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Data Fusion Technique for E-Learning Evaluation Based on Evidence Theory

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Abstract: To reduce the risk of viral infection during the coronavirus pandemic, all academic institutions have turned to online learning in recent years. The evolution of online classes presents new obstacles for academic specialists, particularly in underdeveloped nations where participants have limited access to technological gadgets. Even while some elements of online and traditional on-campus learning are comparable, online learning requires more factors to analyze, such as student evaluation. Because of the various surroundings that participants are exposed to during online education, the topic of electronic learning environments must be discussed. It calls for the development of new methodologies and procedures for assessing participants' knowledge and skill development. Based on evidentiary theory and the data fusion idea, this research provides a new technique to evaluate participation. Because it is versatile in simulating the wide spectrum of uncertainty inherent in natural contexts, evidential theory is progressively spreading. The approach suggested is appropriate for dealing with all forms of online courses. Furthermore, it enables educators to improve academic performance by providing continuous participant feedback. After exposing participants' weaknesses, the instructor can redirect learning processes. The experimental findings of three online university courses demonstrate the efficacy of this strategy.

Keywords: evidential theory, learning evaluation, online education, data fusion, formative assessment, summative assessment, Pignistic probability

1. Introduction

The process of delivering information using electronic resources is known as e-learning (including the Internet, conference, CD, or intranet). It improves knowledge, individual learning, and organizational performance objectives (Clark & Mayer, 2016). E-learning can be defined as a network used to transfer skills and expertise and to deliver education to a large number of people at the same or different times (Kumar Basak et al., 2018). This revolution is based on the introduction of computers, smartphones, tablets, and other electronic devices used in e-learning and traditional classrooms. For instance, optical discs and pen drives have replaced books. Furthermore, classrooms are not required for knowledge delivery (Gao et al., 2021). It can also be shared over the Internet, making it available 24 h a day, 7 days a week (Uprichard, 2020).

Participants, however, do not prefer it due to the rapid advancement of technology and learning systems. One of the most difficult challenges for e-learning systems is determining an accurate method for evaluating participants in the e-learning process in many measurable terms: a participant's knowledge, skills, and attitudes via an online assessment procedure (Mastan et al., 2022). An educator must conduct a course assessment to determine how well a learner has understood the course content. It also assists learners in examining the content in which they are proficient and directing their learning progress. Generally, two types of assessments are used in e-learning systems: formative and summative (Gardner, 2012). The primary distinction between the two is the purpose of the evaluation, with the former focusing on feedback-based learning and the latter on evaluative judgments of participant learning (Arend, 2009; Mubayrik, 2020).

Even though formative assessments have garnered much more attention due to their usefulness, educators still think about evaluations from a summative standpoint (Bello & Abdullah, 2021; Clark et al., 2013). In the traditional learning environment, this assessment is commonly used to determine whether a participant could meet learning outcomes and achieve some accreditation, such as progressing to the next level of studies. Because the grades received in summative assessments are often final and can affect their future progression, this type of assessment typically causes anxiety (Wanner & Palmer, 2018).

Both types of evaluation can be used online in conjunction with various learning techniques (Kebritchi et al., 2017; Liaw et al., 2007). Summative assessments are commonly used by creating online tests with multiple-choice questions that grade the participant based on the number of correct answers (Liaw et al., 2007).

This paper proposes a new approach to evaluating the e-learning process using the formalism of belief function. The theory of belief

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functions – known as Dempster–Shafer (DS) or evidence theory – has recently emerged as an essential tool for managing and dealing with uncertainty, imprecision, and even a lack of information. Belief theory is becoming more popular owing to its ability to model the wide range of uncertainties inherent in natural environments (Liu et al., 2018; Liu & Zhang, 2020; Li et al., 2018).

The primary objectives of this study consist of:

1. Building a new evaluation model for the e-learning process based on the data fusion technique and DS's theory.
2. Giving feedback for students to enhance their study techniques.
3. Providing educators with frequent information about the knowledge and skill progress of their students may help in identifying the need to enhance their teaching methodologies.

To build this model, DS's theory, formative assessment, and summative assessment are used to manage uncertainty and compute an accurate evaluation of each participant based on three dimensions:

- Knowledge represents the growth of cognitive knowledge during the learning process,
- Skill denotes the development of cognitive abilities during the learning process, and
- Interaction is about how each message is linked to the course content.

