e-study course.

1.4. Scientific novelty of the Doctoral Thesis

1. A mathematical model of the knowledge acquisition surface has been developed.
2. A new metrics to measure knowledge transfer has been developed.
3. A knowledge acquisition monitoring (KAM) method for evaluating knowledge transfer in small groups of students has been developed.

1.5. Practical value and approbation of research results

Within the framework of the Doctoral Thesis, scientific literature on the properties of knowledge, tools used in the process of knowledge transfer, trends in the development of learning analytics, situations in the Latvian education sector, as well as methods for promoting motivation and involvement of students have been studied. During the research, practical experiments were conducted, learning data were collected and studied to understand the most appropriate techniques for assessing the severity of knowledge transfer, the motivation of students in the learning process, as well as the quality of the proposed learning content. As a result, a structured approach to the collection and analysis of teaching data has been developed, as well as visualization has been developed to ensure that the results are presented in a format suitable for the tutor. User behaviour data is analysed and visualized using statistical methods.

The KAM method developed within the framework of the study and knowledge acquisition surface allows to understand the progress of students of online courses and their involvement in the learning process as well as points out the need to improve the content of these courses, thereby improving the efficiency of the learning process. Based on them, it is possible for the tutor to ensure the student's active involvement in the learning process, as well as to receive specific information for the improvement and adaptation of the learning content. The KAM method has been tested in practice within the framework of the project "Advanced Resilience Technologies for Secure Service. Education" ARTSS-EDU and is applied to distance and blended learning at various levels of education, covering primary and secondary education, vocational education, higher education, and lifelong learning (Kapenieks et al., 2021).

1.6. Future research.

The author sees further research opportunities in the following directions:

- In-depth study of the KAM method, which includes research on the most suitable pedagogical methods, development of guidelines for the preparation of learning content, including detailed guidelines for the development of orientation and self-examination questions.
- A more detailed interpretation of the results obtained on the knowledge acquisition surface. A wider study of the causes of the placement of points would provide the tutor with more accurate information about the actions to be taken both in the learning process with students and in improving the learning content. The tool to be developed would also include the automatic or semi-automatic preparation of notifications to facilitate the tutor's communication with the students and reduce the amount of work for the tutor.
- The opportunity for students to familiarize themselves with the results obtained on the knowledge acquisition surface, assuming that information is available about the student's personal knowledge acquisition results, offering a related in-depth interpretation of the results.
- The possibility to view the results obtained on the knowledge acquisition surface in dynamics, for different periods of time, offering a related in-depth interpretation of the results.

1.7. Results presented for the defence

1. The developed method of analysing the knowledge flow of the e-study course within the framework of a group of students characterizes the knowledge existing in the topics

of the study content according to the degree of difficulty of their transfer (*easy, appropriate, complicated*).

2. As part of the KAM method, a new metric has been created to quantify knowledge in coordinates as easy, complicated, and appropriate. KAM metrics apply to all learning content within a group of students, a separate topic for an entire group of students, a separate sub-topic, and an individual student within a topic or a whole course.
3. Learning analytics data obtained with the KAM method on the knowledge acquisition surface in real time quantitatively characterize the progress of knowledge acquisition in coordinates *easy, complicated*, and *appropriate*. Numerical values of knowledge perception monitoring in the e-course learning process indicate situations when the student needs an individual approach, or some parts of the e-course need to be transformed or supplemented.

1.8. Scientific publications

1. Daugule, I., Kapenieks, A., Timsan, Z. (2022). Use of Knowledge Acquisition Surface to Monitor and Assess Students' Success. Journal of Emerging Technologies in Learning (iJET), 17(14), 109–125. doi: https://doi.org/10.3991/ijet.v17i14.31281
2. Kapenieks, A. et al. (2021). Proposals for monitoring learning analytics in higher education. Retrieved from lzp.gov.lv: https://lzp.gov.lv/wp-content/uploads/2021/04/ARTSS_Macisanas_analitikas_zinojums_publicesanai.pdf
3. Kapenieks, A., Daugule, I., Kapenieks, A., Zagorskis, V., Kapenieks, J. Jr., Timsans, Z., Vitolina I. TELECI Approach for e-Learning User Behavior Data Visualization and Learning Support Algorithm. Baltic J. Modern Computing, Vol. 8 (2020), No. 1, 129–142.
4. Kapenieks, A., Daugule, I., Kapenieks, K., Zagorskis, V., Kapenieks, J. Jr., Timsans, Z., Vitolina, I. Knowledge Acquisition Data Visualization in eLearning Delivery. Proceedings of 12th International Conference on Computer Supported Education - Volume 2: CSEDU, 507–513, 2020.
5. Kapenieks, A., Daugule, I. (2019). Knowledge Flow Analysis: The Quantitative Method for Knowledge Stickiness Analysis in Online Course. Periodicals of Engineering and Natural Sciences, 7, 3304-3311. doi: 10.21533/pen.v7i1.358
6. Daugule, I., Kapenieks, A. (2018). The Data of the Initial Motivation – a Valuable Source for the Development of the Course Content. A Case Study in the Group of Business Students. International Journal of Engineering and Technology (UAE), 89–94. doi: 10.14419/ijet.v7i2.28.12886
7. Daugule, I., Kapenieks, A. (2017). Collaborative Knowledge Flow – Mapping the E-Learning Environment. EDULEARN17 Proceedings, (pp. 3304–3311)

1.9. Scientific conferences

1. EDULEARN17 the 9th International Conference on Education and New Learning Technologies, Barcelona, Spain, 3–5 July 2017.
2. International Conference on Communication, Management and Information Technology (ICCMIT 2018), Madrid, Spain, April 2–4, 2018.
3. ICCMIT 2019: International Conference on Communication, Management and Information Technology, Vienna, Austria, 26–28 April 2019.
4. CSEDU 2020, the International Conference on Computer Supported Education, May 2–4, Prague, Czech Republic, online.

2. IMPROVING THE EFFICIENCY OF KNOWLEDGE TRANSFER

The data necessary for the research were obtained from study courses that took place in a blended study environment. Data were collected in the period from 2016–2021. To provide e-learning content, 3 learning management systems were used for the course:

- The data of the autumn semester of academic year 2016/2017 are obtained from the course that took place in the edX study environment, the study course "Basic Business" implemented by RTU, the number of students was 52.

- The data of the autumn semester of academic year 2017/2018 are obtained from the course that took place in the edX study environment, the study course "Basic Business" implemented by RTU, the number of students was 61.

- The data of the autumn semester of academic year 2018/2019 are extracted from a course organized in the Sakai study environment, study course "Basic Business" implemented by RTU, the number of students was 63.

- The data of the autumn semester of academic year 2019/2020 are extracted from a course organized in the Sakai study environment, study course "Basic Business" implemented by RTU, the number of students was 61.

- Data from the autumn semester of academic year 2020/2021 have been extracted from Moodle-based study courses designed for different levels of learning (primary, secondary, university, and adult continuing education).

The initial data necessary for the development of research and methodology are obtained from the mixed study course "Basic Business". As part of this course, students learn the basics of business. The course aims to provide students with knowledge and skills related to seven topics – the topicality of a business idea, the technology of product/service development, marketing, competition, financial aspects, risks, and the ability to realize the relevant business idea. All this time, the content, goals, and objectives of the course remained the same. Additional tasks were introduced in the solution of 2019 to obtain more accurate data on the knowledge transfer path.

Phase 1 of the research aimed to identify factors that influence the flow of knowledge and to compare transfer difficulties for different types of knowledge. The analysis included an assessment of the "stickiness" of knowledge, students' motivation, as well as the impact of peer review of works on the acquisition of the topics covered in the course. In Phase 1 of the research, the differences in positive dynamics between different parts of the course were studied and the identification of tacit knowledge was carried out (Daugule & Kapenieks, 2017). The aim of Phase 2 was to understand the aspects of students' initial motivation – how to notice, evaluate and use them for further development of the learning content. As part of Phase 2 of the research, the answer was sought whether students with higher initial motivation learn better, want to learn more, and are ready to learn longer, and research was done to gain an understanding of how the student feels the differences in the complexity of acquiring different knowledge and how to identify and assess the initial motivation of students (Daugule & Kapenieks, 2018). The objective of Phase 3 of the research was to understand whether the burden of knowledge transfer for an individual part of the course remains the same when it is acquired by different groups of students. The essays written by students were structured according to the topics to be studied. Then, with the help of software, the changes in the number of words and letters in the initial and final (after the process of peer-review) version of the essay were compared, and the results obtained were compared with the results of Phase 1 of the research. It was found that tacit knowledge in one group of students does not mean that it will also be tacit in the next group of students (Kapenieks & Daugule, 2019).

In Phase 4 of the research, possibilities were studied to adapt the learning content to the capabilities and needs of the student, considering the peculiarities of the complexity of the course. In Phase 4 of the research, for data acquisition purposes, it was proposed to include learning materials in the course. Data were collected and analysed for the first five chapters of the course "Basic Business". The aim was to find out whether it is possible to identify the extent of knowledge of the student at the beginning of the course and at the end of the course, and based on these two values, to determine the increase in knowledge over the course. To assess the progress of students, the knowledge acquisition surface was modelled, as well as formulas were developed to be able to calculate the location of data points that have arisen in the process of study. The knowledge acquisition surface is based on a set of artificial data calculated based on thresholds for the acquisition of knowledge and the principles of the probability of small groups (Kapenieks & Daugule, 2019).

At the final stage of the study, the KAM method, and the surface for acquiring knowledge were improved, and the developed technology was piloted within the framework of the ARTSS project. Knowledge acquisition surface application strategies were studied to ensure that the developed analytics tool enables the use of every opportunity to teach faster and/or more over a given period. At the same time, the goal is to provide relevant content to ensure student satisfaction with the curriculum and manner of presentation (Daugule et al., 2022) . Asa result of the piloting, it was concluded that the developed tool can be applied to distance and blended learning at different levels of education, covering primary and secondary education, higher education, and lifelong learning (Kapenieks et al., 2021). The KAM method allows the student's progress to be visualized in real time, i.e., during the learning process, thus providing an opportunity for the tutor to notice shortcomings promptly and take action to eliminate them. In the final stage, validation of the results obtained was carried out and confirmation was obtained that the data points reflected on the knowledge acquisition surface provide correct information about student progress, knowledge, and the quality of the learning content.

There are three possible strategies for building the flow of knowledge. The choice of the most appropriate strategy depends on the situation and the goals set for the acquisition of knowledge (Fig. 2.1) (Daugule et al., 2022).

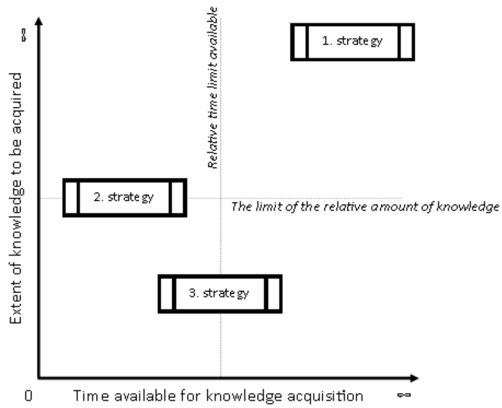


Fig. 2.1. Knowledge acquisition strategies. An image created by the author (Daugule et al., 2022).

Strategy 1. Neither the time nor the amount of knowledge is limited. The aim is to gain as much knowledge as possible. In the case of Strategy 1, the learning content should be designed with the widest possible opportunities to get to the adjacent topics and acquire additional knowledge. The strategy is characteristic of self-education and personal development. In the case of Strategy 1, the learning content should be designed with as much scope as possible to get to the topics related to the chosen topic and acquire additional knowledge (Fig. 2.2) (Daugule et al., 2022).

