Students' Online Learning Strategies: How E-Learning Data Can Help Identify them and Improve Learning Effectiveness

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Abstract

Educational data is a kind of event log that is generated when students engage in different types of online educational activities. The current study aimed to identify the learning strategy of online learning. As e-learning data, the digital footprints of students of two online courses of RUDN-university hosted on the educational platform Stepik were used (a total of 2206 people). The analysis included the following data: the number of course elements (text/video, test task), the number of those who registered for the course and completed the training, the number of those who did not complete a single element, the student drop-out points, the number of course elements viewed, the number of test elements completed, the number of those who successfully completed the final test. The statistical analysis made it possible to identify the four strategies for mastering the material: (1) students who enrolled in the course but dropped out after viewing the first element or never started learning (av.60 %); (2) the students who completed all the tasks and successfully completed the training (about 30%); (3) the students who viewed the first element and completed the final test (5-8%); and (4) the students who actively viewed several elements and then proceeded to the final test (2-3%).The results should draw attention to the importance of including elements or programmes in online learning that promote the development of self-regulation skills, which can help improve learning effectiveness.

Keywords: E-learning data, e-learning effectiveness, self-regulated learning, online learning strategies.

E-learning has become a powerful learning tool as a result of the integration of modern technologies and the education system, particularly through the use of Internet technologies.

The role of e-learning in education, especially during the pandemic, has led to a massive increase in the number of online courses and other e-learning systems. In this context, an important area of research is the search for determinants that would ensure the successful implementation and effective use of e-learning by students. An analysis of the research shows that there is still no agreed definition of e-learning. It is defined as an information system that includes a wide range of educational video, audio or text materials delivered via email, chat, online discussions, forums, quizzes and assignments (Lee et al., 2011), or as the use of modern technologies in the educational process (Sun et al., 2008), or as a way of delivering knowledge using computer technology and the Internet (Wang et al., 2010), or as a process of creating experience through involvement, curiosity, modelling and practice. The following types of e-learning are distinguished: online learning, blended learning, distance learning and mobile learning (via mobile phones) (Harriman, 2010). Online learning is delivered over the internet and can include graphics, animation, text, audio, video, email, teleconferencing, discussion boards, chat rooms and tests. It can be self-paced or on-demand, synchronous or asynchronous.

The quality of an e-learning system and the search for its success factors have received considerable attention from researchers (Ali & Ahmad, 2011; Fathema, Shannon, & Ross, 2015; Islam, 2013; Lee, 2010; Lee & Lee, 2008; Lee et al., 2009; Mohammadi, 2015; Mtebe & Raphael, 2018; Park, 2009; Wahab, 2008; Wang, 2003). However, the issue of criteria for e-learning success, methods for measuring it, and the potential use of learning analytics remains controversial.

Most often, models for analysing and predicting the effectiveness of e-learning use data on students' current academic performance (Valeeva & Rudneva, 2017) or survey data on various aspects of students' satisfaction with the e-learning process. The possibilities of analysing the data generated by students in the process of completing e-learning ('digital footprints') are still underutilised. In this article, a digital footprint is understood as a set of formations about users' behaviour and the structure and content of their activity in the process of completing an online course.

This article summarises the experience of using the analysis of students' digital footprints for learning analytics tasks, namely the determination of learning strategies in an online format, which will help to personalise the learning process and increase the effectiveness of e-learning by changing the design and mechanisms of online course management.

The authors address the following research questions:

- What are the criteria for the effectiveness of e-learning, and which are the most important?
- What methods are there for measuring the effectiveness of e-learning, and which are more objective?
- What strategies for completing an online course can be identified by analysing the digital footprints of students?

Indeed, this article focuses on finding answers to these questions.

