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Measuring efficiency and effectiveness of knowledge transfer in e-learning

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ABSTRACT

With e-learning rapidly gaining popularity, evaluating its effectiveness and efficiency has become a challenge in public education, the public sector, and the corporate sector. Measuring knowledge transfer is crucial in any learning process, but e-learning lacks validated methods for this. Here we examine ways to evaluate that particularly in case of e-learning, conducting a literature review to assess available measurement solutions, developing an evaluation method for knowledge transfer, and validating the method. Using logged data from e-courses, it is possible to assess the knowledge transfer in e-learning. We describe a novel method for classifying effectiveness and efficiency with measured values and measurement instruments. The new measurement method was aligned with a data set of an existing learning management system, and the effectiveness and efficiency of knowledge transfer was analysed using quantitative means, including descriptive statistics, regression modelling, and cluster analysis based on a specific e-learning course. This newly elaborated and validated knowledge transfer measurement technique could be a useful tool for anyone wanting to evaluate e-learning courses and can also serve as a baseline for academics to further develop or implement it on larger empirical datasets.

1. Introduction

This paper focuses on analysing and elaborating knowledge transfer (KT) in e-learning, a specific research topic lacking a developed methodology. Traditional education methodologies cannot be aligned with e-learning, making it crucial to create a common KT measurement method for e-learning.

The use of e-learning has been rising rapidly in recent decades, exponentially boosted by factors like the recent pandemic [1]. E-learning is being used not only in higher education [2], but also in public administration [3] and the corporate sector [4]. The continuous transition from traditional face-to-face learning makes it even more pressing to examine the efficiency of KT in e-learning.

The research question in this paper is about what method can be used to measure the usefulness of the e-learning format in terms of KT. The objective was to develop and validate a methodology capable of measuring the usefulness of e-learning education, as shown in Fig. 1. However, we should highlight that we did not develop a comparative toolset with a conventional face-to-face class, as many other influencing factors make it impossible to compare the two courses, all else being equal.

Our objectives were to describe the available measurement solutions by conducting a literature review, elaborate methodologies for evaluating the usefulness and KT of e-learning and test the novel measurement method with a data series obtained from a concrete university course. We also conducted a quantitative analysis of the usefulness of KT in a specific e-learning course.

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At the initial stage of the research, we thought that we could find and adapt appropriate evaluation methods from traditional learning as benchmarks, which is why we conducted a detailed literature review. In the second part of the paper, we elaborate on a unique mathematical and statistical tool to provide an easily applicable evaluation methodology that does not require additional data. It can be simply applied to the logged data of e-learning courses. To evaluate the usefulness of a given online course, a unique measurement strategy is necessary to be taken. This study builds on some of the conclusions from the author's doctoral thesis research [5], adding new aspects and testing and validating the method on a data series obtained from a concrete university course.

In the next chapter of the paper, we discuss the available measurement solutions for KT and their origins. In the subsequent chapter, we introduce the new methodology for evaluating the usefulness of e-learning. Following this, we test this new methodology on a specific university e-learning course. The last chapter concludes the new measurement method and articulates further development possibilities.

2. Literature review

The literature review will provide an overview of available KT measurement frameworks and their applicability to e-learning courses. We will begin by examining the definitions of effectiveness and efficiency, as they are often misunderstood and used incorrectly. Next, we will explore possible systems for measuring KT and review existing educational frameworks, focusing on successfully implementing them in e-learning courses.

Measuring KT is one of the greatest challenges in education, both in e-learning and face-to-face courses. While exam situations are simple to generate, assessing the level of acquired knowledge and measuring the quality of education based on user satisfaction (student, instructor, system administrator, etc.) is subjective [6]. Knowledge and student satisfaction can also be evaluated in e-learning; these assessment methodologies do not provide sufficient answers to concerns about the two dimensions of efficiency and effectiveness (which, for simplicity, we will refer to as "usefulness") of KT. Our questions focus on the quality of KT as a process rather than the result (the existence of knowledge).

The lack of an accepted method for evaluating the usefulness of KT is the best evidence of the topic's relevance and importance. Although some attempts, such as Favretto, Caramia, and Guardini's examination [7] on compating traditional education to e-learning or the study done by Selim [8] on the adaptability of e-learning to universities, are already in place, measurements continue to focus on traditional face-to-face education. The toolset available for traditional education is heavily criticised [9–11].

The demand for establishing metrics is rising as e-learning may gain popularity among students with technology continuing to advance, and early adopters may even secure economic benefits [12]. However, this requires a consolidated evaluation methodology

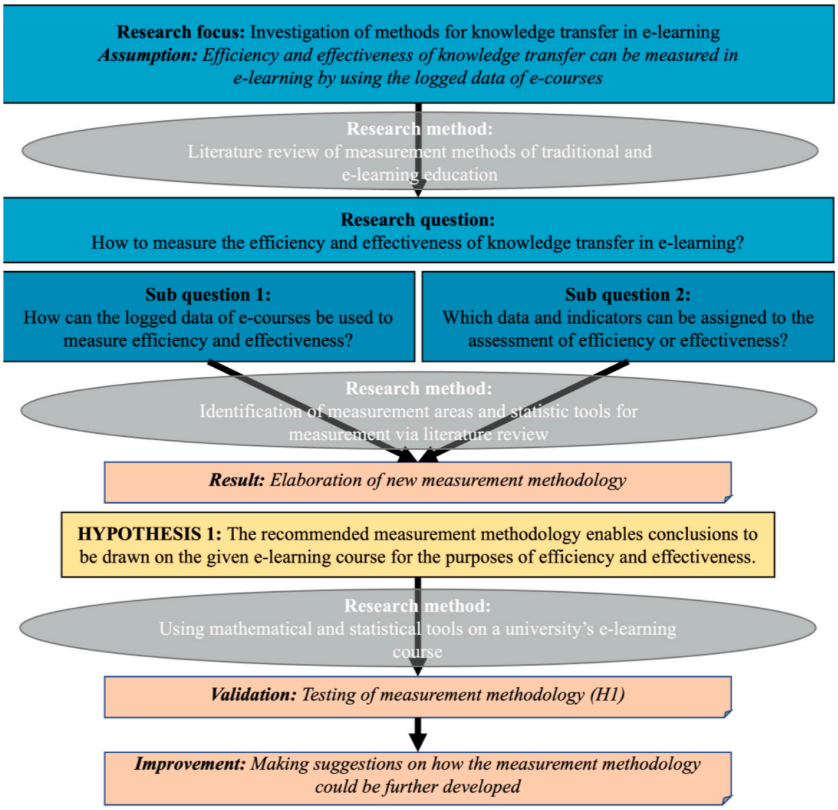

Fig. 1. Research question (own image).

with a proper framework for decision-makers to have the courage to enter this new area. According to a recent systematic literature review, e-learning as a research topic is rapidly growing, and "evaluation" and "evaluation models" are two of the most important keywords associated with this field [13].