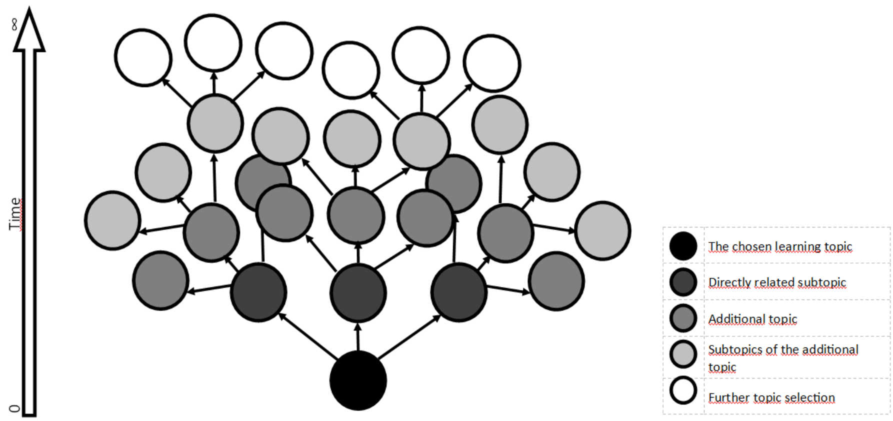


Fig. 2.2. Strategy 1: Self-education, personal development. Image created by the author.

Strategy 2. Time is limited, and the amount of knowledge to be gained is undefined (the more you learn at a given time, the better). Accordingly, it should be possible to include additional knowledge in the curriculum if it is evident that the student can acquire it. The deeper the knowledge will be acquired in the time allotted for training, the better.

Strategy 2 is typical for educational institutions. In the case of this strategy, it is important to be able to include additional in-depth knowledge of the topic being studied in the curriculum if the tutor sees that the student could acquire them in depth (Fig. 2.3.) (Daugule et al., 2022).

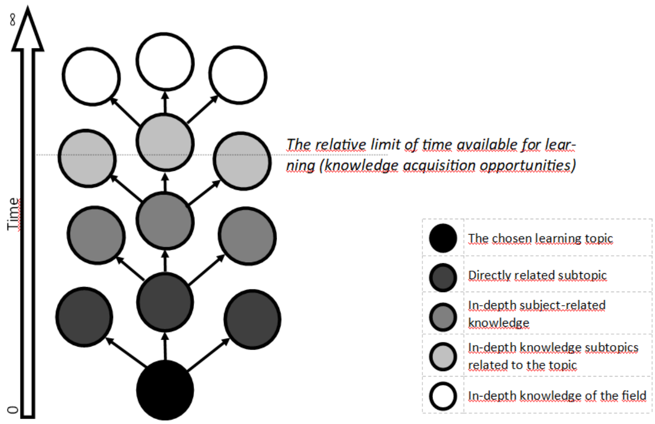


Fig. 2.3. Strategy 2: Educational institution. Image created by the author.

Strategy 3. The amount of knowledge to be acquired is clearly defined, time is undefined, and there are requirements for the efficient use of time spent in learning (the faster the knowledge is acquired, the better). In this case, the emphasis should be placed on solutions that can reduce the stickiness of the knowledge included in the course to facilitate its acquisition in the shortest possible time. There are requirements for the effective use of time spent on training and other resources devoted to them – the faster knowledge is acquired, the better. The strategy is characteristic of the internal training of organizations. In the case of Strategy 3, solutions are important that can reduce the burden of the knowledge being acquired to make it as easy as possible to acquire it and minimise the time and other resources required to acquire it (Fig. 2.4.) (Daugule et al., 2022).

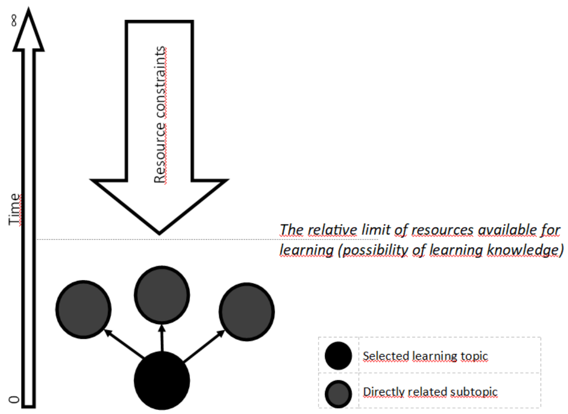


Fig. 2.4. Strategy 3: Internal training of organisations. Image created by the author.

Concurrently with the solutions for the effective conduct of learning from the business environment, in the author's opinion, the selection and successful application of appropriate pedagogical techniques in the digital or blended learning environment is no less important for achieving the goal. Accordingly, solutions can also be found according to the established learning strategy. After evaluating the possible impact of these strategies, the author concludes that Strategy 1 is based on individual preferences and motivation of a person, therefore its implementation is more resource-intensive and focused on individual achievements. Strategies 2 and 3 are aimed at the development of knowledge of a larger group, respectively, in these situations greater predictable usefulness is expected. After evaluating the possibilities of developing a learning environment so that it ensures the implementation of one of these strategies, the author concludes that it is important to find a solution that would improve the possibilities of implementing Strategies 2 and 3.

2.1. The knowledge acquisition surface – model

To reflect the process of knowledge transfer, it is important to understand whether and how successfully the knowledge contained in the learning content is transferred to students. To reflect this, during research, the knowledge acquisition surface was developed and its theoretical model was created. The knowledge acquisition surface is formed in the form of a triangle, in 3 dimensions. N-P values were placed on the *x*-axis, P-P values were placed on the *y*-axis, and X-N values were placed on the *z*-axis. The values of all axes were indicated on a scale from 0 to 1. In its corners are arranged calculated extreme limit values, marked with a black circle. On the left, at the values of the *x* and *z* axes "0", there is a final point describing the situation when the content is too simple – the student has had knowledge of the topic being studied in the course from the beginning and has not learned anything new. The point to the right on the base of the model denotes a situation where the content to be studied is ideal for the student. The point located in the upper part of the triangle describes a situation where the content of the course being studied is excessively complex and the student has not been able to acquire new knowledge (Fig. 2.5).

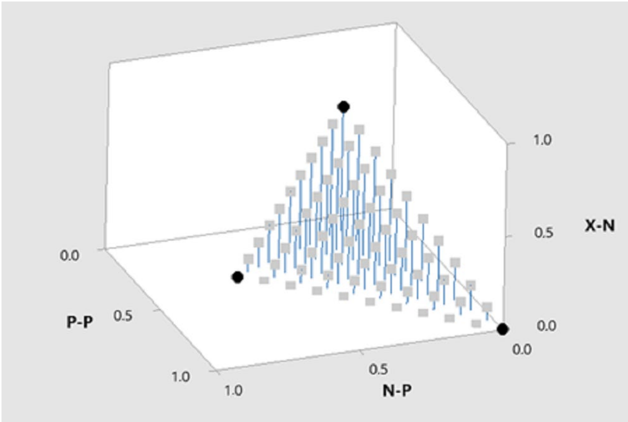


Fig. 2.5. Knowledge acquisition surface. Image created by the author.

During further research, the model was developed by supplementing with zones that show the properties of knowledge transfer. The knowledge acquisition surface was modelled on the condition that the learning content has 3 different degrees of suitability – it may be *easy*, *appropriate*, or *complicated*. The degree of suitability depends on the knowledge embodied in the course and the characteristics of its transfer. The initial versions of the model were developed along with the principle of course restructuring carried out in the 4th stage of the study. It was based on dividing the learning content into smaller passages and supplementing it with orientation and self-examination questions before and after each of these passages. For learning analytics, the answers given by students and these questions will be used, combining answers in pairs.

By collecting and analysing data on the sequential actions performed by students – answers to orientation and self-examination questions, one can get an idea of both the initial knowledge of the student and the increase in knowledge during the course. Both orientation and self-examination questions are designed as multiple-choice questions, where the student can mark one of the 3 multiple choice questions as correct. When both questions are answered for one of the fragments of the learning content, a pair of answers is formed that reflects the progress made on the passage in question. The combination of several (at least 5) pairs of such answers forms a point on the knowledge acquisition surface. If there are fewer pairs of answers, there is too much uncertainty for the result to be reliable enough.

Answer pairs can consist of 4 different combinations:

- correct answer to both the orientation and self-examination question (P-P pair);
- incorrect answer to the orientation question and the correct answer to the question of self-examination (N-P pair);
- incorrect answer to both the question of orientation and self-examination (N-N pair);
- correct answer to orientation, wrong answer to the question of self-examination (P-N pair).

The model was developed on the following assumption:

- The total sum of the coordinates of the points is equal to 1, thus the knowledge acquisition surface forms a 3-dimensional plane of a triangular shape.
- The knowledge acquisition surface is based on a set of artificial data.
- Thresholds calculated based on probability are placed at the peaks of the knowledge acquisition surface.
- The pairs N-N and P-N are summed up and denoted by X-N.
- A value corresponding to a specific type of answer pair is placed on each axis: N-P values are placed on the x-axis, P-P values are placed on the y-axis, and X-N values are placed on the z-axis.
- Points that are formed outside the calculated probability are located next to knowledge acquisition surface, extending it to the side. The shape of the triangle and the sum of the point coordinates also remaining in this situation is equal to 1.
- If only P-P pairs are formed, the content is known to the student, the answers are not mentioned, they are based on existing knowledge.
- If there is a successful process of acquiring knowledge, in an ideal situation, pairs of N-P answers are formed in 2/3 of cases, which indicates that the student has acquired new knowledge, and in 1/3 cases pairs of P-P answers are formed, which indicates that the student also has previous knowledge of the field being studied.
- In situations where the student has not had previous knowledge of the topic being studied and where it has not been mastered during the course, X-N pairs are formed. It is impossible to lose already acquired knowledge by taking a course designed correctly in terms of pedagogy and content. Accordingly, it is assumed that even when starting the relevant lesson, the student did not have the necessary knowledge, and the correct answer to the orientation question is guessed.

The extreme limits of the knowledge acquisition surface are shown in Table 2.1. In determining this limit value – the vertices of the knowledge acquisition surface consider the probability of 1:3 that the correct answer is guessed.

Table 2.1

Values of the peaks of knowledge acquisition surface

	Answer pairs	Easy	Appropriate	Complicated
The possibility of combinations of answer pairs	P-P	1	0.333	0.111
	N-P	0	0.667	0.222
	N-N	0	0	0.444
	P-N	0	0	0.222
Calculated values for peaks of knowledge acquisition surface	P-P (y-axis)	1	0.333	0.111
	N-P (x-axis)	0	0.667	0.222
	X-N (z-axis)	0	0	0.667

P-P is the extreme value of the "easy" situation: all pairs of answers are P-P, the extreme value is 1, while other pairs do not form, respectively N-P = 0, and X-N = 0. N-P describes the extreme value of "appropriate" – a situation when the student has created 2/3 pairs of N-P and 1/3 pair of P-P. The value is determined considering the likelihood of guessing part of the correct answers. X-N is characterized by the extreme value of “complicated”. This, too, is determined by the fact that some of the given answers have been guessed, both the right and wrong answers.

A full set of artificial values used for modelling is available in Appendix 1, and an example of this is given in Table 2.2.