Literature review and research objectives

Effectiveness of e-learning

According to the classic model of D. Kirkpatrick, the effectiveness of training is measured by the following criteria (1) the student's attitude towards the programme; (2) the level of completion of the programme materials; (3) the degree of use of the acquired knowledge in practical activities; and (4) the results of the employee's training for the organisation itself (Kirkpatrick & Kirkpatrick, 2006). The possibility of using the classical model to assess the effectiveness of online learning remains a controversial issue: a number of authors believe that it cannot be measured by the same criteria as traditional learning (Clark, 2018), other researchers argue that there are no significant differences between the learning outcomes of students in online or traditional learning (Fallah & Ubell, 2000; Freeman & Capper, 1999; Chou et al., 2019).

Authors use different theoretical models to determine the criteria for success of e-learning, depending on whether they understand e-learning as a fundamentally new, digitally based learning paradigm or as one of the forms of traditional, student-centred learning, differing only in the way knowledge is delivered.

In the first case, the characteristics of the technological system and related parameters are central to the success criteria of e-learning. The Information Systems Success Model (DeLone & McLean, 1992) includes the following six performance variables: (1) system quality, (2) information quality, (3) usage, (4) user satisfaction, (5) individual impact, and (6) organisational impact. The technology acceptance model (TAM) includes instructor characteristics, computer use self-efficacy, course design, perceived usefulness, perceived ease of use, and intention to use a technology system (Davis, 1989; Ibrahim et al., 2017).

User satisfaction models are numerous (e.g., Mahmoud et al., 2000; Al-Fraihat et al., 2018), they usually link the success of e-learning to the learner's satisfaction with the learning process.The factors influencing satisfaction are user-perceived benefits and convenience, user experience and engagement, organisational factors related to supporting and encouraging the use of technology. The e-learning quality model proposed by Al-Fraihat and colleagues (2018) includes the following variables: technical system quality, information quality, service quality, educational system quality, system quality support, training quality, instructor quality, perceived satisfaction, perceived usefulness, system use and its benefits.

In the second case, the basic criteria of effectiveness are associated with the characteristics of students and teachers, and one of the most important reasons for the decline in the quality of learning is considered to be the "dropout" of a student in the learning process. According to Pekker, the evaluation of the effectiveness of online courses can be carried out using quantitative criteria (the ratio of those who registered for the course and those who successfully completed it, the score of the results, the number of students who viewed at least one course material, etc.) and qualitative criteria (student motivation in the learning process, student goals and their achievement in the process of mastering the programme, the degree of involvement) (Pekker, 2018).

Regmi and Jones (2020) identified the following factors that influence the results of e-learning: student-centred, interaction and collaboration between students and teachers, taking into account the motivation and expectations of students, intuitiveness and user-friendliness of learning platforms and technologies.

K. Swan considers the category of 'interaction' to be central to the effectiveness of learning; for online learning this is the interaction of the student with the content, with the teacher and the interaction of students with each other (Swan et al., 2000). Three types of interaction create a "presence effect in the electronic educational environment: cognitive, social, pedagogical", the lack of which is considered a factor that reduces the results of online learning (Veledinskaja & Dorofeeva, 2015).

S. Eom and N. Ashill, complementing the proposed model, introduce into it, in addition to the course design, the figure of the teacher, the possibility of dialogue between students and dialogue between teachers and students, personal variables of student motivation and self-regulation (Eom & Ashill, 2018).

In the concept of self-regulated (offline/online) learning, the personal variables of students are considered as central factors of learning effectiveness (Zimmerman, 1990; Azevedo & Witherspoon, 2009; Barnard et al., 2009; Cho & Shen, 2013; Dawson et al., 2015; Delen et al., 2014; Onah & Sinclair, 2017; Siadaty, 2016; Winne & Hadwin, 2013). In this model, the success of e-learning is associated with the ability of students to control the process of their own learning and the achievement of educational goals (Nikolaki, Koutsouba, Lykesas, Venetsanou, & Savidou, 2017, Al-Adwan et al., 2022). Self-regulated learning is determined by a combination of external and internal factors: external factors include characteristics of the educational environment and features of educational interaction; internal factors include motivational, metacognitive, cognitive and emotional characteristics of the student (Cho et al., 2009). A study by Rajabalee and Santally (2021) found a direct relationship between motivation and levels of engagement, with learning outcomes being weakly related to these parameters. These authors identified lack of tutor support and technical difficulties as factors reducing the effectiveness of training. Al-Adwan and colleagues (2022) believe that the quality of digital educational content and the design of online courses are the most important predictors of the success of e-learning, and they consider self-regulated learning to be the main barrier to its effectiveness, since self-regulation skills in educational activities most often cause students to "drop out" of the e-learning process.