In step zero of elaborating the measurement methodology, it is crucial to specify the type of users whom will be measured, as the notions of effectiveness and efficiency are often mingled. According to Nelson [14] and Vilaseca & Castillo [15], it is essential to distinguish between the two concepts in education. Efficiency refers to the ability of something to minimise expenditure and effort. On the other hand, effectiveness refers to the ability of something to produce a result.

In education, **effectiveness** refers to whether a participant acquires the required knowledge, while **efficiency** refers to whether a participant acquires the required knowledge while spending no unnecessary resources. In other words, participants may learn more quickly, learn a topic quicker, or retain knowledge for a longer period.

When comparing face-to-face education and e-learning, the question of e-learning's efficiency arises: is e-learning a more useful form of education than face-to-face education? Can it be implemented with fewer resources? Also, the metrics used to evaluate e-learning courses must be able to determine this without needing a control group. It is impossible to set up a control group that is identical to the e-learning course in order to make a realistic comparison. Evaluating the same students starting from a baseline point where they lack the relevant knowledge is practically impossible in the absence of time travel or erasing memories.

2.1. *Available systems for measuring efficiency*

Successfulness of e-learning applications can be investigated from various vantage points and theoretical perspectives. Based on Bhuasiri et al. [16], Table 1 provides a classification of potentially relevant measurement systems.

The evaluation framework mentioned above evaluates the success of e-learning solutions in isolation rather than in comparison to traditional classroom education. This strategy aligns with our objective of making courses assessable and measurable in and of themselves without comparing them to other courses. And yet, none of the evaluation methods focus on the usefulness of KT. Instead, they are significantly easier, focusing primarily on the IT perspective or using a biased measurement scale. Holsapple and Lee-Post's research [25] also deserves to be mentioned as they approach the topic from an ICT perspective, applying a logic similar to the above methods.

2.2. *The existing evaluation framework of education - and its criticism*

This section presents the assessment methods most frequently used in education, along with critiques of the methods presented in the literature, as well as our own critiques.

2.2.1. *Student evaluation of teaching effectiveness (SETE)*

The student evaluation of teaching effectiveness is one of the most common methods for gauging the efficacy of a teacher. However, a study by Galbraith, Merrill and Kline [26] presents an example that contradicts this method, showing that student results do not have a linear relationship with teacher assessments, as substantiated by different mathematical methods. Students who achieve the highest levels of success rate teachers as having an average level of quality, while students with lower levels of success favour extremes, giving either remarkably good or remarkably poor ratings. In assessing the SETE methodology, Galbraith et al. discuss the emergence of new teaching methods, including e-learning and blended courses, which call for a review of the SETE methodology.

Emery, Kramer, and Tian [27] criticise the SETE methodology based on the following aspects.

Table 1
Potential e-learning implementation evaluation tools based on the work of Bhuasiri et al. [16] (own table).

Evaluation tools	Academic foundation and features
Critical success factors (CSF)	The implementation of e-learning is evaluated based on an established, weighted set of criteria. E-learning implementation is classified by comparing the case to the predetermined minimum criteria. The set of criteria may be structured and grouped according to various categories, including technology, teacher, and student aspects [17] and higher-level criteria, like organisational support [8].
Social Cognitive Theory (SCT)	Describes a measurement system with an emphasis on people as opposed to technology. The analysis and measurement focus on so-called "self-efficacy" and output expectations. These can describe the participants' intention to adopt new tech [18].
Motivation theory (MT)	Internal (curiosity, self-satisfaction) and external (e.g., money) motivations are distinguished by this approach, which focuses on the human factor (goal-oriented, aimed at the result/achievement) [19].
Information system success model (ISSM)	This model can be used to evaluate any IT tool, so it is not ideal for evaluating KT, as its primary criteria are customer satisfaction, intentions of using the given technology, information and service, net return and system quality [20]. Aparicio et al. [21] extend this model with a cultural dimension in another paper.
Technology Acceptance Model (TAM)	This model focuses primarily on IT and technology, making it unfit for measuring the usefulness of KT. The first version of TAM separates two parameters, according to Hsu & Lin [22]: the tech's conceived usefulness and the conceived efficacy of use. The original model has been refined by Venkatesh & Davis [23] and Venkatesh & Bala [24], and thus, version 2 and version 3 of the model were created.

- *Popularity and personality contests:* Teacher assessments frequently reflect the teacher's popularity rather than the efficiency of the actual education. Simple factors, such as a teacher offering snacks (e.g., candy) to their students also influence students' subjective ratings.
- *Student achievement:* Although student achievement may be the most transparent and immediate feedback on instructor performance, studies and samples have demonstrated the opposite: student achievements are only minimally reflected in teacher evaluations.
- *Situational factors and validity:* A connection can be observed between courses and their evaluations methods. The researchers collate humanities and STEM-type curriculums, and a general difference is shown between mandatory and optional subjects.
- *User error:* Serious problems can also be caused by incorrectly interpreting SETE results or evaluating them with the incorrect statistical method. Due to the generally small sample sizes (classes below 30 participants), the likelihood of pure statistical error also increases significantly.
- *Rater qualification error and defamation:* The final criterion is critical of the students. Students are generally considered incapable of critical thinking. The evaluators are not screened before being authorised to rate teachers, so extreme instances of intended defamation are possible.

2.2.2. Student satisfaction

Other researchers have examined participant satisfaction and found that student satisfaction strongly correlates with the knowledge acquired [28]. After a decade of clarifying the model, they exposed additional factors that explain student complacency, e.g. the course's planned nature and also the instructors' quality [29]. A recent study [30] also examines student satisfaction with e-learning systems during the COVID pandemic, but none of the mentioned papers focus on KT effectiveness.

Larger empirical research also demonstrates the importance of student satisfaction as a predominant factor. The significance of individual learning characteristics is highlighted, which leads to the conclusion that screening out these factors will make the learning experience similar for everyone [31]. These results are in harmony with another study [32], to be discussed later, which suggests that screening out learners' social and economic backgrounds eliminates the deviation that could be observed in learning achievements.

2.2.3. Student performance

Therefore, the recent measurement framework of teaching efficiency cannot be considered suitable, as Creemers & Kyriakides [32] also suggests. Similar outcomes were reported in two separate papers: Coleman et al. [33], followed eight years later by Jencks et al. [34], who screened out the underlying circumstances of the participants, such as individual abilities, family conditions, and socio-economic characteristics, resulting in a convergence of education factors close to zero. Therefore, various teachers and pedagogical techniques proved efficient for students with similar backgrounds to nearly the same extent. Heyneman [35] also comes to the conclusion that the socio-economic situation of learners quasi-determines their achievements.