Table 2.2

Values of artificial data points of the knowledge acquisition surface model (see Appendix 1 of the Doctoral Theses for the full list)

The knowledge acquisition surface		
N-P	**P-P**	**X-N**
0.000	1.000	0.000
0.067	0.933	0.000
0.022	0.911	0.067
0.133	0.867	0.000
0.089	0.844	0.067
0.044	0.822	0.133

Expanded surface		
N-P	**P-P**	**X-N**
1	0	0
0.9	0.1	0
0.9	0	0.1
0.8	0.2	0
0.8	0.1	0.1
0.8	0	0.2

To place real-world user data on the knowledge acquisition surface, the total number of answer pairs is initially calculated. This is done using formula

$$n_{(\text{"P-P"})} + n_{(\text{"N-P"})} + n_{(\text{"P-N"})} + n_{(\text{"N-N"})} = N_{(\text{ap})}, \qquad (2.1.)$$

where:

$n_{(\text{“P-P”})}$ – the number of pairs of answers in which both answers, both to the orientation and the self-test question, are correct; such pairs are designated P-P;

$n_{(\text{“N-P”})}$ – the number of pairs of answers in which the answer to the orientation question was wrong and to the self-test question correct; such pairs are denoted by N-P;

$n_{(\text{“P-N”})}$ – the number of pairs of answers in which the answer to the orientation question was correct and to the self-test question wrong; such pairs are initially designated P-N; in the course of the calculation, they are summed with N-N pairs and denoted by X-N;

$n_{(\text{“"N-N”})}$ – the number of pairs of answers where both the answers given, both to the orientation and the self-examination question, have been wrong; such pairs are initially designated N-N; during the calculation, they are summed with P-N pairs and denoted by X-N;

$N_{(\text{ap})}$ – the total number of answer pairs obtained for the object to be analysed – a department, subdivision, or individual student.

After calculating the total number of answer pairs, further calculations are made to determine the coordinates of the point associated with these pairs of answers on the three-dimensional knowledge acquisition surface. The values are calculated for each axis separately, considering the conditions for probability effects specified in Table 3.1.

The value on the y-axis (P-P) is calculated by dividing the number of pairs of P-P responses received by the total number of pairs of responses received:

$$"P-P"_{(value)} = \frac{n_{("\text{P-P}")}}{N_{(\text{ap})}} \quad (2.2.)$$

The value on the x-axis (N-P) is calculated by dividing the number of N-P answer pairs received by the total number of answer pairs received:

$$"N-P"_{(value)} = \frac{n_{("\text{N-P}")}}{N_{(\text{ap})}} \quad (2.3.)$$

The value on the z-axis (X-N) is calculated by summing the number of received pairs of N-N and P-N answers, and then dividing it by the total number of pairs of received answers:

$$"X-P"_{(value)} = \frac{n_{("\text{N-N}")}+n_{("\text{P-N}")}}{N_{(\text{ap})}} \quad (2.4.)$$

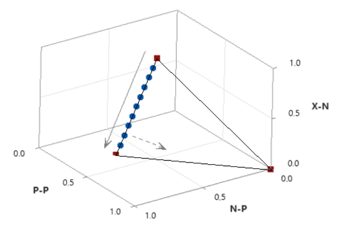
Then, according to the result obtained for each of the axes, the corresponding data point is placed on the knowledge acquisition surface. Depending on the distribution of the types of answer pairs, it can be located at any point on the knowledge acquisition surface. If the distribution of pairs of responses is attributable to any significant adjacent conditions that are beyond the calculated probability, it is expected that the point can be placed outside the knowledge acquisition surface, on its extension.

When the knowledge acquisition surface is used to analyse the data of individual students, it is important to understand that the student's progress can be acted on and directed along the path chosen by the tutor. This is ensured by the display of learning data in real time, which creates an opportunity to make the necessary changes during the course to ensure the student's progress.

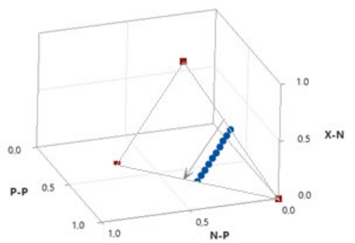
The author has developed 8 models to characterize the most common situations that can be seen using the analysis of data provided by the knowledge acquisition surface. The models are calculated on the assumption that there are 10 units in the course. With the help of these models, it is possible to identify the following situations:

- the student does not have initial knowledge and it is successfully acquired during the course;
- the student has partial prior knowledge that is improved during the course;
- the student's initial knowledge of the course topic corresponds to the goals to be achieved at the end of the course, while during the course new knowledge is not acquired and a situation has arisen when the learning content does not allow progress;
- the student's initial knowledge of the course topic corresponds to the goals to be achieved by the end of the course, while during the course he manages to create new challenges and gain additional knowledge;

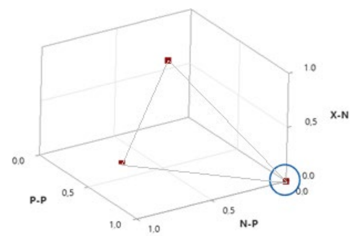
- the initial knowledge of the student partially meets the requirements of the course, and during the course manages to create new learning challenges that the student does not accept and gradually loses involvement without making progress;
- for the student, the initial knowledge does not meet the requirements of the course, but during the course the content becomes too light, without creating challenges for the student;
- the student has initial knowledge and manages to create new learning challenges during the course, which the student partially accepts and makes progress (Fig. 2.6).



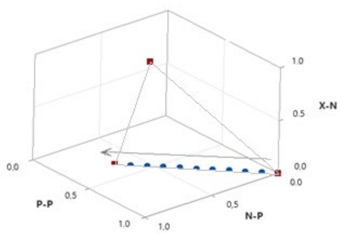
Model 1



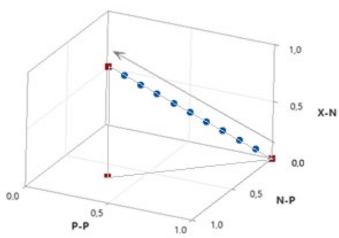
Model 2



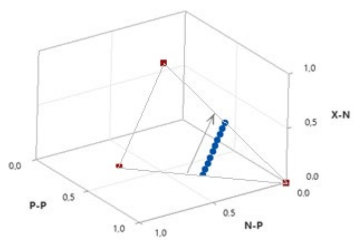
Model 3



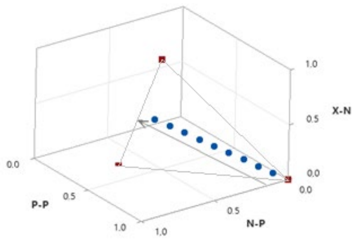
Model 4



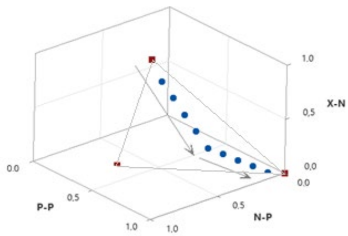
Model 5



Model 6



Model 7



Model 8

Fig. 2.6. Models of progress in the acquisition of knowledge by students. Image created by the author.

The developed models can be used to plan and direct the flow of knowledge in the course, while the active involvement of the tutor is required to achieve the desired progress. It is expected that the real learning data points on the knowledge acquisition surface are not positioned linearly. The tutor, using progress models of progress in the acquisition of knowledge by students, can assess changes in the location of the student's real data points and the progress of the student's acquisition of knowledge and decide on further pedagogical measures to promote the progress of the student's acquisition of knowledge.

2.2. Metrics of progress of the student's acquisition of knowledge and learning content adequacy

One of the challenges is to find a way to analyse the performance of tutors in higher education institutions. Although there is talk of various qualitative and quantitative methods of assessment, for the most part they are based on pre-prepared surveys and graphs that allow the analysis of the results obtained. Since the 1920s, when this practice of student surveys was launched, there has been an ongoing debate about the reliability and usefulness of these surveys, citing as the main concerns the insufficient experience and maturity of students to evaluate the work of the tutor, as well as the fact that student ratings may be influenced by the popularity of the course, the personality of the tutor, the grades received, as well as whether the course was compulsory, or it was the student's free choice. Universities also use the digital datasets available to them, but their analysis is more focused on evaluating students than tutors. As a solution to assess the performance of tutors and the quality of courses, the authors of this study propose a cross-comparison of student survey data conducted using several classification techniques to improve their objectivity in relation to the assessments provided on the quality of tutors and courses (Agaoglu, 2016). The pandemic-induced shift to digital education has created opportunities for researchers to access much more learning data to be used for both policymaking and method-making (Childs & Taylor, 2022).

The analysis of the literature revealed a wide range of different applications of metrics in the field of education, as well as various reasons for doing so. When it comes to metrics in education, there is also talk of a national-level metric that would allow the progress of higher education students to be compared with each other. In this situation, the possibilities of using machine learning to assess and rank the permanence of student satisfaction indicators are evaluated, while student satisfaction data is obtained through surveys (Langan & Harris, 2019). There is a need to improve national data analysis of college students as well, assessing how many of those who have started their studies also complete them (Kelly & Whitfield, 2014). National data are also recommended to be measured to improve physical education standards applicable to preschools (Dyson et al., 2011).

When measuring the process of acquiring knowledge, several indicators can be measured quantitatively. The most common are the test pass/fail ratio, student ratings, satisfaction rates, completion rates and drop-out rates (Colman, 2021). Metrics are also used to predict students' progress by measuring their past results and based on them, predicting future outcomes over the course (Jiang & Wang, 2020). Metrics are also used to measure student performance during the course and provide feedback to tutors both to improve course design and promote student progress, including by focusing on early student achievement. In the considered case, it is adapted specifically for the assessment of the programming course (Sun et al., 2020).

Critical feedback can also be found on the use of metrics in the educational process, especially in matters related to the assessment of tutors and content quality. Opponents of metrics deny the need for metrics in education policymaking, pointing out that decisions in this area should not be based on numbers, as this can limit the autonomy and self-realization of individuals (Normand, 2020). It is also pointed out that national metrics in the field of education, and the decisions made on its basis are not always good for the education sector (Baird & Elliott, 2018). The results of the literature analysis suggest that metrics in the education sector can range from state-level data processing to a highly personalized solution focused on evaluating one course in a particular area. Despite some sceptical opinions, there is a clear tendency to use different types of measurements in decision-making. From the author's point of view, it is more important to answer the question of what and how to measure, rather than whether to measure. It is very important to understand why such a measurement is made and how the obtained result will be used later.

In the case of the KAM method, the measurement is reflected on the knowledge acquisition surface. For the measurement, reference is the location of the point on the knowledge acquisition surface and the distance from the edges of the knowledge acquisition surface. The knowledge acquisition surface is modelled in such a way as to consider the probability that the correct answer has been guessed, as well as the possibility of other random decisions. Student progress assessment data points are expected to be located on the modelled knowledge acquisition surface. Outside the knowledge acquisition surface, points remain when the proportion of the received correct and incorrect answers in the answers to questions is beyond the calculated probability. In this case, the points are located next to knowledge acquisition surface. The position of points on the knowledge acquisition surface results from the proportion of answers given by students to orientation and self-examination questions – how many of them have been answered correctly, and how many are wrong. Accordingly, pairs of responses are formed, which also determine the position of the point. The position of the point describes the progress made by the student or group of students during the study period and allows to draw conclusions about the suitability of the learning content for a group of students or individual students, as well as the progress made by students in mastering the content. If the point is placed outside of the knowledge acquisition surface, on its extension, there is a possibility that there is a technical or substantive problem in the course.