This paper is organized as follows. First, an overview of existing evaluation methods in the literature is introduced in Section 2. Afterward, a background on belief functions theory is reviewed in Section 3. This paper's approach is proposed based on the belief function theory in Section 4. Later, Section 5 presents the results of applying the proposed method to three online courses at the Jinan University of Lebanon, followed by a discussion of the method's benefits. Finally, Section 6 summarizes this paperwork and discusses possible future research directions.

2. Literature Review

The COVID-19 pandemic significantly affected many industries, including businesses, enterprises, and education. As a result, practical strategies for dealing with this pandemic are required. Schools and universities in the education industry have merged into the electronic environment known as e-learning (Ebner, et al., 2020). The authors looked into students' and teachers' behaviors before and after the transition of learning systems. For example, Minghat et al. (2020) investigated student knowledge of e-learning and acceptance of implementing e-learning systems in many universities in Indonesia and Malaysia. However, according to their research, more than 60% of students do not agree with implementing e-learning systems at current universities. Many factors contribute to students' rejection, including a lack of interaction between students and teachers.

Furthermore, Elzainy et al. (2020) described an online learning study at a medical college in KSA during the COVID-19 pandemic. They implemented a procedure for conducting various training sessions for teachers and students via virtual classrooms and online assessments. As a result, their experimental results indicate that the e-learning system is beneficial to both students and teachers. They examined what is beneficial or detrimental to achieving objectives, such as strengths, opportunities, weaknesses, and threats. Maatuk et al. (2022) used two types of questionnaires to conduct an approach used at the University of Benghazi during the COVID-19 pandemic: one for students and one for instructors. Their approach has several dimensions, including the scope of e-learning and the challenges associated with implementing this system in the IT faculty. Following analysis, they obtained encouraging results demonstrating how feasible the implementation of e-learning systems in their faculty for higher education is.

Alqahtani et al. (2021) investigated the factors associated with nursing students' satisfaction with e-learning in KSA. An online survey of various students was used to conduct their research, which showed the percentage of teaching and learning skills among teachers and students. As a result, they concluded that distance education must be developed in order to improve student satisfaction. As a result, Tawafak et al. (2021) investigated the role of technology in distance learning during the COVID-19 pandemic. They emphasized the importance of integrating cutting-edge technologies and learning software to improve student's academic skills and performance.

Because methods and strategies for motivating students are challenging to implement in e-learning systems due to distance education, many research studies have focused on improving procedures for online teaching, course materials, and assessments. For example, Hussain et al. (2018) created a dashboard based on students' participation in online course activities. Their proposed model assists instructors in assessing students' attention in online classes. It enables students to perform better on assessments. However, the evaluation of the skills acquired by students and summative assessments such as the final exam are not considered in this study. Furthermore, Almaiah and Alyoussef (2019) discussed the impact of four factors (course design, course content, course assessment, and instructor characteristics) on integrating e-learning systems into KSA universities' existing learning systems. Their study results show promising performance, implying that improving the above-mentioned factors can assist university administrators and researchers in facilitating student acceptance and engagement with e-learning systems. Tawafak et al. (2020) created an online e-learning model that improves assessment techniques to increase teacher and student satisfaction. The authors focused on four main factors: student motivation, comprehension, usage, and dignity. In this study, a consistent model combining the e-learning model with coursework classes for evaluating student grades and skills performance is proposed. This model is also used to consider the competition of teaching techniques, course outcomes, and knowledge. The satisfaction of students has been computed via a survey. In this method, the coursework is only used to evaluate students. Also, no feedback was sent to students for enhancing their study techniques or to educators to update their teaching methodologies. However, the authors' statistical results demonstrated a high evaluation of teaching methods and course outcomes.

However, the literature did not mention how models and strategies could accompany students in various activities throughout the course study (Kasani et al., 2020; Montebello et al., 2018). Grading, for example, is regarded as critical for students as an evaluation process for information gathering. As a result, assessing students using appropriate grade schemes is critical to improve their performance and ensure their satisfaction. As a result, this paper discusses a novel approach to assessing student performance and updating material content based on regular formative assessments. Formative assessment data are combined with the educator's belief function framework to update materials content and educational methodology. Finally, the summative assessment assesses students' overall performance in the course over the semester.