Another study [36] highlights that students' family background greatly influences student performance in advanced economies. Hanushek & Luque [37] look at the relationship between student performance and the extent of consuming "resources" but conclude that these issues are independent of the quantity of accessible resources based on a comparison of developed and emerging countries.

The Tennessee Value-Added Assessment System (TVAAS) may also be worth considering, as it is intended to measure the effectiveness of education while excluding socioeconomic status. However, others, including Ballou, Sanders, and Wright [38], have attempted to modify this evaluation system. A recent paper claims that such measurements may not be helpful and calls for more meaningful measures [39].

2.2.4. Critique

The literature widely critiques the current measurement methodologies that serve as metrics for traditional education. Various problems with validity, reliability, and biases have been identified, among other concerns. As a result, there is a need for more comprehensive and effective measurement methodologies for evaluating the usefulness of e-learning courses. Table 2 summarises the relevant research in the literature, including the critique, proposals, and criteria sets set out in those research studies.

Table 2
Major criteria used in the literature criticising current education measurement systems (own table).

Criticism of student evaluation of teaching effectiveness	Emery et al., 2003 [27] Berk, 2005 [40] Galbraith et al., 2012 [26]
Research on the effect of student satisfaction	Creemers & Kyriakides, 2006 [32] Eom et al., 2006 [28] Eom & Ashill, 2016 [29] Li et al., 2016 [31]
Studies attributing a substantial impact to the (socioeconomic) background of students	Coleman et al., 1966 [33] Jencks et al., 1972 [34] Hanushek & Luque, 2003 [37] Ballou et al., 2004 [38] Woessmann, 2004 [36] Heyneman, 2005 [35] Creemers & Kyriakides, 2006 [32]

It has been determined that **the main frameworks for metrics of face-to-face education and KT which evaluate the teacher, are unsuitable for measuring the effectiveness of KT in e-learning**, despite the proposals adopted to develop this system. While academic results or competencies attained by the students should unquestionably be the deciding criterion for evaluation, our previous research [41] has shown that this does not always result in representative answers for the following reasons: exams and grades may not reflect actual knowledge; evaluating knowledge and competence during or after the KT process requires too many resources and is too expensive; the abilities and input conditions of individual students prior to education are unknown or known only at a high level; the particular features of the education process, such as the identity of the teacher, teaching intensity, and methods used, cannot necessarily be identified and assigned to the person measured; and performance may be greatly dependent on the current personal conditions of the student, such as their mental state and mood, which are difficult to measure objectively.

The somewhat contradictory relationship between how "good" a teacher is and learning achievement, as described in Galbraith, Merrill, and Kline's [26] article, further justifies the importance of measuring KT, even if it must be measured through the teacher's performance. However, it is also essential to note that the role of the educator can also be decisive for e-learning [42]. In light of the previous factors, it is necessary to establish a new system of metrics with an emphasis on KT that enables the evaluation of e-learning curricula without comparing it to other instances.

The proposed method for measuring e-learning efficiency is unique for several reasons. First, there is no established methodology in the literature for this purpose. Second, the proposed measurement method does not require a control group and can assess the selected course. Third, instead of relying on subjective analysis, such as text analysis of questionnaires, the methodology is objective and calculates indicators logged by a computer using mathematical methods. These factors make the proposed method a promising and innovative approach to measuring the efficiency of e-learning courses.

3. Material and methods

After reviewing the measurement solutions in the relevant literature, we aim to establish and test a measurement methodology for e-learning, specifically evaluating its usefulness and KT. For testing, we used real data from an e-learning course provided by a university. Given the IT background of e-learning, we leveraged mathematical methods to develop a methodology that capitalises on the opportunities presented by automatic and digitised data recording. The quantitative analysis in Chapter 4 of this paper, which focuses on the usefulness of KT, employs the following statistical methods: (i) deviation, kurtosis, and skewness indicators; and (ii) correlation, regression, and clustering based on student activity and scores.

Regarding the content of the evaluation, we propose two perspectives for calculating the usefulness of e-learning: a KT-focused measurement method and a measurement method based on student activity and scores.

The KT-focused measurement method and the measurement method based on student activity and scores both provide different perspectives for evaluating the usefulness of e-learning. The KT-focused measurement method analyses e-learning users' behaviour using deviation, kurtosis, and skewness indicators, assuming that learning via e-learning follows a normal (Gaussian) distribution. On the other hand, the measurement method based on student activity and scores compares the input knowledge assessment results with the final results of the participants using correlation, regression, and clustering techniques. Analysing the relationships between the three parameters collectively provides insight into the quality of the e-learning course. Both methods provide a comprehensive evaluation of the e-learning course and help in understanding the effectiveness of KT in e-learning.

3.1. KT-focused measurement method

In general, measuring the efficiency of KT in e-learning can be carried out with normality testing and the analysis of deviation indicators for the indicators listed below. We have classified the indicators as either efficient or effective. This provides a reasonably straightforward and easy-to-implement evaluation methodology, which also serves as feedback in the planning and development of e-learning courses in the future. However, it is important to note that the following indicators are part of a wider list of indicators that may be extracted differently based on the course and e-learning framework system. This means that data may not be available for all indicators during analysis, as will be seen in the course analysis later in this paper.

- *Indicators related to comprehensibility (this is treated as a factor independent of the subject's composition):* Distribution and deviation of student results (effectiveness); recurrence of returning to e-learning materials (efficiency); recurrence of using supplementary contents (efficiency); and quantity of clarifications, interpretations, and clarification questions asked by participants (efficiency).
- *Indicators of student satisfaction (a crucial marker of focus preservation):* The proportion of quitting educational units (i.e., the percentage of modules where the first exists) was calculated from the given module (efficiency); learning sections (i.e., the total number of instances of viewing the complete material) (efficiency); and average return period by student (how much later the student re-entered the module after each exit) (efficiency).
- *Learning ability indicators (both content and volume):* The quantity of participants completing the course properly, by the ratio of similar indicators of all the courses (as an exception, this indicator requires participation in further courses) (effectiveness); and the total amount of time being active in the LMS (efficiency).
- *Reliability testing markers:* Percentage distribution of the ratio of the right answers given to the questions (effectiveness); average time spent by participants solving a particular question; (effectiveness); representativity of the exam questions compared to the total knowledge domain (none).

The efficiency of an e-learning course is determined by examining the normality testing and the analysis of deviation indicators for the indicators listed below. These indicators are classified as either efficient or effective. This evaluation methodology is easy to implement and provides feedback for planning and developing future e-learning courses. However, it should be noted that the indicators presented are only part of a wider list of indicators that may be extracted to a different extent by course and by e-learning framework system, meaning that data may not be available for all of them during analysis. The e-learning course with a general average efficiency is always represented by a normal (Gaussian) distribution. It is important to note that investigating an indicator by itself might be misleading; indicators should be looked at in their entirety to conclude. For instance, taking the frequency of returning to course elements, a distribution skewed to the left (peaked on the right) may indicate that students return to the course more frequently compared to the average e-learning course, which means that knowledge is acquired only after several attempts, indicating a low efficiency of KT in e-learning. On the other hand, an indicator or learning fragmentation skewed to the right (peaked on the left) may indicate that students complete an e-learning material by opening it fewer times than the ordinary e-learning course, indicating a well-designed and easy-to-understand e-learning course or appropriate prior knowledge of the topic.