During the piloting, it was observed that the placement of points on the knowledge acquisition surface suggests two fundamental aspects. The original goal was to make sure that the points show the behaviour of students and their progress in the course. During the piloting, it was observed that they also testify to the content and technical quality of the course (Daugule et al., 2022). Given this circumstance, the expanded knowledge acquisition surface was modelled to get a transparent picture of the possible position of such points. Using artificial data, both surfaces were modelled: the knowledge acquisition surface (blue dots) and the extended surface (red dots). The knowledge acquisition surface is modelled from expanded surface data, considering probability. The calculated probability includes situations for which the correct answer is guessed, as well as the likelihood of other random decisions. Accordingly, situations where students' answers to questions are beyond probability remain outside the knowledge acquisition surface. In this case, there is a reason to believe that there is some other explanation for their location, and it is necessary to understand its causes (Fig. 2.7) (Daugule et al., 2022).

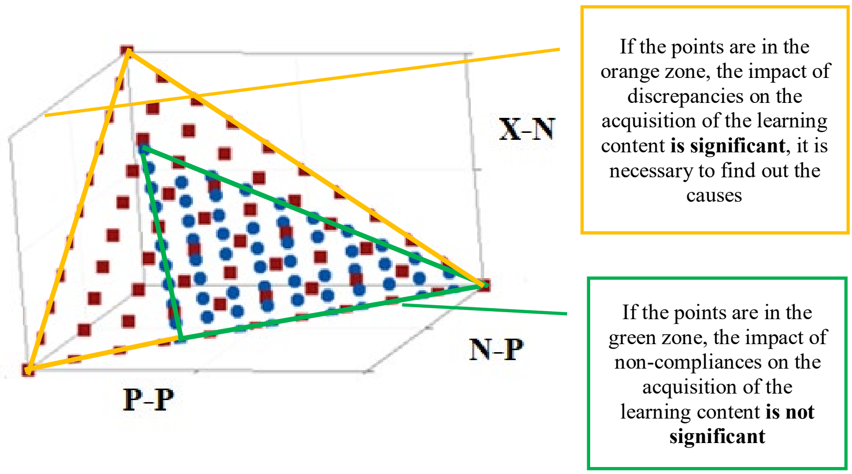


Fig. 2.7. The knowledge acquisition surface and the expanded surface. Image created by the author (Daugule et al., 2022).

84 artificial data points have been used to model both surfaces, based on extended surface data, where it is determined that the sum of 3 axes for one point = 1. To model the knowledge acquisition surface, an additional recalculation has been carried out, considering that the student's correct answer may have been influenced by probability that it has been guessed.

By evaluating the data displayed on the knowledge acquisition surface and noticing deviations from the intended one, the proposed algorithm for determining the causes is to initially focus on a technical flaw, then evaluate whether there are any substantive gaps, and then evaluate the behaviour of students. The most significant technical flaw and common cause is an insufficient amount of raw data for further statistical processing. For the results to be interpretable, the minimum required number of answer pairs is 5, whereas the optimal number is 8 pairs of answers. This type of mismatch can occur when the analysed course has insufficient number of units or students (less than 5). In order not to confuse the user of the knowledge acquisition surface with information that does not meet the requirements of analytics, it would be necessary to automatically block the appearance of points that are not based on enough data on the knowledge acquisition surface (Daugule et al., 2022).

By eliminating the above described cause, individual points are still marked in the orange zone, which are located outside the knowledge acquisition surface. The position of these points is not justified by insufficient data; therefore, it is necessary to conduct an in-depth study of the cause, assuming that the positioning of the point as a cause is a significant defect or error in the content. Technical flaws can be incorrect or incorrectly inserted correct answers in any of the multiple-choice questions. This may be a situation where none of the answers are indicated as correct, the correct answer is replaced by the wrong one, or vice versa, or all the answers are indicated as correct. Technical errors may also be present elsewhere in the learning content. Care should be taken to ensure that all classes in the course are included in the overall flow. If the content includes video, check that it can be played, has not lost its sound, and has no other defects. If you have included a link in your content, make sure it is up to date and working.

After checking the technical shortcomings, the next step is to check the quality of the content. This step is much more difficult, since the quality of the content and compliance with the goals of the course is significantly more difficult to assess. This area requires in-depth study, but there are situations when these factors can affect analytical results and several possible substantive causes have been identified for piloting in time:

- Question A is fundamentally more difficult than question B.
- The content of the training does not place an insufficient emphasis on the topic on which Question B is finally asked.
- Question B is not related to the issues covered in the curriculum.

It is necessary to make sure that both the orientation and self-examination questions correspond to the content of the course placed between them. To obtain adequate results, both questions should be the same in content and complexity, and at the same time they should not be identical. The proposed answers are also important. There may be situations when the correct answer can be assessed visually rather than in content, for example, one of the answers is broader and more data-based than the others. Content gaps also include a situation where the learning content contains misleading content that causes misunderstandings among students. In this case, an undesirable situation is created when there is an error in the content section of the lesson, while both questions and answers to them are correctly written. Accordingly, the students consciously choose the wrong answer, thinking that it is correct (Daugule et al., 2022).

As for the behaviour of students, there is a characteristic situation when students answer an orientation question and get acquainted with the content of the course but avoid answering a self-test question. Another option is the dishonest behaviour of students when a group of students have discussed the correct answer option among themselves and based their responses on the recommendation of the most persuasive member of the group who has made a mistake. This situation can be avoided by applying the various constraints available to Moodle in creating a content feed if the content, tasks, and goals of the course allow it. This may also be due to low activity of students, which, accordingly, is associated with insufficient formation of raw data necessary for analytics and can be prevented by improving the mechanism for selecting points that appear on the knowledge acquisition surface. At the same time, it is necessary to think about a mechanism for not missing those students whose activity is insufficient (Daugule et al., 2022).

To facilitate the interpretation of the results located on the knowledge acquisition surface, it was coloured in 3 colours, thus dividing it into three different zones characterizing progress. The zones marked on the knowledge acquisition surface are based on the establishment of opportunities and directions for the adaptation of teaching materials to the needs of students. Zones indicate situations when the learning content is too light or, on the contrary, when there is some tacit knowledge in the learning content. There are 3 zones: zone A (green); zone B (blue); and zone C (red). The preferred situation is that as many points as possible are in the green zone (zone A). The green zone marks a situation where the content of a course or course is appropriate for a group of students or an individual student. In such a situation, every opportunity to teach the maximum possible amount of knowledge has been used, and the student has not encountered significant difficulties in their acquisition, while improving his knowledge (Daugule et al., 2022).

The blue zone (zone B) indicates a situation where there are missed opportunities in the learning process. Although the student had no difficulty in mastering the subject, the tutor had the opportunity to teach more in the available time. The course has been too easy, the student used a lot of previously acquired knowledge in completing the tasks, thus losing the opportunity to learn something new. Also, there is a possibility that the blue area indicates easily flowing knowledge, since teaching does not require special efforts. This could make it possible to increase the amount of knowledge included in each flow to achieve a better final knowledge of the student, or to reduce the time planned for the acquisition of this study material (Daugule et al., 2022).

The red zone (zone C) indicates a situation where the proposed study material is too complex for the student and therefore has not been mastered. The desire to teach more than the student can master, or an explanation that is too complex leads to the opposite effect than intended – the student has not learned anything. In such a situation, the tutor must either review the amount of material or the way it is presented to achieve the desired goal – the acquisition of knowledge (Daugule et al., 2022).

The points obtained on the knowledge acquisition surface enable drawing conclusions about the suitability of the course or course for a group of students or individual students. The assessment of suitability is carried out considering the area of the knowledge acquisition surface where the obtained data point is located. These zones are shown in Fig. 2.8.

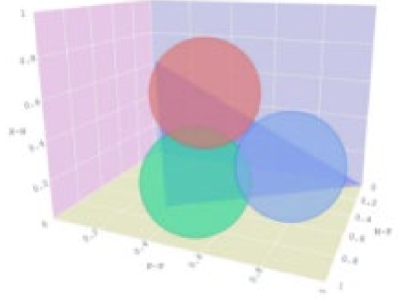


Fig. 2.8. Assessment of the suitability of e-content in coordinates P-P, N-P, X-N. Image from system piloting (Timsan, 2020).

If the learning content has been suitable for the needs of students and learning progress is being made, then the point is placed close to the bottom edge of the knowledge acquisition surface. If the point is in the lower left corner of the knowledge acquisition surface, this indicates optimal knowledge acquisition. In this situation, pairs of P-P and N-P responses are formed, and depending on their proportion, the point moves about the lower part of the knowledge acquisition surface. The formation of such pairs suggests that students have already had prior knowledge on some issues and have not had it on some issues. During the course, the existing knowledge has been strengthened, as well as new, previously non-existent knowledge has been acquired.

2.3. The KAM method and knowledge acquisition surface – the requirements of the learning analytics tool

As part of the study, learning analytics corresponding to the KAM method were developed. Given that the content of the course can include both explicit and tacit knowledge, it is important to determine which knowledge suits what type and, consequently, to develop the appropriate knowledge transfer. The goal of the KAM method is to use all the possibilities to teach faster and/or more over a certain period, providing content that meets the student's needs. The goal is to offer a convenient, easy-to-use learning analytics tool that is compatible with a popular learning management system, thus being accessible to a wide range of users. The KAM method is suitable for providing learning analytics for small groups of students and individual students. Collecting the necessary data should not complicate the learning process and create an additional load for the course tutor. The KAM method involves a way to involve students more in the course and learning process and to promote their motivation (Daugule et al., 2022).

The KAM method can be applied to distance and blended learning at different levels of education, covering primary, secondary and vocational education, higher education and lifelong learning. The KAM method and the knowledge acquisition surface allow the student's progress to be visualized in real time – during the learning process, thus providing an opportunity for the tutor to notice shortcomings in time and take actions to eliminate them (Kapenieks et al., 2021).

The developed learning analytics system is aimed at assessing the progress of knowledge acquisition and the suitability of the learning content. The main benefits it brings in comparison with the information available to the tutor in the learning management systems used daily is the ability to assess the progress made by students, as well as the availability of this information in an easy-to-understand format. The data needed to evaluate what has already been achieved and to plan future tasks to facilitate the completion of the course is available in a simple and transparent way. Accordingly, it is easier for the tutor to decide both on the sections of the course to be improved as well as on the necessary personalization solutions. By promptly establishing that the student is not sufficiently involved in learning the course or has encountered significant difficulties in learning the content, the tutor could turn the situation in his favour already during the course, reducing the possibility that the student may decide to stop his studies without completing them.

The development of the analytics tool considers the current situation in the Latvian education system. Using the data on students published by the Ministry of Education and Science in 2019, it was studied what is the expected size of the group of students, and, accordingly, what is the optimal solution for learning analytics. The MoES provides data on 1254 study programmes offered in higher education institutions and colleges. Of these, there are 16 state higher education institutions, 8 state higher education agencies – colleges, 9 state colleges, 11 higher education institutions founded by legal entities, 8 colleges founded by legal entities and 2 branches of foreign higher education institutions. 75 programs were excluded from further data processing, in which no students were registered in 2019. Data have been processed for 1179 study programmes. The average number of students per study programme is 67.34; however, it should be considered that there is a very high standard deviation of 116. The smallest number of students registered in one programme is 1, and such a number is registered in 30 study programmes, while the number of students in 3 study programmes exceeds 1000: 1987, 1301, and 1162 students, respectively, while the number of students in the next most popular study programmes is 823 and 817, respectively. In total, in 33 study programmes the number of students exceeds 300, which is 2.8 % of the total number of active programs. The largest number of study programmes is implemented with the number of students up to 25 students (in total 480 programmes with such number of students, 40.7 % of the total number), the second most common result is study programmes with 25 to 75 students (in total 399 programmes with such a number of students). In the next range (from 75 to 125 students) there are only 131 study programmes, and further the number continues to decline sharply (MOES, 2019).