One of the most exciting tasks for an educator or an artificial instructor embedded in an intelligent tutoring system is the prediction of the achievement of his/her students to sufficiently change the educational materials and techniques during the learning journey. Moradi et al. (2014) proposed a multichannel decision fusion approach that uses the achievement in "assignment categories," such as homework assignments, to determine a student's overall achievement. In this approach, the collected data are used to specify four classes of "expert," "good," "average," and "weak" achievement levels. This classification is performed on both overall achievement and achievement in assignment categories. Then, a link from the achievement in "assignment categories" is understood and is exploited to predict the overall achievement. This approach can assess students' achievement after only a few assignments. Therefore, it can support the educators to control their classes better and change educational methodology to avoid underachievement. However, the authors did not consider the interaction during the session nor the skills acquired by the students.

The essential task of an effective learning process is to be able to perform effective assessment techniques. The primary commitment of any educational organization is the participant's learning process. Assessments represent a meaningful way to answer to this commitment (Trumbull & Lash, 2013). Regardless, participant assessment performed only for responsibility reasons does not necessarily conduct learning. Educators must select the goal of assessments, the criteria being computed, and the planned outcomes before effective assessment techniques can be performed (El-Senousy, 2020). Indeed, the main objectives of the assessment are (Bland, 2022):

- Survey participant learning process,
- Improve academic programs, and
- Enhance the teaching and learning processes.

In the e-learning process, the assessment challenges are more critical. In recent years, researchers and academics have focused more on finding effective techniques to assess participant learning during online learning due to the corona pandemic. However, this technique has not yet been handled correctly (Garg & Goel, 2022). Some academic professionals say that during the e-learning process, effective online assessment techniques must be performed according to unique traditional learning: challenging participants thinking, providing a reason to attend classrooms, displaying a willingness to provide help when necessary, and giving meaningful assignments. However, the online assessment also needs a more persistent, organized approach than traditional instruction.

Furthermore, because the assessment methods must match the desired competencies, online assessment necessitates educators to adapt their education methods to be more innovative than traditional instruction because it alters human interaction, communication, learning, and evaluation methods. As a result, several researchers have discovered significant difficulties in evaluating participant learning in online courses.

According to Rouhani et al. (2022), effective online assessment techniques include creating realistic learning scenarios, aligning learning objectives with realistic scenarios, implementing software on the spot, accessing online mentors, and training tailored to individual participant learning differences. More online teaching and learning research are required to identify effective online instructional and assessment techniques.

3. Belief Function Theory

Evidence theory (Denoeux, 2008, 2017) – also known as DS or belief function theory – has recently captured the attention of researchers as an essential tool for managing and dealing with uncertainty, imprecision, or a lack of information. This section will review the main concepts of evidence theory used throughout the paper (Zhu et al., 2021).

3.1. Basic definition

Let Ω be a finite set of jointly exhaustive and exclusive hypotheses, called the frame of discernment. The set of all subsets is denoted by 2^{Ω}. The impact of an evidence piece on different subsets of the frame of discernment is represented by a Basic Belief Assignment, called mass function m. This function m can be represented as a relation from 2^{Ω} to the interval [0, 1] that verifies:

$$\sum_{A\subseteq\Omega} m(A) = 1 \tag{1}$$

Each mass function $m(A)$ represents a mass of belief given to the subset A and cannot be given to any subset of A based on a given piece of belief. Every subset that verifies the condition $m(A) > 0$ is a focal set of the mass function m. A mass function m is known to be:

- Regular if the null sign ∅ is not a focal element
- Categorical if it has one focal element
- Empty if m is categorical and ∅ is a central element.

3.2. Combination rules

Since a different source can deliver belief of information, any two mass functions – m_1 and m_2 – are combined by the conjunctive rule defined as:

$$m_1 \cap m_2(A) = \sum_{B\cap C=A} m_1(B) * m_2(C),\ \forall A \subseteq \Omega \tag{2}$$

The conjunctive rule of combination may produce a non-normal mass function, even if the combined mass functions are normal. Therefore, the mass $m_{12}(\varnothing)$ represents the degree of conflict between m_1 and m_2. A normalization step may obtain a typical mass function if the degree of conflict differs from (1), leading to a new rule of the combination called DS's rule denoted by ⊕:

$$m_1 \oplus m_2(A) = \frac{\sum_{B\cap C=A} m_1(B) * m_2(C)}{\sum_{B\cap C=\varnothing} m_1(B) * m_2(C)} \tag{3}$$