3.2. Measurement method based on student activity and scores

This section presents an alternative measurement method for evaluating the effectiveness of e-learning, which focuses on the "end status" of the student, i.e., their test results using traditional knowledge assessment techniques. However, it is important to note that relying solely on the final exam is insufficient for measuring the KT's usefulness. To address this, the method requires additional assessment variables to infer causal relationships beyond the final exam outcome. While this method is simpler than the previously proposed indicators, it still requires preparation to ensure that the final exam accurately reflects the knowledge acquired through the e-learning course.

In this method, the success of KT is measured by considering three measurable student outcomes.

1. *Knowledge assessment (input) test:* Before or at the beginning of the course, students' knowledge is to be evaluated by a quiz that is the same level and difficulty as the final examination.
2. *Activity during the course:* Student participation in the e-learning course can be measured using a weighted aggregation of the following metrics: a) total or average time spent acquiring e-learning materials, b) the number of completed e-learning material units, c) the number of questions asked in the forum, d) test results achieved, and e) the number of attempts with practice exercises. This paper proposes that the metric be defined based on an analysis of an e-learning course, with its applicability determined by the course's structure.
3. *The final test* is the same as the final examination and should have the same difficulty as the assessment (inpit) quiz taken at the beginning of the course to ensure comparability.

Therefore, the relationship between the abovementioned variables evaluates the effectiveness of KT rather than its efficiency. Conclusions regarding efficiency could only be drawn boldly or by gathering further information. Nevertheless, the approach's easy applicability may assist in determining the quality and usefulness of numerous e-learning courses selected and analysed.

3.2.1. Measurement method based on linear regression

One of the methods to determine effectiveness involves using linear regression tools. To do this, a regression model is constructed using the three indicators mentioned above (knowledge assessment test, activity during the course, and final exam), and its parameters are analysed. Before calculating the regression, the correlation between the three indicators is examined to determine how closely they are related.

At the start of the learning process, the student has an initial knowledge level that is assumed to be expandable by increasing their activity during the course. Afterwards the student finishes the course with a closing knowledge level. Following this logic, the success of KT is determined by the final test score, which is selected as the dependent variable. The explanatory variables (independent variables) will be the student's initial knowledge and activity during the course, which will determine the student's knowledge at the end of the course with some degree of certainty.

The assumption is that the sum of the course-acquired and initial knowledge will yield the final knowledge level. The linear regression method was chosen based on this additive approach.

3.2.2. Measurement method based on cluster analysis

By grouping student results based on similarity, the other method attempts to answer the question of to what extent the e-learning course contributed to effective teaching and, consequently, to the acquisition of necessary knowledge. The same three variables will be used to construct the regression model but will be treated equally and without distinction. That is, there will be no explanatory or result variables or any other classifications.

Creating student groups also justifies using cluster analysis to reveal the size and "quality" of groups that complete the final test with a higher score following a weak initial test and high course activity. The greater the number of students in a cluster with these parameters, the more effective the KT of this e-learning course is. Conversely, the existence of a cluster where there is no difference between the initial and final tests of the students and their activity during the course will also demonstrate the effectiveness of the e-learning course. In contrast, in an e-learning course where a large cluster of students can be created, the differences between the initial and final tests are insignificant. Course participation is high and not considered effective.

4. Discussion (Evaluation and testing of the technique for measuring KT)

The measurement system created aims to provide a method for measuring the effectiveness of KT that enables conclusions regarding the quality of e-learning. To confirm this, a subject taught at a Hungarian university was adapted into e-learning format.

All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional review board of Corvinus University of Budapest. According to the Provisions of the Rector No. 2/2020. (V. 26.) on setting up the CUB Ad Hoc Research Ethics Committee[1] prior to launching any research project, a self-review shall be undertaken for any research project involving human participants. By conducting an ethical risk analysis, the leader of the research project shall assess whether the research is acceptable from the viewpoint of research ethics. On the basis of the Review Questionnaire, a specific permission is not required for the research if none of the questions in Part 2 of the Review Questionnaire has been answered in the affirmative, which condition was fulfilled in our case. All the data used in the research was recorded by the university's LMS by default with the standard consent of all the students attending the university regardless of the research. The data used in the research was collected anonymously, no personal details of the students were used during our calculations at any point, thus the research cannot link any of the results with the participants' identities.

The evaluation of the above-mentioned method was broken down into three phases. First, the **adaptability of the data** was assessed. Next, the **relevancy of findings that could be concluded from the evaluation methods** was evaluated. Third, **observations, criticism, and recommendations for further development** were proposed. After preparing and cleaning the data, it was successfully adapted to the measurement methods based on KT and to those based on results. Therefore, we managed to conclude that the e-learning course could be interpreted and used.

4.1. Characteristics of the revised course

Third-year "Business and Management" majors had to take the E-business course in 2021/2022. The course syllabus covered various topics, including digital culture, "the smartphone effect", data, business models, b2c logistics, b2b e-business, e-payments, the price of information, binding and feedback, online marketing, e-sport, startup businesses, e-commerce, e-health, and e-learning. The course lasted 12 academic weeks, and the total expected learning time was 60 h. With a sample size of 200 enrolled students, the results are statistically relevant and representative, which may help to identify any weak points or elements of the measurement methods that require improvement.

As the teachers of this course, we had the opportunity to properly prepare for the subject regarding methodology and digital technology. As a result of collaboration with colleagues teaching the subject, we incorporated e-learning teaching with its required contents into the course. We then extracted data from the University's Moodle system about the course's students' learning process and aligned the data with the measurement methods described and presented previously.

4.1.1. Structure of the course

The primary aspect when reconsidering the methodology for the course was the inclusion of e-learning teaching components in the course contents and structure while considering the scope of data to be measured. We aimed to record all of the students' actions completed in the e-learning course. The course was extended using the following components (Fig. 2):

1. **Initial test:** Students complete a test before the first lesson, equivalent in complexity to the final test. The test is not included in the subject evaluation to prevent preparation, but students receive a score for completing the test, which encourages participation. The purpose is to compare the results with the final exam scores, determining the extra knowledge gained during the course using the calculation method based on results.
2. **Lecture slides:** Slides of the weekly face-to-face lectures are produced in a version that can be embedded in Moodle, allowing for tracing when and how frequently students view these static (non-interactive) sources and which parts they look at.
3. **Weekly e-learning materials:** Additional professional content (~30 min per 2 weeks) not presented in the lectures are uploaded as e-learning materials.
4. **Short weekly tests:** Separate tests are created for the knowledge components presented in lectures or available in the e-learning system.
5. **Supplementary, non-mandatory components:** A glossary, a collection of links and references, and interesting (topical) articles are uploaded to the LMS.
6. **Forum:** A platform for asking questions is provided, where even students can answer questions other students ask.
7. **Final test:** Students complete an end-semester test with the same difficulty level as the initial and practice tests.