S. S. Noesgaard and R. Ørngreen (2015), based on an analysis of 93 publications on e-learning, identified 19 criteria for determining its effectiveness: learning outcomes, their application in practice, perception of learning, skills or competence, attitude, satisfaction, acquired skills, use of the product, sustainability of acquired knowledge/skills, completion of training, motivation and involvement, organisational results, application to work practice, self-efficacy, confidence, cost-effectiveness, connectedness, few errors, increased awareness, and success of (former) training participants.

As can be seen from the analysis, most researchers consider the cognitive, motivational and regulatory characteristics of users as important factors for the success of e-learning; these parameters are studied in depth in the model of self-regulated learning (Wong et al., 2018). Online learning is a variation of this, as it involves the development of students' time management skills, self-regulation, self-organisation, critical thinking, metacognition, memorisation and repetition, building interaction and the ability to ask for help.

Methods for identifying the effectiveness of online learning

The success of e-learning is most often assessed by learning outcomes: in the higher education system, they are measured by the knowledge testing procedure (Boghikian-Whitby & Mortagy, 2008), in the professional development system, the effectiveness is determined through knowledge transfer, i.e., the use of acquired skills in professional activities (Angeli, 2005). The quality of the “transfer” can be determined through students’ self-assessment (Maloney et al., 2011).

Research on the effectiveness of e-learning often presents effectiveness models based on literature analysis (Amin I. et al., 2022), whereas empirical studies are usually based on comparisons of students’ self-report interviews, sociodemographic indicators and performance (Hollister et al., 2022; Cruz-Jesus et al. (2020).

Saks and Leijen (2014) , after analyzing 30 empirical studies, concluded that most often the characteristics of self-regulation and success in e-learning are studied using self-assessment questionnaires, such as: Online Learning Readiness Scale (Hung et al., 2010), Online Self-Regulated Learning Inventory (Cho et al., 2009) and others. Roth, Ogrin, and Schmitz (2016) emphasize that learning outcomes in higher education are often studied and predicted using psychometric methods, including: Motivated Strategies for Learning Questionnaire (MSLQ), Learning and Study Strategies Inventory (LASSI), and Situational Judgment Tests (SJT); and interviews such as Self-Regulated Learning Interview Schedule (SRLIS), think-aloud protocols, and learning diaries.

At the same time, an increasing number of researchers propose using data analysis methods, machine learning and artificial intelligence in the development of educational policies and practices (Baek C., Doleck T., 2023; Cruz-Jesus et al., 2020; Yağcı M., 2022; Belonozhko et al., 2017).

According to Araka and colleagues (2020), learning analytics (LA) and educational data mining (EDM) are increasingly being used to analyze the process and outcomes of e-learning: it is a new and rapidly developing field that focuses on the use of student data obtained from different learning environments. Educational data are a kind of event logs that are formed when students are involved in various types of online educational activities. Unlike using self-report instruments to collect information about how students regulate their learning based on subjective self-perceptions, these methods rely on the "footprints" that students leave as they navigate an online course. EDM helps generate insights that can be used as indicators to take measures to reduce student dropout rates, profile students, model learning strategies, and design interventions (Arnold & Pistilli, 2012; Romero, López, Luna, & Ventura, 2013). Winne and Baker (2013) believe that educational data analytics can help study, model and predict students' behavior. Naif and colleagues (2019) argue that learning analytics helps not only predict students' behavior but also develop early intervention strategies that increase learning engagement, which is directly linked to academic achievements. A number of researchers (Alharbi et al., 2014; Cicchinelli et al., 2018; Davis, Chen, Jivet et al., 2016; Lee and Recker, 2017) have used educational data to study self-regulation strategies in online learning as well as digital tools for its formation and development, which can be used by both students and teachers.