3.3. Pignistic probability

Consider a mass function m on Ω produced after combining all available pieces of evidence. Suppose that a decision should be made by selecting one element of Ω. This decision can be made using one of the decision rules of evidence theory, such as maximum belief, highest plausibility, or highest Pignistic probability (Smets & Kennes, 1994; Xu et al., 2021). In this paper, Pignistic probability is used. It is defined as:

$$betp(\omega) = \sum_{A\subseteq\Omega/\omega\in A} \frac{m(A)}{(1-m(\phi)|A|},\ \forall A \subseteq \Omega \tag{4}$$

where ω is an element of the set Ω and $|A|$ is the cardinality of A.

The Pignistic probability function is thus obtained from m by distributing each normalized mass $m(A)$ / (1 – $m(\varnothing)$) among the elements of A equally.

4. Proposed Approach

In this section, the authors propose and explore in detail the new evaluation approach based on the data fusion technique, belief function theory, and summative and formative assessments.

4.1. Evaluation approach using belief function theory

The proposed approach in this paper (see Figure 1) is based on the data fusion technique for information gathered from formative and summative assessments under the evidence theory. The formative assessment involves diverse methods that assist academic specialists in estimating participant understanding, educational advancement, and knowledge requirements over the course (Trumbull & Lash, 2013).

These assessments also allow specialists to specific concepts that participants struggle to understand, skills they are having difficulties developing, or education standards that they have not completed yet. Therefore, educators can update education methodology, instructional strategies, and academic support. On the other hand, summative assessments evaluate participants' education at the end of the learning journey. These assessments compare participants' improvement according to the course standards and learning objectives.

In this evaluation process, three sources of information exist:

- Synchronous session(s) can be elaborated such that the educator can detect student interaction with the course content. In addition, they allow the educator to detect the evaluation of knowledge among the students by detecting the keywords used in their conversation.
- Formative assessment(s) can be made several times during education. It may consist of a pool of multiple-choice questions or peer-to-peer reviews. It helps education evaluate students' progress according to three dimensions cited in Section 1.
- Summative assessment(s) can be made at the end of the course (or twice during the course). It gives educators. As a result, a set of grades represents the evaluation of students.

The information gathered from these three sources of information or fusion together under evidence theory. The outputs of the data fusion step are:

- Feedback helps students detect their weaknesses and update their studying techniques.
- Feedback to education assists him in updating the course content and his education methodology. In addition, this feedback is used to set the students' final evaluation.

Figure 2 represents the general structure of the data fusion unit. Indeed, during synchronous sessions, educators can create a table (see Table 1) containing all students' names and three columns representing the knowledge, skill, and interactions.

Table 1 represents the complete ignorance of the student level (Φ) (absent student or no interaction with the educator of the session).

Based on Table 1, a mass function miSy can be created for each session on the set Ω that contains the three dimensions cited above, $\Omega = \{k, S, I\}$, where K represents the knowledge, S represents the skill, and I represents the interaction.

The mass function can be computed only by dividing the content of Table 1 by 100. An illustrative example is elaborated in Section 4 to understand how Table 1 is filled. These mass functions can be combined under conjunction combination rules for creating one mass function m_{Sy} for synchronous sessions:

$$m_{Sy} = \oplus_{i=1}^{n} m_{Sy}^{i} \tag{5}$$

where n is the number of synchronous sessions, and m_{sy}^{i} is the mass function representing the final belief gathered by synchronous sessions.

In addition, each formative assessment generates a mass function named miFo on the set Ω. The mass function representing the final belief given by all the formative assessments, called m_{Fo}, is the conjunction combination of all assessments named m_{i}:

$$m_{Fo} = \oplus_{i=1}^{m} m_{Fo}^{i} \tag{6}$$

where m represents the total number of formative assessments done during the online courses.