4.2. The structure of the empirical study

Moodle has a fundamental characteristic of recording and storing participant activities, which is available to teachers. Once the course is set up correctly, data is recorded automatically without requiring manual intervention during the semester. However, the

[1] https://www.uni-corvinus.hu/fooldal/egyetemunkrol/szenatus-egyetemi-testuletek/kutatasetikai-bizottsag/letoltheto-dokumentumok/.

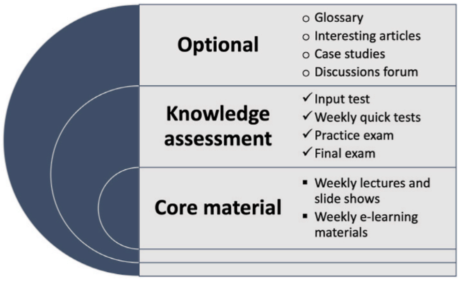

Fig. 2. Modified course components for evaluation (own image).

functions and data were tested in a pilot "mini-course" before the start of the course to ensure suitability for analysis.

4.2.1. Recording of the data

While everything is recorded mechanically, unprocessed data available from Moodle is unsuitable for the required measurements. Therefore, the system allows for download of two distinct data arrays as a final result.

1. **The gradebook and scores of online quizzes (and other graded exercises)** are recorded during the semester and can be downloaded as a spreadsheet. The spreadsheet contains participants in rows and the Moodle activities in which they receive scores in the columns. The scores earned by students can be found in the corresponding section of the given row and column.
2. **The report contains student activity during the course** in.xlsx. It is a time-series data array with ~95,000 lines in our case, containing all activities of all students during the course, including the number of course enterings, studying training materials, quiz completion, supplementary teaching components (glossary, etc.), and downloading lecture slides. Each record includes a name (identifying the student), a category (e.g., viewing of training material, entering the course), an event description containing specific identifiers (also containing the location of the training material unit) with a time stamp.

The data table holding test results did not require any additional sorting. However, the reports containing the activity of students during the course required manual corrections to enable normality testing, which cannot be detailed due to constraints regarding the scope of this study. All data preparation was feasible using Excel functions and simpler Visual Basic for Applications (VBA) codes.

In the following list, we also defined a unique indicator (*activity during the course - sc_act*) composed of the weighted average of the standard normalised variables. We aimed to give greater weights to the components that, in our opinion, offer a good representation of the activities and behaviours that contribute most to increasing knowledge during the course, based on our subjective assessment.

- Number of days spent actively in the course (25%) - *days_act*
- Number of views of the training material components of the course (10%) - *view_mod*
- Frequency of returning to the course, i.e., total number of course openings (5%) - *ent_cou*
- The average period of return of the students, i.e., the average amount of days between two days actively spent in the course, calculated with the reciprocal (20%) - *passive_days*
- Results of interim tests ($5 \times 8\% = 40\%$) – *quiz_scores*

4.3. KT-focused measurement method

In the first step of the analysis, the variables described above were subjected to a normality test, summarised in Table 3. Both tests show the same results. The analysis indicates that none of the investigated indicators have a normal distribution.

To dig deeper in the assessment of the variables, it is important to examine the histograms presented by them and investigate the deviation, asymmetry, and peak indicators as well. To increase transparency, we have separated our eight indicators into two groups.

Table 3
Normality tests on the variables (own table).

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
sc_ass	0.137	219	0.000	0.909	219	0.000
sc_cou	0.166	219	0.000	0.792	219	0.000
time_pas	0.085	219	0.001	0.967	219	0.000
ent_cou	0.103	219	0.000	0.894	219	0.000
view_mod	0.075	219	0.005	0.918	219	0.000
days_act	0.083	219	0.001	0.970	219	0.000
sc_act	0.046	219	.200*	0.993	219	0.380

First, the scoring indicators (quizzes) will be analysed (*sc_ass*, *sc_act*, *sc_cou*, *question_score*). Then, we will move to the indicators describing activity (based mostly on behaviour) (*ent_cou, view_mod, days_act, time_pas*).

Beyond the easily interpretable indicators like mean and deviation, skewness and kurtosis are also worth examining. The variables *sc_act* and *sc_cou* exhibit a more peaked distribution. On the other hand, the initial test score has a positive skewness, indicating a distribution that stretches to the right and peaks to the left, resulting in flatter distribution. Table 4 presents the details of the descriptive statistics and deviation indicators of the scoring indicators.

The histograms corresponding to the skewness indicators confirm the results of the indicators (Fig. 3). The significant difference between *sc_ass* and *sc_cou* can be explained by the fact that, although the participants had no prior education on the subject matter at the start of the course, the achieved results are clustered around higher grades, presumably due to the success of the course (KT). However, the causal relationship will not be examined until subsequent analyses (based on regression and cluster analysis).

The result curves of the examination test peaking to the right provide us with two types of conclusions. The higher average response rate might indicate the excessive simplicity of questions posed to the participants, or knowledge acquisition may be assumed to be analogous to what was previously stated.

Based on the indicators and their visual representation, the indicator with unique weights measuring the activity during the course (course activity) approximates most closely to the normal distribution. According to the CLT discussed in the previous section, the distribution of multiple variables will converge to a normal distribution if combined.

Moving on to the analysis of activity indicators, it was found that these distributions peaked more than normal, as indicated by the positive values of all the kurtosis indicators. Additionally, all four variables investigated had positive skewness values, indicating that these indicators peak to the left and stretch to the right. The descriptive statistics and deviation indicators of the activity indicators are provided in Table 5.

Examining the histograms depicting the distributions indicates their shapes are similar to the normal distribution (Fig. 4). Unsurprisingly, all the considered indicators, except for extreme cases that deviate from the pattern, have their peak to the left, given that they are all constrained at the bottom (starting from zero). Although the investigated sample may have yielded samples with a standard distribution, we also considered these values relevant. These measures all assess student behaviour in the e-learning course from different perspectives.

In conclusion, the analysis reveals that while the e-learning program is of average quality standard (as indicated by distribution peaking to the left of the *ent_cou* variable), the students have successfully improved their knowledge from the beginning of the course. To examine causality and perform further analysis, regression calculations are required.

4.4. Efficiency assessment based on result-regression calculation

According to the prior plan, the following variables will be included in the model for calculating regression: the **dependent variable**, the course's final grade (*sc_cou*); and **explanatory variables**, the initial test's score (*sc_ass*), and the unique measure for activity during the course (*sc_act*).