If you compare full-time and part-time study programmes, you can see that there are no significant differences in the size of groups. Part-time studies take place in 297 study programmes, the average number of students in one study programme is 74, with a standard deviation of 118.8. Full-time studies take place in 882 study programmes, the average number of students is 65.09, with a standard deviation of 115.1. Considering that students in the program are divided by courses, it can be concluded that the average size of the group of students in programmes with a total number of participants up to 75 is less than the total number of students enrolled in the program. This may vary according to the type of programme, as programmes have different implementation times. Accordingly, if the goal is to develop a learning analytics tool that would be valid for analysing the data of 75 % of college and university study programs, it must be capable of analysing the data of very small groups of students: from 6 to 37 students. It is necessary to consider that learning data accumulates slowly, throughout the semester, and a new group of students starts the course once per year. This amount and pace of incoming data makes significant use of the possibilities of applying machine learning methods and forecasting algorithms. The small number of students allows the tutor to find an opportunity to develop a personal approach, provided that reliable data on the needs of students are available.

Typically, systems that include machine learning and prediction algorithms use large amounts of data sets (Tamang et.al., 2021). For example, to predict the results of sports games, a set of data is used which includes information about 10 seasons and more than 500 games, reaching an accuracy of up to 75.5 % (Thenmozhi, et al., 2019). Looking at the amount of data needed to provide deep learning, one points to datasets containing 120,000 images for the training part and 40,000 for image testing, as well as a dataset of 130 million for further use in product personalization for 1000 different user groups. To improve credit risk management, a data set of 80,000 units per day is processed (Lee & Shin, 2020). To identify consumers' needs for certain products, only 1.75 million posts have been gathered in various discussion forums related to the topic. During preparation, about 5000 records were manually marked. To analyse inconsistencies associated with a possible high impact on end users of a technological product, 80,000 entries in forums related to this topic were filtered out, while 5700 solutions were considered to analyse the possible success of groups of innovation creators, collecting data for a 3-year period. To identify promising crowd solutions related to the development of new products, data was collected on the event, in which just over 1000 people from 60 countries participated, developing 470 solutions. These results were analysed by a random decision forest containing 500 decision trees (Kakatkar et. al., 2020).

The datasets used in the education sector are significantly smaller. A set of 1282 cases has been used to predict student grades, containing data on students' exam final grades between June 2016 and December 2019. The dataset contains information on 641 students who have taken 2 basic courses. At the same time, references to previous studies can be found in this study, where the sample size varies from 50 to 748, for some of these solutions exactly the small amount of data analysed is indicated as a limitation (Bujang et. al., 2021). When developing a machine learning solution to prevent situations where a student's average grade in a learning module may negatively affect his overall progress, a set of data from 127 courses with data collected on 4 semesters has been used; however, here, too, the amount of the data set is indicated as a limiting factor, since it is small (Yanes et. al., 2020). To predict student satisfaction with study courses during Covid-19, a dataset with 18,691 entries and 20 variables was used (Abdelkader et.al., 2022). A study conducted in Indonesia contained a set of data on 4741 students, out of 120 classes in 18 different subjects, and was used to conduct predictive and prescriptive analysis based on their demographic profile and behaviour during the course (Purwoningsih, 2020).

Evaluating the amount of raw data required for machine learning and artificial intelligence solutions in the scientific literature in the context of the average number of students in one course (group) in Latvian colleges and higher education institutions, it can be concluded that in at least 75 % of cases the required amount of data cannot be obtained, or the time required for its acquisition may render the obtained results obsolete. Study courses require constant improvement and keeping them uniform for 10 years or more to obtain the necessary data, can at the same time lead to significant shortcomings in their relevance and quality. Given the large variety of programme sectors, topics, levels and types of study, the author does not consider it useful to combine and uniformly analyse data from several study programmes (MOES, 2019)

In the Latvian higher education programme, in 75 % of cases, the learning analytics tool is based not on bulk data processing, but on statistical solutions that are suitable for processing small data sets. The mission of the learning analytics tool is to make the learning process in the digital environment more understandable and manageable. Knowledge transfer must be clearly measurable and manageable in a timely manner. Adapting the learning content to retrieve the data needed for analysis should be technically simple and pedagogically justified.

The aim of the learning analytics tool is to provide the online or blended course tutor with the necessary information about student progress and involvement, as well as the quality of the learning content and its relevance to the student's needs, providing opportunities to take the necessary measures to improve the course and promote student motivation already during the course. To achieve the set goal, the following tasks are set:

- collect and analyse student learning data according to the established methodology;
- the learning analytics tool and the collection of the necessary teaching data should not hinder the learning process;
- during the learning process, student involvement and motivation is promoted;
- ensure that analytics results are presented in an easily visually perceptible way;
- ensure the availability of analytics results in real time;
- ensure that the analysis of student teaching data is possible for small groups of students (starting from 5 students);
- ensure that the learning analytics tool provides data on the learning progress of an individual student;
- ensure that the learning analytics tool allows to assess the student's motivation;
- ensure that the learning analytics tool allows to assess the student's involvement in the learning process;
- ensure that the learning analytics tool allows to spot technical shortcomings in the course;
- ensure that the learning analytics tool allows to notice situations where changes in pedagogical approach are needed.

Courses that are tailored to bring their learning data to the knowledge acquisition surface and become available to the tutor are expected to be able to generate more added value than those for which such analytics data are not available. Given that the results are offered in real time, the tutor could fill in the knowledge gaps during the acquisition of knowledge by immediately adjusting the content and tasks, or conducting individual consultations for those students who have turned out to need it.

During the research, the author got acquainted with several online learning environments and their technical capabilities to create learning content allowing data collection in a way that is suitable for providing a learning analytics tool. During the research, 3 different learning management systems – Sakai, edX, and Moodle – were used to conduct experiments. All these environments are open-access and allow for various adjustments and, as has been observed during the experiments, provide the necessary technical capabilities to create a learning environment adapted to the needs, objectives, and tasks of the course in question and to ensure the collection of the necessary data. As the final option for the operation of the system, the author chose the Moodle environment. The most important reasons for this were the widespread use of this environment in the Latvian education sector, in educational institutions of various levels, as well as the stability of the operation of this environment. Considering that the successful operation of the learning analytics tool also requires the application of access controls and the fact that the learning analytics tool to be developed is aimed at using the obtained data to adapt the learning process, the author sees that such a choice will allow to achieve the set goals.

To make the system accessible to a wide range of users, it is necessary to structure access not only according to courses, but also to separate groups of students in these courses, considering that each group may have a different course tutor. Such an approach would make it possible to create content that meets certain requirements and make it available to the wider public. Taking into account that the information obtained from the knowledge acquisition surface requires an immediate response within the framework of the already ongoing learning process, it is necessary to provide an appropriate number of tutors who work with a group of students corresponding to the learning content, providing the necessary additional materials, tasks, consultations and other activities both online and in person in order to achieve the set learning goals and complete the set tasks.

The developed knowledge analytics tool and knowledge acquisition surface are designed to be applied to small groups of students, up to 40 persons. When applied to larger groups, there is a need to think additionally about solutions to make points on the knowledge acquisition surface readable even if there are a lot of them. Perhaps, at a high score, it is necessary to find a different type of visual representation so that the results obtained are easy to read, understand and easy to interpret. Also, in the case of a larger number of trainers or courses, it is necessary to rethink menus and access to ensure both transparency of the data and protection against access by persons who do not need it to perform the tasks assigned to the system.

To build a successful online learning environment, it should be possible to gain insight into the student's level of engagement and motivation, as well as the relevance of the course's progress and content to the student's needs. This requires an analytics tool that allows to collect and analyse data on the initial level of knowledge of the student and in addition to the acquired knowledge during the course. This data should be collected and analysed in a way that allows to determine students' motivation and actual involvement in the course. It is no less important that the solution of learning analytics allows you to determine the transfer properties of the knowledge included in the course and to judge the suitability of the learning content for the relevant group of students.

Given that the question system motivates students to take an active part in the course, the system should also be built considering this circumstance (Kapenieks et al., 2020). It is necessary to create an ecosystem that includes the support students need and helps them adapt to the study process to positively influence their learning progress (Dennis et al., 2005). Adult education providers need to identify the nature of their students' motivation and take this into account when running the programme. The unique interaction of individual and environmental factors is important, and if this aspect is not considered, it is likely that the program will not be successfully implemented (Simpson, 1997). The assessment of students' knowledge before the start of the course and after the conclusion of the course is essential to understand the actual increase in knowledge. To determine the increase in knowledge, it is recommended to measure theoretical knowledge, competences, and skills. Also, the need to evaluate student behaviour and its changes before and after study is indicated. When evaluating behaviour, the focus is on the passion for learning, the attitude towards learning, the abilities demonstrated by the student and the effectiveness of the performance (Zhou, 2021).

The proposed learning analytics system, which contains orientation and self-assessment questions and short subunits of learning content, is designed to ensure the student's active involvement in the study process and to provide course tutors with specific information to update the content. The obtained data allows to understand the type of knowledge flow and improve the content, thereby improving the efficiency of the learning process. The data is visualized, so the tutor has access to graphical information about the relevance of the learning content/teaching approach to the student's abilities. User behaviour data is analysed and visualized using statistical methods (Daugule et al., 2022). Dividing the learning material into small fragments has a positive effect on the student's ability to perceive and remember this information. The optimal volume of such fragments that the student can perceive, process, and remember is seven (+/–2) fragments (Miller, 1956). This is based on the previously developed question system, which divides the study materials into small parts, and the associated visualization (Kapenieks et al., 2020).

By combining this approach with Gagne learning events, a learning environment is created that focuses on both the acquisition of knowledge and the acquisition of data necessary for the needs of learning analytics. While working on the development of the solution, the possibilities of implementing the learning events offered by Gagne within the framework of the e-study course were analysed.

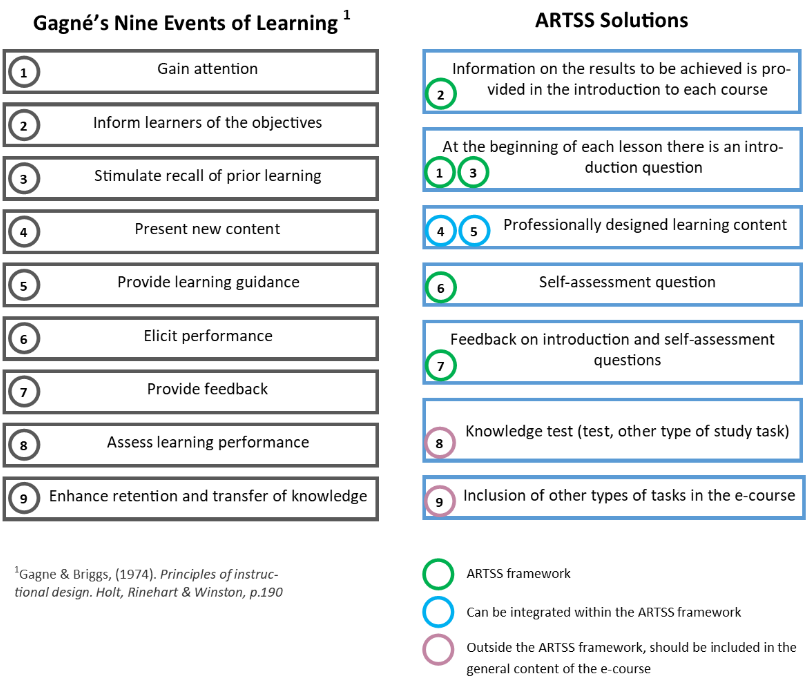


Fig. 2.9. Gagne's learning events and proposed solutions within the KAM method. Image created by the author (Kapenieks et al., 2021).