It is proposed to use the following systems as a source of educational data: learning management systems (LMS), student information systems (SIS), intelligent teaching systems (ITS), massive open online courses (MOOC), and other web-based education systems (Casquero et al., 2016; Fidalgo-Blanco et al., 2015).

An analytical review by Abdulkareem Shafiq and colleagues (2021) found that machine learning, educational data analytics and deep learning techniques can be effectively used to study predictors of student retention and/or motivation.

According to Kashpur and colleagues (2021), studying a student's digital footprint makes it possible to improve the quality of educational analytics and prognosis due to the following advantages: the digital footprint contains a large amount of open user data about students' personal (cognitive, motivational, psychological) characteristics; these data are generated naturally by the respondents themselves but not in an artificial testing or survey situation. Online methods are unobtrusive because the measurements are taken without students' knowledge and therefore do not affect their involvement and performance (Schraw, 2010).

The theoretical analysis suggests that university managers will now and in the near future generate requests for the development of analytical tools and models to work with the digital footprints, which will improve the quality of decisions in the field of managing the educational process in general and the educational trajectories of students in particular (Agatova et al., 2022).

A literature review revealed a lack of studies dedicated to identifying and evaluating specific strategies for mastering online courses. Nevertheless, some researchers have identified a number of key principles that must be adhered to in order to successfully complete educational courses on online platforms.

1) Time management system. Nam et al. (2024) posit that it is essential to devise a study schedule that considers the periods of peak cognitive activity of an individual. This approach to the scheduling of online courses will enhance learning efficiency and foster greater involvement in the educational process.

2) Active Communication. Cunff et al. (2024) posit that active discourse with classmates and instructors regarding the immediate subject matter will assist in reducing cognitive load. This principle is of particular significance for students who experience challenges in utilising online platforms. Active communication enables them to ascertain the requisite skills for navigating these platforms with greater expediency (Ren et al., 2024).

3) Goal setting and motivation. The establishment of transparent objectives and the sustenance of motivation throughout the learning trajectory have a considerable influence on the efficacy of online courses. It is not uncommon for individuals to elect to pursue online courses on their own. Consequently, the majority of students may demonstrate a deficiency in extrinsic motivation, which can have a detrimental impact on the educational process. The presentation of clear goals and specific objectives that facilitate their attainment will enhance intrinsic motivation and, in turn, enhance productivity during the educational process (Levin, 2024).

We defined the purpose of the study because there was a lack of research aimed at identifying online learning strategies based on the analysis of educational data (students' digital footprints). Understanding these strategies will make it possible to adapt course design to improve the level of self-regulation in learning by increasing motivational and emotional involvement and cognitive presence, which are directly related to learning effectiveness.

Materials and methods

Context of the study

The study used data characterising the behaviour of students taking online courses on the Stepik educational platform. The analysis used educational data from RUDN-university students of two courses: Designing Digital Educational Products (1) and Modern Digital Technologies for the Service Sector (2) (2200 people in total). The course Designing digital educational products includes theoretical blocks, and each theoretical block is followed by a control block with several test tasks. These tasks are not compulsory: in order to receive a certificate of completion of the course, the student only needs to pass the final test. In the course Modern digital technologies for the service sector there are no intermediate control blocks; it contains only a final test.

Research design

The analysis included data that characterise the design of the course: the number of course elements (text/video, test task), the number of people who enrolled in the course, the number of people who completed the training, the number of people who did not complete any of the course elements, the student drop-out points, the number of course elements viewed by the students, the number of test elements completed, and the number of people who successfully completed the final test (Table 1).