Before establishing the regression model, carrying out a correlation analysis can be informative, which revealed statistically significant relationships between all three variables. The correlation between the final course grade and the initial exam is of moderate strength (0.46). The relationship between *sc_ass* and *sc_act* is weak (0.22), while the relationship between activity during the course and the final grade is the strongest (0.58), confirming our hypothesis. Table 6 displays the details of the correlation analysis between the examined variables.

After examining the correlation between variables (as summarised in Table 7), a regression analysis was conducted. The R^2 value is worth noting, as it indicates that the combination of explanatory variables included in the linear regression accounts for approximately 38% of the value of the dependent variable.

Despite the limited explanatory power of the model, its significance remains strong. It has been established at several points in the research that the effectiveness of KT depends on multiple factors that are nearly impossible to measure. With a significance level of 5%, our model may be declared significant confidently. Details of the ANOVA table are provided in Table 8.

Let us look the interpretation and significance of the coefficients (see Table 9). Our model suggests that the initial test and the activity measures during the course appear as significant model parameters. Assuming all the other factors remain constant, a one-point increase in the initial test score will result in an average end-of-course score of 2.365 points higher. Contrary to this, increasing the unique activity score during the course by one point (ceteris paribus) results in a score of 11.253 points higher after the

Table 4
Scoring indicators - Descriptives and deviation indicators (own table).

		sc_ass	sc_cou	sc_act
N	Valid	219	240	241
	Missing	22	1	0
Mean		3.836	83.492	−0.159
Std. Deviation		3.144	22.242	0.811
Skewness		0.467	−1.802	−0.392
Std. Error of Skewness		0.164	0.157	0.157
Kurtosis		−1.113	3.145	0.712
Std. Error of Kurtosis		0.327	0.313	0.312

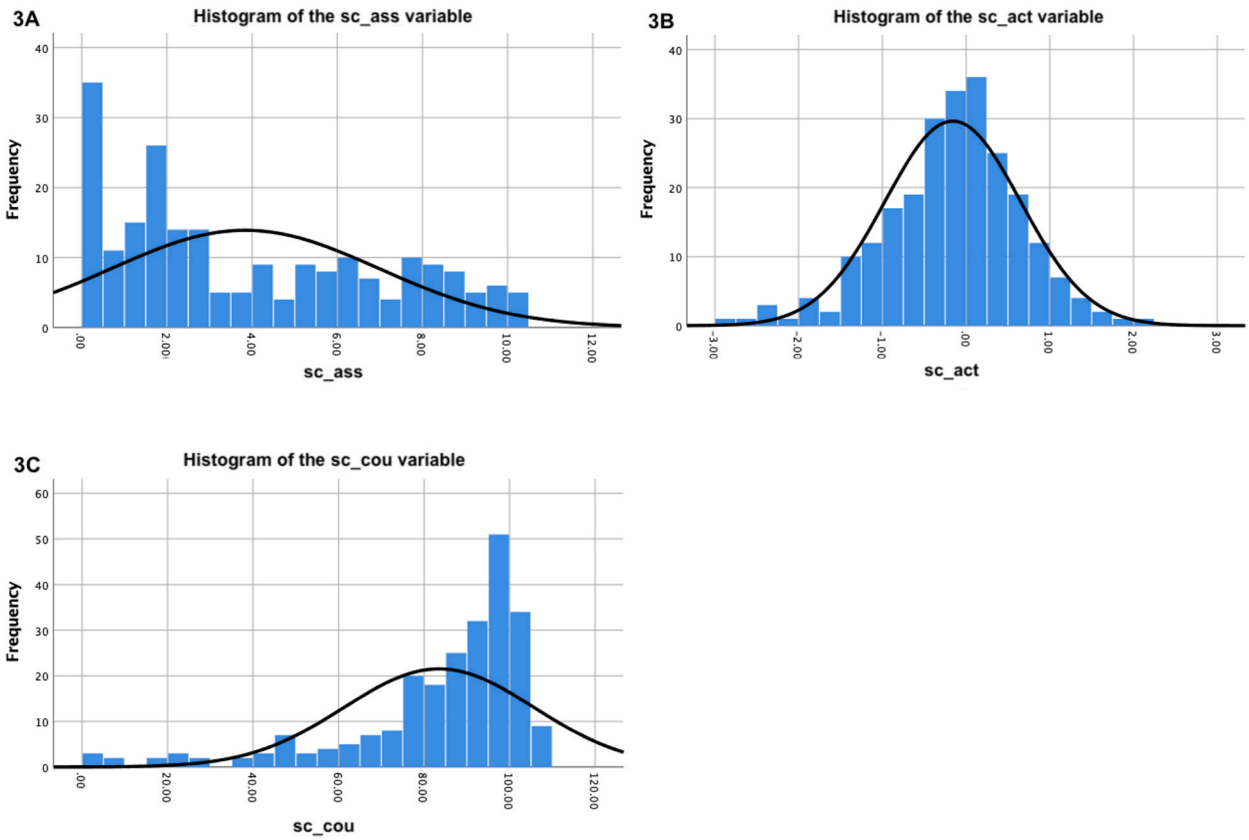

Fig. 3. Histograms - sc_ass (3A), sc_act (3B) and sc_cou (3C) variables (own image).

Table 5
Activity indicators - descriptives and deviation indicators - (own table).

		time_pas	ent_cou	view_mod	days_act
N	Valid	241	241	241	241
	Missing	0	0	0	0
Mean		30.160	108.672	107.452	33.929
Std. Deviation		10.961	55.000	48.406	11.868
Skewness		0.504	1.460	1.238	0.486
Std. Error of Skewness		0.157	0.157	0.157	0.157
Kurtosis		0.491	3.621	3.235	0.691
Std. Error of Kurtosis		0.312	0.312	0.312	0.312

course.

Hence, the linear regression model can be described with the following equations:

$$y_{\text{total score for the course}} = \beta_0 + \beta_{\text{initial test}} x_{\text{initial test}} + \beta_{\text{activity}} x_{\text{activity}} + \varepsilon$$

$$y_{\text{total score for the course}} = 77.562 + 2.365 x_{\text{initial test}} + 11.253 x_{\text{activity}} + \varepsilon$$

in summary, it can be stated that linear regression was effectively applied to the total course score as well as the measures of the initial test and activity during the course. The model's explanatory power was moderate, but its significance is indisputable. It is not possible to draw a clear-cut conclusion on the quality of the e-learning course based on the results, but it is evident that activity during the course, in comparison to initial knowledge, has significant explanatory power for the participant's outcome score, indicating that the e-learning program makes substantial contribution to the KT.