Most of Gagne's learning events can be implemented within the framework of the KAM method, while the rest can be included in the same e-course, but outside this framework (Fig. 2.9). Very simply, within the framework of the KAM method, Training events 1–3, as well as Training events 6 and 7 are included:

Training event 1: Attention is drawn to the question of orientation.

Training event 2: At the beginning of the training, the course tasks, and goals to be achieved are indicated.

Training event 3: The orientation question, after the student's attention is drawn, makes you rethink the answer to this question, thereby activating the previously acquired knowledge.

Training event 6: The question of self-assessment makes it necessary to apply the newly acquired knowledge.

Training event 7: The student is given feedback on the correct answer, accompanied by a signal of the appropriate colour. This allows the student to make sure that his answer was correct, or to understand why it was wrong.

For the results of the learning analytics to be presented correctly, it is very important that the issues of orientation and self-assessment are equally complex and correspond to the topic of the viewer in the content section.

Training events 4 and 5 can be included in the proposed framework, as well as freely supplement the learning content outside it. In a situation where the “offer new information” of Trainin event 4 requires inclusion in the framework of the KAM method, it should be placed in the *content* section, between the orientation question and the self-examination question, according to the objectives and tasks of the course. Regarding the type of content to be placed in the content section, or the teaching methods to be used, it is permissible to have this content developed by each tutor individually, as well as the possibility that it is centrally prepared by the content creator and then offered to the trainers to include it in their courses. Training event 5 in the “direction and support learning” framework can be incorporated using the “*lesson”* tool in the preparation of guided content. Also, if the tutor actively follows the changes on the knowledge acquisition surface, he could notice in a timely manner where the learning difficulties have arisen with the content part and consider possible solutions. In this case, however, there is a possibility that they will have to be implemented outside this framework, adding additional sections to the course. Completely beyond the KAM method, but still possible within the framework of the e-study course, Training events 8 and 9 are feasible. Training event 8 “assess performance” must be developed separately between tests and final tests, considering that orientation and self-examination questions are not used in the final assessment. Training event 9 “promoting transference, generalization” is also to be created separately. In this case, the tutor, considering the results obtained on the knowledge acquisition surface, can form appropriate further tasks to facilitate the transfer and generalization of knowledge.

Approaches designed to achieve an equivalent amount of knowledge in the shortest possible time have also been proposed in advance. The results show that with a well-designed approach, the time spent on acquiring knowledge can be 3 or 4 times shorter than in a conventional academic course (Delerue et al, 2018) . With knowledge acquisition surface, instead of accurately predicting the student’s learning progress, the focus is on finding an opportunity to spot the problem, giving the tutor the opportunity to engage in time and turn the learning process in a positive direction. The input used in the learning analytics tool solution allows to significantly increase the presence of these factors even during distance learning. The developed analytics tool aims to implement Strategies 2 and 3 (Figs. 2.1, 2.3, and 2.4) (Daugule et al., 2022).

One of the tasks of the developed question system is to maintain the attention of students by regularly involving them in answering to questions in the context of the subject being studied. The e-course used in the original study was adapted to produce more user behaviour data in each unit of the course. This was ensured by the placement of relevant questions at the beginning and end of each topic. Students were informed that the answers to these questions would not be considered in the final assessment, however, the answer to them is part of the learning process. Students accepted follow-up questions as motivating and helpful (Kapenieks et al., 2020).

In developing the knowledge acquisition surface, the focus was on student activity data in the context of a short system of e-content chapters and many choices included in the learning content. The purpose of this system is to transform the student from a passive observer into an active thinker, thereby facilitating the acquisition of his knowledge. When developing a KAM method, it is important that it fosters genuine engagement and inner motivation.

By choosing the appropriate settings in Moodle learning management system, it is possible to ensure that the student begins the learning of the content with an orientation question. It simultaneously allows the student to prepare for the acquisition of content, refreshes in memory the knowledge previously acquired, and allows to obtain the data necessary for the assessment of the student's initial knowledge. After answering the question, feedback is provided, informing the student about the correctness of the given answer. For data collection, it is important that the orientation issue in the title is identified by a single pattern. In the current situation, a single designation "A" was chosen.

Next, the feed is created by inserting a "Content" page. The content is created considering the topic to be studied and the principles of e-pedagogy. The content section may include text, images, infographics, videos, links to external educational materials, and more. It is important that the content matches both orientation and self-examination questions, providing the knowledge necessary to answer them. A content page can be one or more consecutive pages. The design of this section and the content included have no technological limitations related to the requirements on the part of data analytics, directly the data from this section in the studied solution is not analysed.

After the content, a self-assessment question is placed in the lesson on the page. This question allows the student to conduct a self-test, making sure that the knowledge contained in the course has been mastered. After answering the question, feedback is provided, informing the student about the correctness of the answer given. This element allows to obtain the data necessary for assessing the amount of knowledge of the student at the end of the course. For data collection, it is important that the orientation issue in the title is identified by a single pattern. In the current situation, a single designation "B" was chosen.

Both questions "A" and "B" are designed as *multiple-choice* questions with 3 multiple choice answers, of which 1 option is correct and 2 are incorrect. When creating questions, relevant feedback is also set up to provide the feedback you need.

When creating a lesson flow, an "A" question is placed first, followed by a content page (pages), and at the end of the lesson there is a "B" question. Regardless of whether the student has given the correct answer to the "A" question, he is directed to the content page. After mastering the content, he is directed to the "B" question. Regardless of whether the student has given the correct answer to question "B", he is directed to the next lesson until he reaches the end of the chapter (Fig. 2.10).

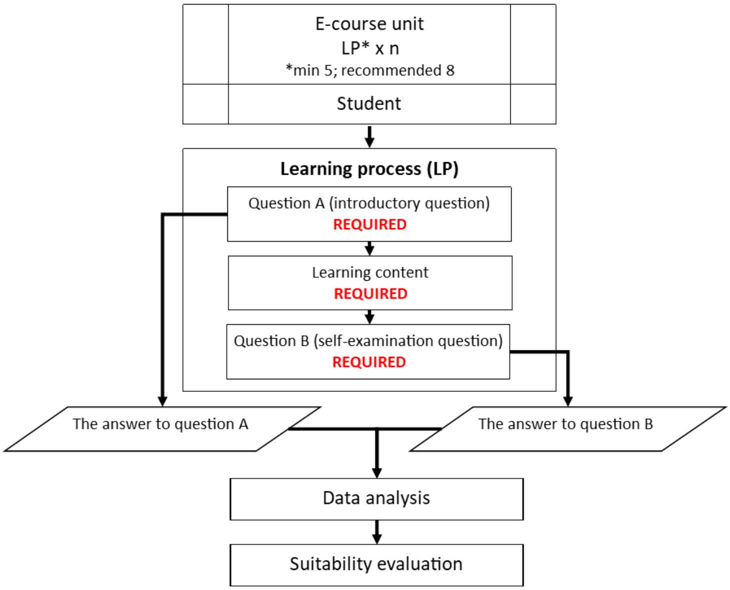


Fig. 2.10. Learning analytics tool for e-content evaluation. Image created by the author (Daugule et al., 2022).

After calculating the values, the resulting value forms a point on the knowledge acquisition surface. This paragraph can be used to assess the suitability of learning content for a student or group of students. Since the results are provided by means of an application in the **.html* format, it is possible for the user to view the knowledge acquisition surface and the points located on it at the desired scale and angle.

The teaching analytics tool needs to provide a set of functions that allow you to achieve the goals and objectives set for the system. The author identified the following functions as the basic elements of the system: authentication, password protection, data analysis request, retrieval of data necessary for analysis from learning management system, data structuring, data analysis, reflection of results, delivery of results in an appropriate format and method of access to the obtained results.

The system implementing the KAM method includes a learning management system, a learning analytics tool attached to the learning management system as a plug-in, and a knowledge acquisition surface – an application with a learning analytics tool to reflect the results obtained (Fig. 2.11).

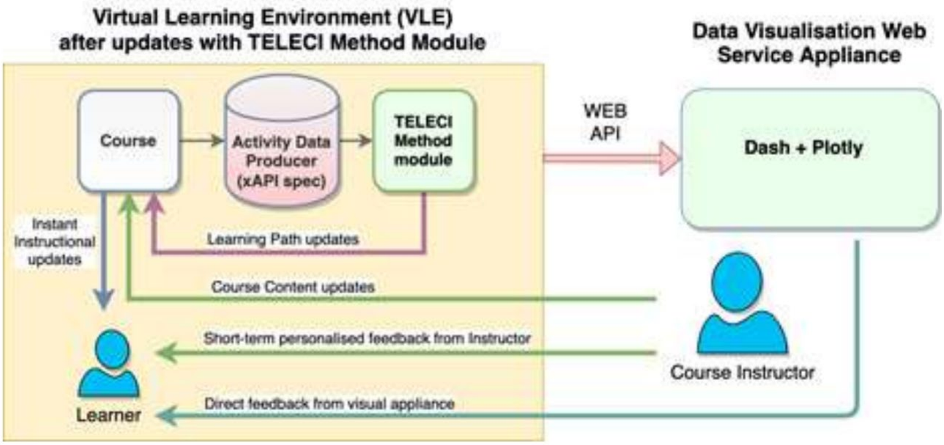


Fig. 2.11. Graphical diagram of the operation of the analytics tool (Kapenieks et al., 2021).

The users of the system are course tutors who use the learning management system to transfer knowledge and the knowledge acquisition surface to assess the results achieved and the necessary improvement, as well as the authors of the learning content (who may themselves be, and may not be, course tutors). The system also includes administrators who monitor and support activities in both learning management systems and track the proper functioning of the analytics tool and the delivery of the obtained results to the knowledge acquisition surface.

The task of the system to be designed is to retrieve students' learning data from the learning management system and perform their structured analysis. The system allows to identify knowledge transfer, indicating in which places explicit knowledge can be found in the course and in which places – tacit knowledge. The user of the system shall be able to choose the cut in which to obtain the results of the analysis. The aim of the development of the system is to provide the developer and tutor of e-courses with as much information as possible on the relevance of the materials available in the course to the needs of the relevant group of students or individual student, as well as to get an idea of the involvement of a group of students or an individual student in the learning process and the increase in knowledge gained during it. The learning analytics tool can be used by combining one of the leading LMS with Moodle or, by adjusting it accordingly, to form a single system.

During the study, several solutions were considered to ensure the operation of the analytics tool, including access to the results of analytics on the knowledge acquisition surface. After analysing the possible technical solutions, an analysis of their interoperability was carried out. Based on the results obtained in the compatibility analysis, an analysis of possible alternatives to technical solutions was carried out. Its goal was to find the optimal set of solutions to use as a basis for building a system. As the optimal chain of the system solution, a chain was chosen that includes an authorized request for information using the password of the training management system. The password is protected using SSL, and data is transferred from the learning management system to the learning analytics tool in the *.csv format. The data is structured in text. Users have the option to make a request for data analysis, depending on their needs, by choosing one of the predefined options. Data analysis is carried out statistically and its results are reflected in a graphical image. The output format of the results is *.html in the form of a page, on an open website. These results can be accessed by logging in using the learning management system password.