According to the results presented by Moreno-Marcos and colleagues (2020), variables related to students' interaction with exercises continue to be the best predictors for determining online learning strategies.

Table 1. Data analysed

No.	Course	Total students	Completers	Dropouts	Course elements (text, video)	Test elements	No element completed	Dropout points
1.	*Designing digital educational products*	804	355 (44.2%)	449 (55.8%)	76	26	74 (16.5%) dropouts	First course element: 225 (50.1%) dropouts Second course element: 26 (5.8%) dropouts

2.	*Modern digital technologies for the service sector*	1396	523 (37.5%)	873 (62.5%)	28	15	117 (13.4%) dropouts	First course element: 566 (64.8%) dropouts Second course element: 47 (5.4%) dropouts

The collected data were processed and prepared for subsequent analysis using the following techniques: cleaning, integration, reduction (clustering) and quantitative comparison. During the cleaning procedure, the data of the students who who viewed one or two elements and dropped out, or who did not view any element of the course (1322 people) (55.8% (1) and 62.5% (2) of those who registered for the courses) were removed.

The reduction (clustering) of similar results was carried out using Ward's hierarchical clustering method. As the purpose of the study was to identify learning strategies, the cluster analysis included data on the number of theoretical elements of the course completed. Three clusters were identified in each online course (Tables 2,3).

Table 2. Results of the cluster analysis of the digital footprints in the course Designing Digital Educational Products

Ward's Method					
		Frequency	Percentage	Valid percent	Accumulated percent
Valid	1	73	20.6	20.6	20.6
	2	262	73.8	73.8	94.4
	3	20	5.6	5.6	100.0
	Total	355	100.0	100.0	

Table 3. Results of the cluster analysis of the digital footprints in the course Modern Digital Technologies for the Service Sector

Ward's Method					
		Frequency	Percentage	Valid percent	Accumulated percent
Valid	1	411	78.6	78.6	78.6
	2	67	12.8	12.8	91.4
	3	45	8.6	8.6	100.0
	Всего	523	100.0	100.0	

Extracted clusters were compared by the number of theoretical elements, practical tasks completed (only for course 1, Course 2 don`t have intermediate practical blocks), and the number of attempts to pass the final testing. The differences were verified using the Kraskal-Wallis criterion for independent samples with Bonferroni correction. For all the units of theoretical material, significant differences were obtained between the three groups but no significant differences in number of attempts to complete the final test were found. (Tables 4,5, figures 1,2).

Table 4. Differences in the number of completed units in the course Designing Digital Educational Products

Number of theoretical units completed					
Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
1-3	-52.129	22.926	-2.274	0.023	0.069
1-2	-187.042	12.022	-15.559	0.000	0.000

3-2	134.913	21.072	6.402	0.000	0.000
Number of test elements completed					
Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
1-3	-34.095	25.307	-1.347	0.178	0.534
1-2	-147.046	13.271	-11.081	0.000	0.000
3-2	112.951	23.261	4.856	0.000	0.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is 0.05.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

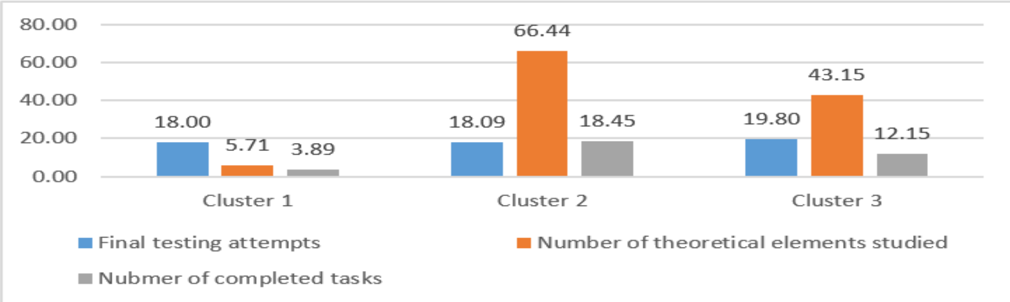

Figure 1. Differences among the groups in the number of completed units and final testing attempts in the course Designing digital educational products