4.5. Efficiency assessment based on result - cluster analysis

After the regression analysis conducted in the previous section, it was found that the course's initial assessment quiz and

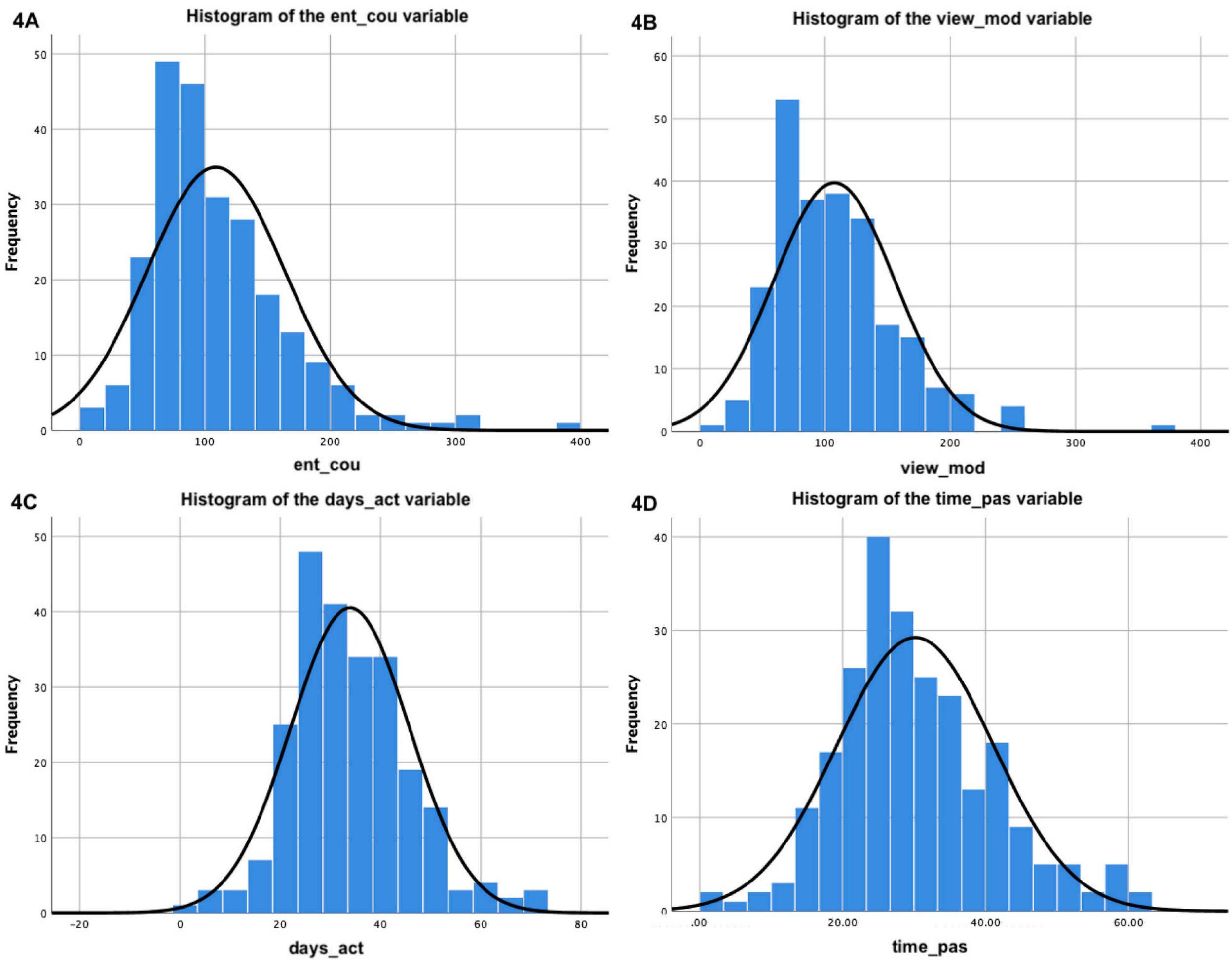

Fig. 4. Histograms - ent_cou (4A), view_mod (4B), days_act (4C) and time_pas (4D) variables (own image).

Table 6
Correlation analysis of the score variables (own table).

		sc_ass	sc_cou	sc_act
sc_ass	Pearson Correlation	1	0.464	0.217
	Sig. (2-tailed)		0.000	0.001
	N	219	219	219
sc_cou	Pearson Correlation	0.464	1	0.576
	Sig. (2-tailed)	0.000		0.000
	N	219	240	240
sc_act	Pearson Correlation	0.217	0.576	1
	Sig. (2-tailed)	0.001	0.000	
	N	219	240	241

Table 7
Linear regression – summary (own table).

Model	R	R Square	Adjusted R Square	Std. The error in the Estimate
1	0.619	0.383	0.377	15.738

participants' activity throughout the course played a significant role in determining the final grade of the participants at the end of the e-learning program. To further examine this relationship from a different perspective, a cluster analysis was performed to classify course participants into distinct groups. In order to ensure reliable and consistent results, cluster analyses was conducted using both

Table 8
Linear regression - ANOVA table (own table).

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33208.050	2	16604.025	67.037	0.000
	Residual	53499.870	216	247.685		
	Total	86707.920	218			

Table 9
Linear regression - coefficients (own table).

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	77.562	1.726		44.933	0.000
	sc_ass	2.365	0.347	0.373	6.807	0.000
	sc_act	11.253	1.469	0.420	7.662	0.000

the hierarchical and k-means procedures, with three different clustering methods used for the hierarchical procedure.

4.5.1. Hierarchical cluster analysis

Hierarchical clustering was performed first. Before conducting the cluster analysess, the three variables to be included, namely *Zscore (sc_ass)*, *Zscore (sc_act)*, and *Zscore (sc_cou)*, were standardized using SPSS. Hierarchical clustering was then performed using the between-groups linkage method. Larger cut-off points were used to determine the number of clusters, which is accepted in similar analyses. The students were ultimately classified into three clusters based on all three used methods.

4.5.2. K-mean cluster analysis

Since in k-mean cluster analysis, the desired number of clusters is determined by the analyst, the same number was chosen for k-mean analysis that was determined in the hierarchical analysis, thus our model for k-mean cluster analysis also included three clusters. The first aspect that warrants investigation is the ANOVA table, where the significance of F probes indicates that each variable used in the cluster analysis is valuable (Table 10).

The headcount of the groups generated by k-mean cluster analysis is shown in Table 11. The first group contains 18 students, the second group contains 60 students, and the third group contains 141 students.

Table 12 shows the means of each cluster compared to the standard scores (Table 12). In the present instance, we derived these categories:

- 18 participants in the first group show results below average for all three metrics (and outstandingly low for the total course score). Therefore, this group may consist of **uneducated and lazy** students with a low initial knowledge level combined with inactive participation, which reflected clearly in their final grades.
- 60 participants in the second cluster represent the **average** group: having earned an initial score that was significantly below average, they showed activity close to average and scored an end-of-course total score that was slightly lower than the average.
- The third cluster, with 141 members, includes **highly-educated and motivated students** who achieved outstanding scores on the initial test, displayed above-average activity during the course, and ultimately achieved overall results well above average upon course completion.