The process is then repeated on the summative assessments (m_{Su}):

Figure 1
The proposed approach for student evaluation in online courses

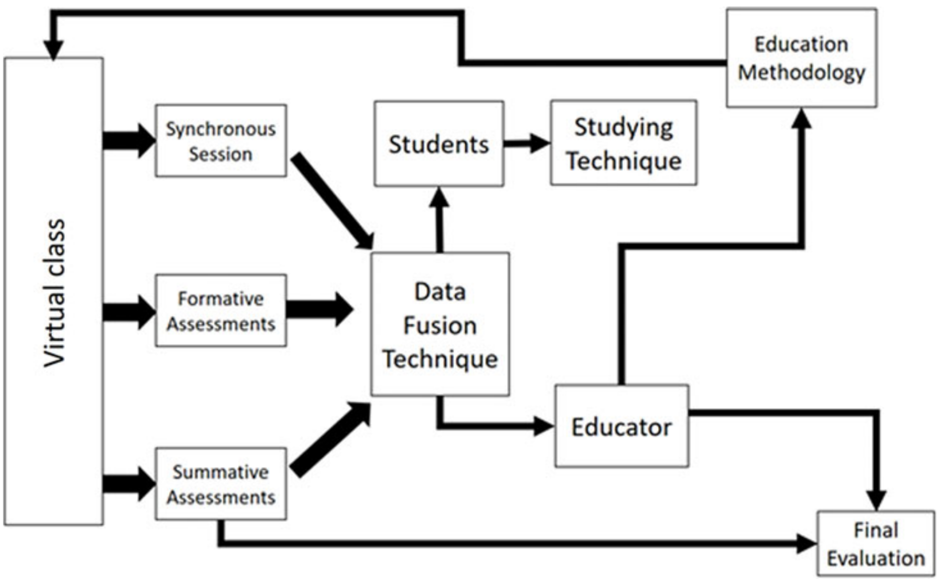


Figure 2
The architecture of the data fusion unit

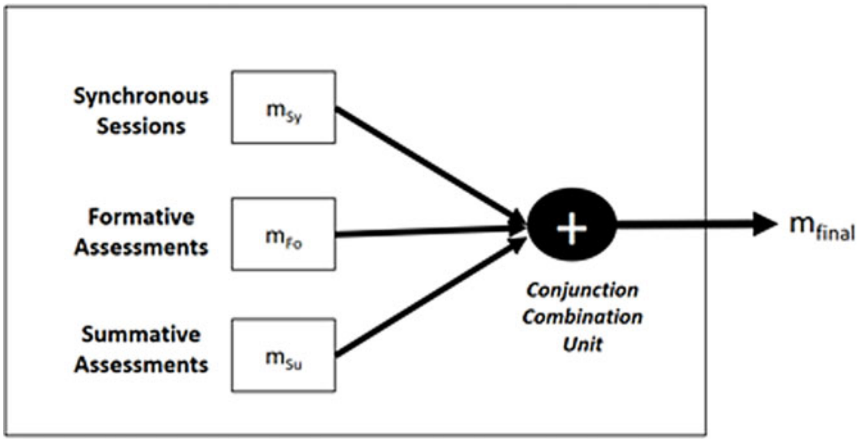


Table 1
The results are shown according to the synchronous sessions for evaluating student performance

Set	*Φ*	*K*	*S*	*I*	*K, S*	*K, I*	*S, I*	*K, S, I*
S1	100	0	0	0	0	0	0	0
S2	0	40	20	20	20	0	0	0
S3	0	100	0	0	0	0	0	0

$$m_{Su} = \oplus_{i=1}^{m} m_{Su}^{i} \quad (7)$$

Finally, m_{Final} is the resulting mass function representing the final belief on the set Ω:

$$m_{Final} = m_{Sy} \oplus m_{Fo} \oplus m_{Su} \quad (8)$$

This mass function is used to create a Pignistic probability to compute the evaluation percentage of each participant according to knowledge, skill, and interaction dimensions using (4). This probability represents the percentage of the final grade associated with a single dimension. This probability is sent to students and educators. It helps students in evaluating their progress during the course and in updating their studying strategies. In addition, it will give the educator a quick evaluation of overall class performance to update the course syllabus and teaching methodology. Using Pignistic probability and summative assessments, each participant gets a score as an evaluation percentage based on knowledge, skill, and interest dimensions in the evaluation process.

The results of applying the proposed approach to an online course at the Jinan University of Lebanon are presented in the next section.