Table 5. Differences in the number of theoretical units completed in the course Modern Digital Technologies for the Service Sector

Number of theoretical units completed					
Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
2-3	-55.981	23.080	-2.426	0.015	0.046
2-1	283.993	15.777	18.001	0.000	0.000
3-1	228.011	18.803	12.127	0.000	0.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is 0.05.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

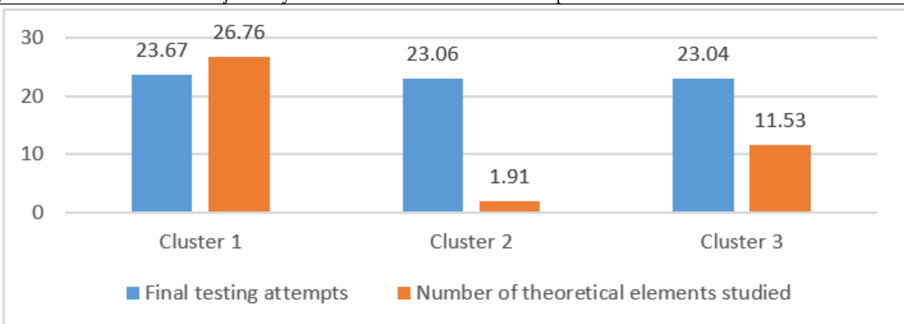

Figure 2. Differences in the number of theoretical units completed and final testing attempts in the course Modern digital technologies for the service sector

The results show a significant difference in the strategies of mastering the theoretical material of the online course by the representatives of the different clusters.

The students included in the largest cluster (cluster 2 of the course Designing Digital Educational Products and cluster 1 of the course Modern Digital Technologies for the Service Sector) mastered the theoretical material as completely as possible, they mostly completed all the theoretical elements of the course.

Students in the second largest cluster (cluster 1 of the course 1 and cluster 2 of the course 2) watched the first theoretical units of the course and then went straight to the final test.

The students of cluster 3 (the smallest) started to master the theoretical material on the same level as the representatives of cluster 1; they watched the first blocks, then selectively watched individual topics and moved on to the final test.

The process of mastering the practical material of the online course Designing Digital Educational Products by the students included in each cluster is similar to the process of mastering the theoretical material. The students of cluster 2 completed almost all the intermediate tests, although it was not a prerequisite for their completion; the students of cluster 1 completed the minimum number of test tasks (3.89 out of 20), the students of cluster 3 selectively completed some practical tasks (12.15 out of 20). It should be noted that statistically significant differences were found in the results of clusters 1, 2 and 3, while no differences were found between clusters 1 and 3, i.e. there are no significant differences in the number of tasks completed in these clusters.

Results and discussion

The analysis made it possible to identify three strategies (learning styles) that should be taken into account when designing, implementing and evaluating the effectiveness of online courses.

The first strategy, used by about 30% of all students taking online courses (70 to 80% of those who complete them), is characterised by a high level of involvement in learning. Students strive to fully master the theoretical and practical material and to pass intermediate and final tests. They can be characterised as students with well-developed self-regulation skills, demonstrating "personal initiative, persistence and adaptability" in the learning process (Zimmerman, 2002). The analysis of their digital footprints allows us to conclude that they have developed skills to plan and manage their time, efforts and focus on goals, skills that allow them to characterise their learning process as self-regulated learning. Self-regulation is a critical factor for effective online learning (Ejubovic and Puška 2019), including learning on online platforms, and research shows that it is directly related to the level of educational attainment (Greene et al., 2018).