Overall, we can conclude that the cluster analysis gave a technique that was considerably more subjective than prior statistical methods, and the different procedural methods allowed for finding somewhat distinct student groups.

5. Conclusions

The main objective of this paper was to develop a KT measurement method for e-learning independently, without comparison or control groups. To achieve this, we reviewed the literature and identified no specific evaluation method designed for e-learning.

Table 10
K-mean cluster analysis - ANOVA table (own table).

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
sc_ass	310.819	2	7.097	216	43.793	0.000
sc_cou	37181.176	2	57.155	216	650.528	0.000
sc_act	11.933	2	0.448	216	26.661	0.000

Table 11
K-mean cluster analysis - element numbers of the clusters (own table).

Cluster	1	18.000
	2	60.000
	3	141.000
Valid		219.000
Missing		22.000

Table 12
K-mean cluster analysis - means of the final clusters (own table).

	Cluster		
	1	2	3
sc_ass	2.086	1.431	5.083
sc_cou	32.625	75.722	96.900
sc_act	−1.037	−0.243	0.123

Subsequently, we developed a new and unique KT measurement method that can be used for e-learning courses individually. Finally, we tested and validated our new method and concluded that it could be used for measuring effectiveness and efficiency in KT on e-learning courses.

5.1. Significant findings of the study

During the empirical stage of our research, we adapted the data set of an academic course to the developed method using e-learning tools. To evaluate the usefulness of the measurement methodology aimed at e-learning, two crucial questions need to be addressed:

1. Can the evaluation instruments **be tailored to the data** gathered from the e-learning environment (and readied for measurement)?
2. **Are inferences possible** on the usefulness of the e-learning course?

The **first question** is straightforward, as it calls merely for confirming technical feasibility. We found that the data series of a correctly designed e-learning program is adaptable to our new methodology. The evaluation approach is based on well-established statistical and mathematical models, so their applicability is indisputable. Yet, it is crucial to note that the quantity, quality, and format of the data created and stored by different e-learning systems vary. Therefore, it is impossible to generalise that data of an e-learning program may be processed with the evaluation model. Nonetheless, the e-learning program we evaluated utilised data gathered from Moodle, the most extensively used e-learning system with open-source code. Therefore, the measurement methodology will be generally applicable. The variety of data captured by Moodle will continue to expand (e.g., by tracking course withdrawals), resulting in a more efficient application of our evaluation technique.

The **other question**, whether one can form inferences on the usefulness of an investigated e-learning program, is challenging. Throughout the empirical investigation for this study, we attempted to create mathematically and statistically supported claims about the e-learning activity evaluated according to the measurement method's parameters. It is essential to remember that the measurement method includes subjective evaluation components. This is the most important lesson that can be learned from the application of empirical research in practice: the variety of tools provided by our measurement methodology enables more accurate and correct conclusions to be drawn if they are examined in conjunction and terms of relationships rather than individually. The interpretation of deviation, skewness, and kurtosis indicators on their own may be highly misleading in terms of measuring the e-learning course. However, comparing these indicators and their combination with correlation calculation, also considering the regression model construction combined with clustering, enables the drawing of reasonable conclusions regarding the chosen e-learning program. **Utilising the measurement approach to its fullest extent, it is possible to conclude that the methodology is suitable for reaching conclusions on the chosen e-learning program's effectiveness and efficiency.**

5.2. Improvement opportunities

During the development and validation of the new KT evaluation method, we discovered some potential areas for improving the evaluation approach, so we recommend the following:

- Develop a standardised indicator for measuring activity during the course by identifying ideal metrics and determining their weight using correlation calculation or sensitivity testing. The new KT evaluation method we elaborated derived a new variable from various other e-learning course data to simplify our model. However, this method may need some fine-tuning to get more precise results in determining student activity.
- Enhance the explanatory power and relevance of the linear regression model by adding further variables. As every e-learning course is different, research on the diverse learning elements used in these courses and the associated measurement opportunities could be

an interesting topic. New variables could be introduced to our KT evaluation model, such as for online group work or assignments in other courses.
- Incorporate additional variables into the cluster analysis processes to generate more precise groups. The new variables could also be considered in the cluster analysis.
- Restrict the scope of cluster analysis processes to a more manageable size for e-learning course analysis after testing in multiple courses.
- Propose specific limits for interpreting the results produced by the measurement methodology to provide analysts with additional help. This would require sample data for comparison, such as skewness indicator values to determine whether an e-learning course is somewhat medium or very efficient.

Realistic additional proposals can be made after implementing the measurement methodology in several courses, which could number in the tens or hundreds. Upon completing this research, several new practical and theoretical pieces of advice may emerge, making future research less time-consuming and more simple.

5.3. Limitations

It is important to note that the new KT method was tested on only one e-learning course. Further empirical research should be carried out on several other courses, including various e-learning training, to prove its broad usability.

As our KT evaluation method depends on data gathered by an LMS (in our specific case it was Moodle), other fellow researchers should note that different learning management systems might record slightly different data, which would need somewhat different dataset preparation before using our KT evaluation method. That would also mean an opportunity, as other learning management systems could provide some additional variables to be included in the analysis. Of course, process-data logging in e-learning courses is essential to use the recommended methodology. In other words, the quality of a methodology is intricately linked to the quality of its input data.

It is also worth mentioning that all e-learning programs contain different learning elements, creating the need to use different variables in the regression model or at least weigh them differently when creating the unique activity score variable. This leads to the conclusion that applying our KT measurement method on different e-learning courses would always need some proactive modification and alteration to adjust to the examined e-learning course. It will always be the researcher's responsibility to choose the proper variables in order to get valid and justifiable results from the evaluation of the KT.

In addition to deeper validation, an interesting research topic could be examining and comparing e-learning education and KT on large samples, which could provide new and exciting data about how we think about e-learning and its usability. The presented KT evaluation method works on single e-learning courses without the need of a control group or another course to compare with. However, after carrying out this research on several e-learning courses (e.g., across multiple universities), these results can be compared to each other. Furthermore, new hypotheses can be set to examine the usefulness of e-learning KT in general, not only for specific courses.

Overall, we believe that the elaborated and validated new KT method for e-learning courses is a significant step forward in this research field that may inspire other researchers to further develop this method or create alternate versions. Our study can be useful, among others, for course instructors working in academic or other educational institutions who want to measure the effectiveness and efficiency of their educational activities. Using our method, the course instructor can receive an evaluation of the course's usefulness, from which they can draw conclusions and develop the course further.

Author contribution statement

Vitéz Nagy, László Duma: Conceived and designed the experiments; Performed the experiments; Analysed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

The authors do not have permission to share data.

Additional information

Supplementary content related to this article has been published online at [URL].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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