4.2. Synchronous session: Mass function creation

Suppose three students: Elie (E), Suzan (S), and Yasser (Y), took the online course "Introduction to Java programming." This course comprises 16 sessions; six of them are synchronous, and the first two sessions were asynchronous. During these sessions, the educators upload a video with a PowerPoint file explaining the lectures' ideas. Table 2 summarizes the content of the first two sessions.

Table 2
Content of the first two asynchronous sessions

Session #	Content
1	Introduction
	What is the central processing unit? (brief)
	Memory (brief)
	The machine language versus the programming language
	The compiler (as a translator to machine language)
	A simple java program
	Block styles
2	Writing a simple program (class naming convention)
	Variables (variable naming convention)
	Assignment statements and assignment expressions
	Reading input from the console (nextDouble() only)
	Named constants (constant naming convention)
	Solve programming exercises

Based on Table 2, the students should be ready to answer comprehension questions about the computer's components, the central processing unit, and memory in the third session, known as the synchronous session. In addition, they should recognize the main structure of Java programming and know what is variable in programming. Based on this, during the third session (synchronous), the educator starts by asking students some questions:

- Q1: What are the computer's primary components?
- Q2: What is the role of memory?
- Q3: What is a variable?

Table 3 represents some examples of students' answers and Table 4 is the educator's evaluation updates.

According to the type of questions in Table 3, the educator cannot evaluate the student's skills. Thus, he continued the session and shared the following part of the code with the students, as shown in Figure 3. Afterward, the educator asks the students to find errors in the code. Their answers are depicted in Table 5.

Using this example, the educator can update the evaluation table (see Table 6).

Table 3
Some students' answers to the first set of questions

Question	Elie's answer	Suzan's answer	Yasser's answer
Q1	–	RAM, screen, keyboard	Memory and CPU
Q2	Store data	Store data	Store data
Q3	Name	–	Location in memory

Table 4
First update of the evaluation table

Set	Φ	K	S	I	K, S	K, I	S, I	K, S, I
E	50	50	0	0	0	0	0	0
S	50	50	0	0	0	0	0	0
Y	0	100	0	0	0	0	0	0

According to Table 6, the educator believes that:

- Yasser (Y) has the interaction, skill, and Knowledge (100 on the set $\{K, S, I\}$).
- Suzan (S) interacts less and has less knowledge and skills (she took 25 on Φ because she did not interact all the sessions)
- Elie (E) interacts less and answers some questions correctly. He gets some knowledge, skills, and interaction.

Afterward, m1Sy can be computed (see Table 7).

Table 5
Answers of students for the second set of questions

Student	Answer
Elie	Missing a semicolon in line 5
	Missing a quotation in line 7
Suzan	Missing a semicolon in line 5
Yasser	Missing a semicolon in line 5
	Missing a quotation in line 7
	Variable a should be declared

Table 6
First update of the evaluation table

Set	Φ	K	S	I	K, S	K, I	S, I	K, S, I
E	15	30	30	25	0	0	0	0
S	25	25	25	25	0	0	0	0
Y	0	0	0	0	0	0	0	100

Table 7
Mass function for the first synchronous session

Set	Φ	K	S	I	K, S	K, I	S, I	K, S, I
E	0.15	0.3	0.3	0.25	0	0	0	0
S	0.25	0.25	0.25	0.25	0	0	0	0
Y	0	0	0	0	0	0	0	1

5. Results and Discussion

The approach proposed in this paper was used on four courses in a class of 27 students at Jinan University of Lebanon during the academic fall semester of 2020–2021. The educator developed four formative assessments (oral quiz, assignment, written quiz, and project) and two summative assessments for these courses (Midterm and Final Exam). The educator used Google Meet software to proctor the midterm and final exams. Furthermore, assignments and oral quizzes are completed prior to the midterm exam. On the other hand, written quizzes and projects are completed after midterm and final exams. Table 8 depicts a sample of eight students and the mass function provided following the first formative assessment on one of their courses.

The set Ω represents the participant's uncertainty about their progress. However, $m(K)$ represents the mass of the belief function for the participant obtaining knowledge about the assessment's portion, and $m(K, S)$ represents the mass of belief that the participant obtains the knowledge and skill (but not both) of the part covered by the assessment.

This mass function can assist educators in keeping track of the evaluation of their course participants based on the three dimensions depicted in Section 1. Table 8 shows that the participants (S2, S3, S4, S5, and S6) are not engaged with the course content. Furthermore, following the initial assessment, the educator is entirely unsure about the evaluation of participant S5. However, participant S8 evaluates all dimensions equally.