2.4. KAM method and knowledge acquisition surface – pilot prototype results and their validation

Both verification and validation were performed to test the KAM method and the surface performance of knowledge acquisition. To make sure that the points located on the knowledge acquisition surface were placed correctly as a result of the operation of the analytics tool, a check of the calculations included in the analytics tool was carried out, comparing the obtained results using two different methods. Verification was carried out by simultaneously retrieving the log files of the respective course from the used learning management system (*Moodle*) and performing an alternative recalculation using Minitab. The result obtained was compared with the position of the points displayed in the application. Verification is considered successful if the position of the points on the knowledge acquisition surface in both solutions coincides. If the points have deviated, this indicates an error, and in such a situation it is necessary to detect and eliminate the reasons why this has happened. Verification of the knowledge acquisition surface modelled with the Minitab and comparison of the result obtained with the one displayed in the application (Fig. 2.12), on which the real learning data is placed, confirmed that the results obtained coincided, and in both cases, it is a spatially placed plane in 3 dimensions. Verification confirmed that the knowledge acquisition surface and the expanded surface are in the same plane, and the knowledge acquisition surface fully fits into the expanded surface.

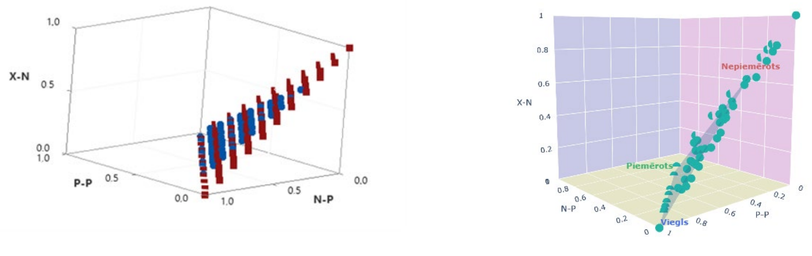
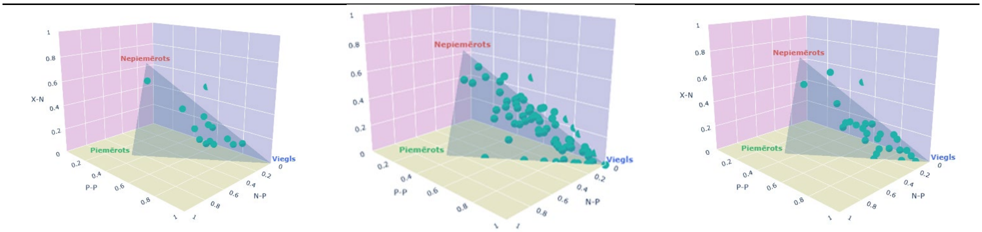


Fig. 2.12. Modelled knowledge acquisition surface and extended surface – artificial data (left) and the knowledge acquisition surface available in the application, where the learning data are also placed on its extension (right). Image created by the author.

Modelling situations with real data, and later, already during the trial of the prototype of the system were recorded when data points were located outside the calculated knowledge acquisition surface. At the same time, it was observed that in the 3D model, these data points retain their position in the same plane as the knowledge acquisition surface (Daugule et al., 2022).

To validate the results obtained with the knowledge analytics tool and placed on the knowledge acquisition surface and their interpretation, these results were validated using the expert knowledge method. Persons with high scientific and practical competence in the field of e-learning technologies and practical experience in the implementation of distance learning were invited as experts. Validation was carried out for courses conducted by experts in Moodle, and the courses were previously adapted to retrieve the data required by the learning analytics tool. The results obtained during the piloting of the knowledge acquisition surface were validated against the interpretation of the results obtained by the knowledge acquisition surfaces with expert opinion on the progress made by the same group of students during study. The experts were directly involved in teaching the course in question and as the tutors of each coursewere familiar with the composition of the group of students being assessed, their previous knowledge, and other aspects that might influence learning progress. The course tutor had at his disposal information about the knowledge shown and acquired during the study of this group, as well as involvement in the learning process.

Validation includes 5 stages. Initially, the interpretation of the results visible on the knowledge acquisition surface is prepared. For interpretation, previously developed models, metrics, and conditions for the interpretation of the knowledge acquisition surface are used as the basis. These results are then summarised and submitted in the form of a questionnaire to an expert for evaluation. The expert carries out an evaluation of the results obtained by comparing them with the experience gained during his or her studies and knowledge of the student or group of students. The expert is invited to indicate whether and to what extent the results obtained with the knowledge acquisition surface differ from his practical observations, as well as to clarify what differences exactly have been observed. The difference is estimated as a percentage. Then, based on the assessment given by the expert, an assessment of the accuracy of the interpretation is made and the average percentage error is estimated. On its basis, conclusions are drawn about the measurement error of the results obtained and interpreted with the knowledge analysis tool. During the validation, data on 9 courses were processed, in one case the course had 2 tutors, and both gave their views as experts. The total amount of data analysed for these 9 courses covers 49 topics, which included 367 sub-topics. As part of the piloting, 397 students were registered for the courses, who created 6619 pairs of questions in the learning process. The courses were designed in Moodle, implemented online, and the results of these courses were attached to the learning analytics tool and the knowledge acquisition surface during the learning process. The participants of the courses were both pupils (grades 7–12) and adults (students). Figure 2.13 depicts an example of how the results of learning analytics were reflected on the knowledge acquisition surface.



Basic business | Media literacy | Total quality management

Fig. 2.13. The knowledge acquisition surface. Progress of students' knowledge acquisition. Image created by the author.

An interval chart was used to reflect the validation results, which reflects the mean confidence interval of the data. The results show that the claims made in relation to students are rated with 92 % credibility and the confidence interval varies from 86–97 %, depending on the type of statement made. When evaluating the results of the validation on topics, the results obtained show that the claims made regarding the suitability of the topics are assessed with 87.5 % reliability and the confidence interval varies from 69–100 %, depending on the type of statement made. When evaluating the results of the validation on sub-topics, the results obtained show that the statements made in relation to the sub-topics are assessed with 93 % reliability and the confidence interval varies from 81–100 %, depending on the type of statement made. The results are shown in Fig. 2.14.

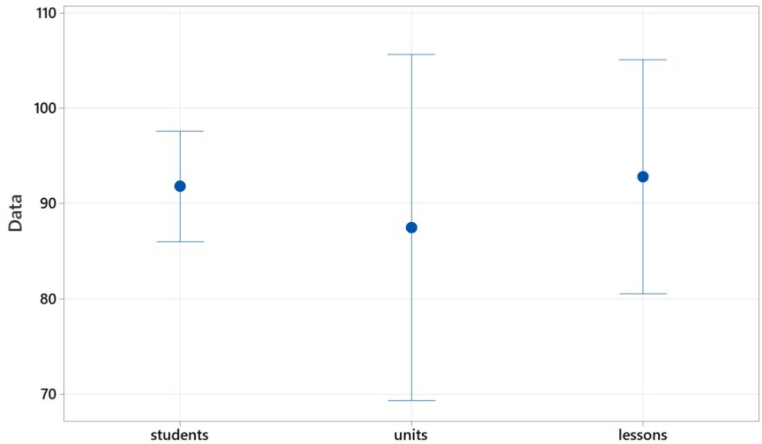


Fig. 2.14. Interval chart – expert assessment of the relevance of the statements made. Image created by the author.

The results obtained during the piloting confirm theoretical assumptions about the behaviour and progress of students during the course and the application of the knowledge acquisition surface make it possible to assess the suitability of the learning content for a group of students and an individual student, as well as provide the tutor with information about the need for a content update. It should be considered that different tutors of the same course may also have different visions of the situation in the course. The results obtained show that for these situations, the position of the points on the knowledge acquisition surface has been interpreted correctly, indicating that the student in question does not encounter difficulties during the learning process. It is possible to draw conclusions appropriate to the situation about the efforts made by students in the learning process. Depending on how much a point is shifted upwards from the bottom edge of the knowledge acquisition surface, one can judge how suitable the topic is for the corresponding group of students. The scattering of topics on the knowledge acquisition surface testifies to how equivalent they are in terms of complexity: the denser the points, the more equally complex content is included in them. By using the knowledge acquisition surface, it is possible to understand whether students have mastered the sub-topics and whether there are any technical or substantive problems in them, and it is possible to get an idea of how complex the sub-topic or set of sub-topics in question is. Depending on how much a point is shifted upwards from the bottom edge of the knowledge acquisition surface, one can judge how suitable the sub-topic is for the relevant group of students, while the scattering of the sub-topics on the knowledge acquisition surface suggests how equivalent they are in terms of complexity: the denser the points, the more equal is the complexity of the content included in them.

CONCLUSIONS

1. The goal set for the Doctoral Thesis has been achieved and the proposed hypothesis has been confirmed.
2. The developed KAM method, the proposed metrics and the knowledge acquisition surface make it possible to monitor the progress of students' knowledge acquisition and involvement of students in the learning process, as well as to assess the suitability of the learning content for the student or group of students. The coordinates of the points on the knowledge acquisition surface specifically indicate to the author of the content about the needs for improving the course.
3. The placement of points on the knowledge acquisition surface allows to draw conclusions about the transfer of course knowledge. The results are available in real time and allow the tutor to immediately make the necessary changes to both the learning content and the teaching approach during the further learning process.
4. Greater reliability is found in the data generated by the student in the e-learning environment during the learning process. The answers to the questions given by the student in various types of surveys can only be used as additional material.
5. The placement of points on the knowledge acquisition surface shows that within the framework of a single course both easily and unwieldy flowing knowledge is embodied, and it is possible to identify it. One of the most important descriptors of the knowledge transfer properties is the amount of effort that a student must make to acquire knowledge.
6. Data collection should be carried out by finding a balance between the structuring of the course for the purposes of information analysis, the reliability interval, and the learning content, which is arranged in accordance with the stated goals of acquiring knowledge, so as not to unnecessarily complicate or interfere with the learning process.
7. To obtain reliable results, it is important to ensure that the question of orientation and the question of self-examination are of equivalent complexity in content and nature, as well as both questions are directly related to the fragment of the learning content that is placed between them in the course knowledge flow.
8. The used data visualization on the knowledge acquisition surface with the KAM method makes the obtained data easy to use and is suitable for reflecting learning analytics data. The KAM method allows to view data in different sections – about the course, its separate section, about a group of students and an individual student, which is considered a significant advantage.
9. The obtained quantitative data make it possible to assess the relevance of each part of the course (topic, sub-topic) to the appropriate group of students, in addition, differences between different topics and sub-topics of the course are shown. With the help of the KAM method, it is possible to obtain a characteristic of a group of students –the average level of abilities of a group of students and the characteristics of individual students.
10. Answers to orientation and self-examination questions are an appropriate way to determine the actual involvement of the student in the learning process. The KAM

method has a positive impact on the student's learning progress and has contributed to students' motivation to participate in the learning process. Orientation and self-examination questions can be used for the online part of the courses to promote student engagement and motivation.