The second strategy, chosen by 5 to 10% of all those who enrolled in the online course (12-20% of those who completed the training), is characterised by the dominance of the motivation to obtain a certificate of completion of the training (external motivation); at the first acquaintance with the course material they decide to proceed to the final test; they are focused on the goal, but for them the goal is pragmatic, i.e. they do not want knowledge and skills, but a document confirming that they have completed the training. It can be assumed that these students lack motivational skills which do not allow them to fully control their behaviour at all stages of learning. In addition, they initially have a low level of involvement in learning and an undeveloped ability to regulate effort, which is confirmed by the findings of Lee and colleagues (2020) that the task value indicator is closely related to the use of self-regulated learning strategies. Despite the fact that all students in Cluster 2 completed their studies, their results were questionable.

When organising work with such students, it is important to pay attention to the development of their internal motivation and awareness of the value of tasks. A study by Chang (2005) shows that the use of tasks aimed at self-observation and self-assessment of learning effectiveness in the learning process increases motivational involvement and the value of the learning material. The design of the course is important, including the content of the final tasks, which in our opinion should not test the knowledge of specific information, but the ability to use the studied material to solve practical problems, which is an essential criterion for the effectiveness of training (Davis, 1989; Ibrahim et al., 2017). The e-learning environment created should encourage students to apply their knowledge (Vovides et al., 2007). In addition, the early identification of such students will help to organise effective support for their learning process (Bote-Lorenzo & Gómez-Sánchez, 2017).

The third strategy, chosen by 2-3% of enrolled students (5-9% of those who completed the training), is characterised by a gradual decrease in participation in the training, which leads to the fact that, at a certain stage of mastering the theoretical and practical material, students stop familiarising themselves with it and move on to the final exam. This strategy suggests that the main problem of this group is most likely a lack of self-regulation (mainly effort regulation and time management). The lack of online learning management skills has been highlighted by many researchers (Anthonysamy et al., 2020; Theobald, 2021). When educating such students, it is important to pay attention to the development of their metacognitive and cognitive elements of self-regulation, encouraging them to plan, select relevant content, monitor and evaluate their learning. As research has shown, this can lead to an increase in the motivational and behavioural components of self-regulated learning, even if it is not specifically designed (Vovides et al., 2007).

And, of course, the fourth category of online learners presents the greatest difficulties for educators and researchers: these students enrolled in the course but dropped out after viewing the first element (50-60% of the total number of students). This is a so-called "grey area" for science, as access to this audience is limited to self-assessment interviews and questionnaires for specialists, which does not allow them to fully assess the reasons for their dropout and, accordingly, to develop measures to support them. According to researchers, the basis for dropout may be insufficient development of digital skills (Anthonysamy et al., 2020) and lack of self-regulation skills (self-management, self-control, motivation and goal-focus) (Broadbent & Poon, 2015; Ergen & Kanadli, 2017), as well as course design features (Salomon, 2012).

Limitations and future research directions

The limitation of this study is that only traditional digital footprints were used as pedagogical data, in particular the viewing of video material, the completion of exercises and the final test. From our point of view, the use of additional elements in the analysis, such as the sequence of tasks, the temporal characteristics of the behaviour, the importance of which is written, for example, by Moreno-Marcos et al. (2020), will allow us to clarify and deepen our understanding of online learning strategies.

The disadvantage of the data used in relation to the design of the courses is the lack of scores for the final test: this indicator would allow us to correlate the effectiveness of the learning strategy chosen by the students.

It is important to develop predictive models of students' behavioural strategies, based on machine learning and artificial intelligence, which can help to predict at an early stage the possibility of dropping out and to implement personalised support strategies for students who have lost high engagement and have deficits in self-regulation skills.

Another direction of research could be to compare the learning strategies that a student uses during online and offline learning; such information will help to understand whether the choice of a particular strategy is a situational variable depending on external organisational factors or a personal characteristic related to self-regulation skills and other personal constructs.

Finally, an important direction for further work is the development of personalised web programs to support online students in maintaining the necessary level of engagement, developing and maintaining skills of self-organisation, self-motivation and self-regulation in the learning process.

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