Table 9 shows the results of some participants' first summative assessments.

Moreover, Table 10 shows the associated Pignistic probability based on the midterm exam, oral quiz, assignments, and all synchronous sessions completed before the midterm exam.

Figure 3
An example of a simple Java program that consists of four lines with some syntax errors

```
1   package javaapplication351;
2
3   public class JavaApplication351 {
4       public static void main(String[] args) {
            System.out.println("Example 1")
            System.out.println("Synchromous Session 1);
            a=3;
8           System.out.println("EnD");
9       }
10
11  }
```

Table 8
The mass function after the first formative assessment on one course

Set	Φ	K	S	I	K, S	K, I	S, I	K, S, I
S1	0.2	0.2	0.2	0.1	0.1	0.1	0	0.1
S2	0	0.4	0.2	0	0.2	0.1	0.1	0
S3	0	1	0	0	0	0	0	0
S4	0	0.33	0.33	0	0.34	0	0	0
S5	1	0	0	0	0	0	0	0
S6	0	0	1	0	0	0	0	0
S7	0	0.1	0.1	0.2	0.1	0.1	0.2	0.2
S8	0	0.2	0.2	0.2	0.1	0.1	0.1	0.1

Table 9
Summative assessment (midterm exam) on one course

Set	Midterm exam	Set	Midterm exam
S1	92	S5	48
S2	72	S6	69
S3	74	S7	92
S4	89	S8	88

Table 10
Pignistic probability

Set	K	S	I	Set	K	S	I
S1	0.4	0.4	0.2	S5	0.1	0.2	0.7
S2	0.6	0.2	0.2	S6	0.4	0.3	0.3
S3	0.8	0	0.2	S7	0.4	0.3	0.3
S4	0.5	0.4	0.1	S8	0.3	0.3	0.4

The educator receives a final grade for each participant and an evaluation percentage based on knowledge, skill, and interaction dimensions. For example, participant S1 receives a final exam score of 92/100. According to the Pignistic probability, 40% of this score is related to knowledge evaluation, 40% represents skills gained during this course, and 20% shows the participant's interaction with the course content.

Furthermore, Figure 4 depicts the grades of 10 participants who completed the formative assessment course activities (oral quizzes, assignments, and exams). The formative assessments 1 and 3 and the summative assessment (midterm exam) are shown as samples, considering the time intervals during which the participants submitted the assessments.

Based on the graph in Figure 4, almost all students outperform in the summative assessment. It is the result of an adjustment made by the educator to the educational methodology based on feedback from formative assessments.

Table 11 represents the average, minimum, and maximum grades of all assessments done during this course, where FAi is the formative assessment number i. SA1 (midterm exam) and SA2 (final exam) are summative assessments.

The average of the students' summative assessment (final exam of the course) is better than the averages of the four formative assessments. The overall average had noticeably improved from 52.51 on the first formative assessment to 73.33 on the summative assessment. The increase in the class average during the whole semester proves the performance of the proposed approach in this paper.

Similarly, Tables 12, 13, and 14 show the average, minimum, and maximum grades of the second, third, and fourth courses, respectively. They show the improvement of the averages between FA1 and the second summative assessment. These results show the advantage of the belief evaluation approach.

This method cannot detect cases of cheating in summative or formative assessments. In addition, as the mass function of the synchronous session is filled by the educator, it can be inaccurate. Therefore, a precise model of how to build this mass function should be developed.

5.1. Proposed approach vs. traditional techniques

This paper's proposed approach has shown to be more efficient for educators and students to determine the strengths and weaknesses

Figure 4
The formative assessments (FA) and midterm grades of 10 participants on one course