11. The results obtained during the piloting of the KAM method confirm that the relevance of the content to the learning needs of students is essential. Too complex a course can lead to a loss of interest, while too simple learning content does not provide an opportunity to gain new knowledge.
12. The results obtained during the piloting of the KAM method and the expert assessment confirm the theoretical models developed by the author on the behaviour of students and the progress of the acquisition of the knowledge gained during the course, and the associated point trajectories on the knowledge acquisition surface.
13. The application of the knowledge acquisition surface allows to assess the suitability of the learning content for a group of students and an individual student and provides the tutor with information about the need for content update. Using the knowledge acquisition surface, one can understand whether students have mastered topics and sub-topics, and whether they require technical or substantive improvements.
14. The results of the validation show that the position of the points on the knowledge acquisition surface has been interpreted correctly, and the placed points allow conclusions to be drawn about the existing and newly acquired knowledge of students, as well as conclusions about the efforts made by students in the learning process and the relevance of the learning content to the learning needs of students.

BIBLIOGRAPHY

Abdelkader et.al. (2022). An Efficient Data Mining Technique for Assessing Satisfaction Level With Online Learning for Higher Education Students During the COVID-19. *IEEE Access, 10*, 6286-6303. doi:10.1109/ACCESS.2022.3143035

Adzovie et al. (2022). Assessment of the effects of Covid-19 pandemic on the prospects of e-learning in higher learning institutions: The mediating role of academic innovativeness and technological growth. *Cogent Education, 9*(1). doi:10.1080/2331186X.2022.2041222

Agaoglu, M. (2016). Predicting Instructor Performance Using Data Mining Techniques in Higher Education. *IEEE Access, 4*, 2379-2387. doi: 10.1109/ACCESS.2016.2568756

Aremu et al. (2022). The impacts of integrated e-Learning system toward the challenges facing education sector during and post Covid-19 pandemic. *Journal of e-Learning and Knowledge Society, 18*(1), 34-44. doi:https://doi.org/10.20368/1971-8829/1135385

Baird & Elliott. (2018). Metrics in education—control and corruption. *Oxford Review of Education, 44*(5), 533-544. doi:https://doi.org/10.1080/03054985.2018.1504858

Becerra-Fernandez & Sabherwal. (2014). *Knowledge Management: Systems and Processes.* Routledge.

Bujang et. al. (2021). Multiclass Prediction Model for Student Grade Prediction Using Machine Learning. *IEEE Access, 9*, 95608-95621. doi:10.1109/ACCESS.2021.3093563

Childs & Taylor. (2022). The Internet and K-12 Education: Capturing Digital Metrics. *Technology, Knowledge and Learning During the COVID-19 Era*. doi:https://doi.org/10.1007/s10758-022-09612-y

Colman, H. (2021, 09 06). *Employee Training Metrics: How to Measure eLearning Effectiveness*. Retrieved 08 09, 2022, from Ispringsolutions: https://www.ispringsolutions.com/blog/training-metrics-how-to-measure-elearning-effectiveness

Daugule & Kapenieks. (2017). Collaborative Knowledge Flow — Mapping the E-Learning Environment. *EDULEARN17 Proceedings*, (pp. 3304-3311).

Daugule & Kapenieks. (2018). The Data of the Initial Motivation – a Valuable Source for the Development of the Course Content. A Case Study in the Group of Business Students. *International Journal of Engineering and Technology (UAE)*, 89-94. doi:10.14419/ijet.v7i2.28.12886

Daugule et al. (2022). Use of Knowledge Acquisition Surface to Monitor and Assess Students' Success. *Journal of Emerging Technologies in Learning (iJET), 17*(14), 109–125. doi:https://doi.org/10.3991/ijet.v17i14.31281

Delerue et al. (2018). A Massive Open Online Course on Particle Accelerators. *Journal of Physics: Conference Series, 1067*(9). doi:doi:10.18429/JACoW-IPAC2018-MOPML050

Dennis et al. (2005). The Role of Motivation, Parental Support, and Peer Support in the Academic Success of Ethinc Minority First-Generation College Students. *Journal of College Student Development, 46*(3), 223-236. doi:10.1353/csd.2005.0023

Dewanti et al. (2022). A Comparative Study on E-Learning Implementation in Higher Education In Response to The Covid-19 Pandemic. *Acitya: Journal of Teaching and Education*.

Dyson et al. (2011). Development of PE Metrics Elementary Assessments for National Physical Education Standard 1. *Measurement in Physical Education and Exercise Science, 15*, 100-118. doi:10.1080/1091367X.2011.568364

Gagne, R. M., et al. (1992). *Principles of instructional design. 4th ed.* Holt, Rinehart & Winston.

Grigoryan et al. (2022). ON THE METHOD FOR ASSESSING THE QUALITY OF E-LEARNING RESOURCES. *Main Issues Of Pedagogy And Psychology, 21*(1), 90-98. doi:https://doi.org/10.24234/miopap.v21i1.430

Husin et al. (2022). Full enforcement of e-Learning during first movement control operation of COVID-19 pandemic: are Malaysian university students ready? *Journal of e-Learning and Knowledge Society, 18*(1), 87-93. doi:https://doi.org/10.20368/1971-8829/1135471

IZM, I. u. (2019). *izm.gov.lv.* Retrieved from Statistika par augstāko izglītību. Studiju programmas.: https://www.izm.gov.lv/lv/media/2128/download

Yamani et al. (2022). Evaluation of Learning Management Systems: A Comparative Study Between Blackboard and Brightspace. *International Journal of Emerging Technologies in Learning (iJET), 17*(07), 125-144. doi:https://doi.org/10.3991/ijet.v17i07.28881

Yan. (2020). Using Learning Analytics and Adaptive Formative Assessment to Support At-risk Students in Self-paced Online Learning. *IEEE 20th International Conference on Advanced Learning Technologies (ICALT)*, (pp. 396-398). doi: 10.1109/ICALT49669.2020.00125

Yanes et. al. (2020). A Machine Learning-Based Recommender System for Improving Students Learning Experiences. *IEEE Access, 8*, 201218-201235. doi:10.1109/ACCESS.2020.3036336.

Jiang & Wang. (2020). Preference Cognitive Diagnosis for Student Performance Prediction. *IEEE Access, 8*, 219775-219787. doi: 10.1109/ACCESS.2020.3042775

Kakatkar et. al. (2020). Innovation analytics: Leveraging artificial intelligence in the innovation process. *Business Horizons, 63*(2), 171-181. doi:10.1016/j.bushor.2019.10.006

Kapenieks & Daugule. (2019). Knowledge Flow Analysis: The Quantitative Method for Knowledge Stickiness Analysis in Online Course. *Periodicals of Engineering and Natural Sciences, 7*, 3304-3311. doi:doi:10.21533/pen.v7i1.358

Kapenieks et al. (2020). Knowledge Acquisition Data Visualization in eLearning Delivery. *Proceedings of the 12th International Conference on Computer Supported Education - Volume 2: CSEDU*, (pp. 507-513). doi:10.5220/0009803505070513

Kapenieks et al. (2020). TELECI Approach for e-Learning User Behavior Data Visualization and Learning Support Algorithm. *Baltic Journal of Modern Computing, 8*(1), 129-142.

Kapenieks et al. (2021). *Priekšlikumi mācīšanās analītikas monitoringam augstākajā izglītībā.* Retrieved from lzp.gov.lv: https://lzp.gov.lv/wp-content/uploads/2021/04/ARTSS_Macisanas_analitikas_zinojums_publicesanai.pdf

Kelly & Whitfield. (2014). Postsecondary Education's Most Popular and Prickly Metric. *Change*, 56-58.

Khan et al. (2022). Investigating Learners' Experience of Autonomous Learning in E-learning Context. *International Journal of Emerging Technologies in Learning (iJET), 17*(08), 4-17. doi:https://doi.org/10.3991/ijet.v17i08.29885

Langan & Harris. (2019). National student survey metrics: where is the room for improvement? *Higher Education, 78*, 1075–1089. doi:https://doi.org/10.1007/s10734-019-00389-1

Lee & Shin. (2020). Machine learning for enterprises: Applications, algorithm selection, and challenges. *Business Horizons, 63*(2), 157-170. doi:10.1016/j.bushor.2019.10.005

Li et.al. (2022). E-Learning during COVID-19: perspectives and experiences of the faculty and students. *BMC Med Educ, 22*(328). doi:https://doi.org/10.1186/s12909-022-03383-x

Miller, G. (1956). The Magical Number Seven, Plus or Minus Two: Some Limits on our Capacity for Processing Information. *Psychological Review, 63*, 81-97.

Mo, S. (2010). *Teaching online: a practical guide.* Routledge.

Nissen, M. E. (2005). *Harnessing Knowledge Dynamics: Principled Organizational Knowing & Learning.* IRM Press.

Normand, R. (2020). The Politics of Metrics in Education: A Contribution to the History of the Present. In G. P. Fan, *Handbook of Education Policy Studies* (pp. 345-361).

Polat et al. (2022). Are K–12 Teachers Ready for E-learning? *The International Review of Research in Open and Distributed Learning, 23*(2), 214-241. doi:https://doi.org/10.19173/irrodl.v23i2.6082

Pozdniakov et al. (2021). Question-driven Learning Analytics: Designing a Teacher Dashboard for Online Breakout Rooms. *International Conference on Advanced Learning Technologies (ICALT)*, (pp. 176-178). doi:10.1109/ICALT52272.2021.0006

Purwoningsih. (2020). *Fifth International Conference on Informatics and Computing (ICIC)*, (pp. 1-8). doi:10.1109/ICIC50835.2020.9288540

Robinson & Cook. (2018). "Stickiness": gauging students' attention to online learning activities. *Information and Learning Science, Vol 119*(7/8), 460-468. doi:https://doi.org/10.1108/

Simpson, T. (1997). The Initial Motivation of Students Enrolling in an Adult and Workplace Education Programme. *Asia-Pacific Journal of Teacher Education, 25*(1), 67-77. doi:10.1080/1359866970250106

Squier, M. (2006). *The Principles and Practice of Knowledge Management.* University of Pretoria.

Sun et al. (2020). Toward Understanding Students' Learning Performance in an OO Programming Course. *IEEE Accesss, 8*, 37505-37517. doi:10.1109/ACCESS.2020.2973470

Tamang et.al. (2021). Improving Business Intelligence through Machine Learning Algorithms. *2nd International Conference on Intelligent Engineering and Management (ICIEM)*, (pp. 63-68). doi:10.1109/ICIEM51511.2021.9445344

Thenmozhi, et al. (2019). MoneyBall - Data Mining on Cricket Dataset. *International Conference on Computational Intelligence in Data Science (ICCIDS).* doi:10.1109/ICCIDS.2019.8862065

Timsans, Z. (2020). *ARTSS datu vizualizācija*. Retrieved from https://telecides.herokuapp.com/

Vlies van der, R. (2020). Digital strategies in education across OECD countries: Exploring education policies on. *OECD Education Working Papers, 226*. doi:10.1787/33dd4c26-en

Whitby, G. (2013). *Educating Gen Wi-Fi: How We Can Make Schools Relevant for 21st Century Learners.* HarperCollins Publishers Australia.

Zhenchenko et al. (2022). Ukrainian E-Learning Platforms for Schools: Evaluation of Their Functionality. *The International Review of Research in Open and Distributed Learning, 23*(2), 136-150. doi:https://doi.org/10.19173/irrodl.v23i2.5769

Zhou, L. (2021). Effect Evaluation and Influencing Factors of E-Learning Training in Colleges. *International Journal of Emerging Technologies in Learning (iJET), 16*(22), 73-86. doi:https://doi.org/10.3991/ijet.v16i22.26877

Zuhairi et al. (2020). Implementing quality assurance system for open and distance learning in three Asian open universities: Philippines, Indonesia and Pakistan. *Asian Association of Open Journal 15*, 297-320.

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