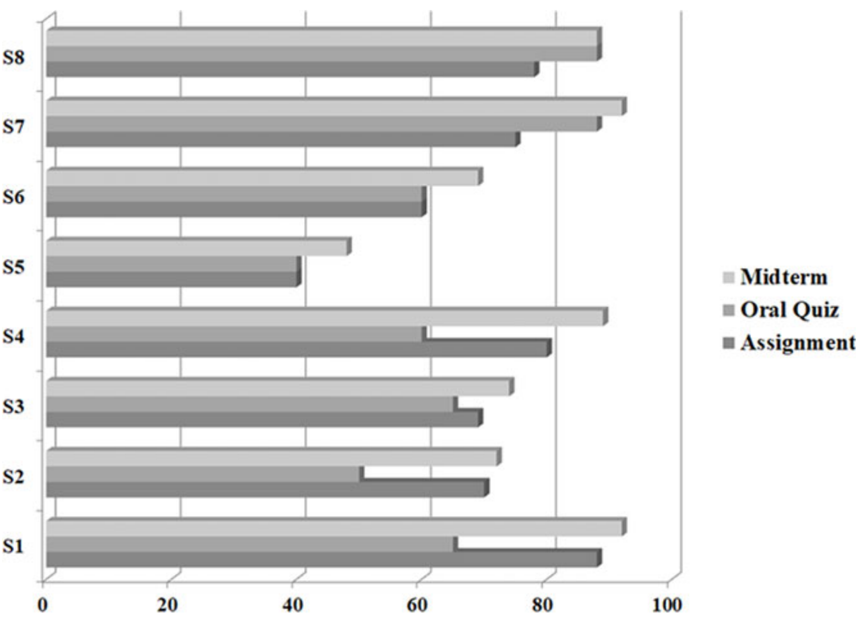


Table 11
First course: Average (Avg), minimum (Min), and maximum (Max) grades over 100

Measurement	FA1	FA2	SA1	FA3	FA4	SA2
Avg	52.51	61.07	68.23	66.44	69.62	73.33
Min	28	2	20	30	40	40
Max	80	82	92	100	90	98

Table 12
Second course: Average (Avg), minimum (Min), and maximum (Max) grades over 100

Measurement	FA1	FA2	SA1	FA3	FA4	SA2
Avg	50.3	62.28	69.12	68.02	70.44	73.21
Min	32	35	40	50	55	58
Max	78	95	92	88	90	32

Table 13
Third course: Average (Avg), minimum (Min), and maximum (Max) grades over 100

Measurement	FA1	FA2	SA1	FA3	FA4	SA2
Avg	55.61	58.5	63.9	62.58	64.01	70.22
Min	40	60	52	62	58	62
Max	85	88	92	92	95	89

Table 14
Fourth course: Average (Avg), minimum (Min), and maximum (Max) grades over 100

Measurement	FA1	FA2	SA1	FA3	FA4	SA2
Avg	52.34	55.68	63.9	64.58	64.01	63.22
Min	33	43	44	55	58	56
Max	84	90	91	88	92	89

of the topic studied than a traditional method. Thus, the results of the proposed approach and a traditional evaluation technique for the first course are compared, as illustrated in Figure 5.

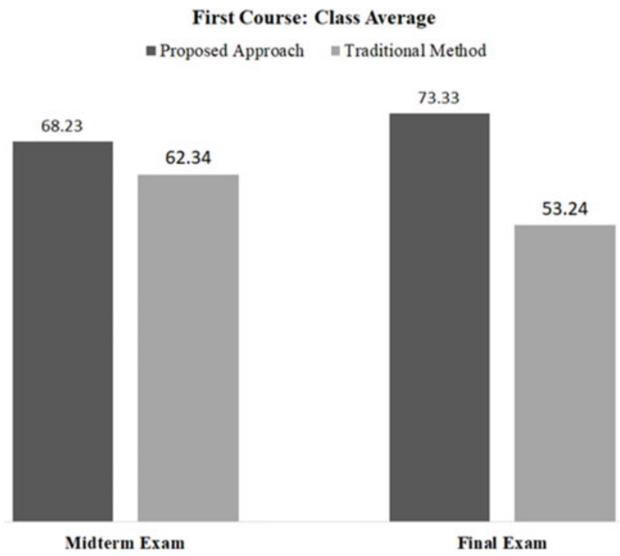
In the traditional technique followed in a different academic semester, the educator examined students through four activities: two assignments, one midterm, and one final. He gave the students their grades without any feedback about their performance or evaluation. In addition, in the traditional technique, the educator cannot modify the course's content or methodology. They are fixed from the beginning of the course. According to Figure 5, students' performance based on the proposed method is more remarkable.

Furthermore, the final exam results are better in the proposed method due to the improvement made by the educator to the dynamic teaching methodology. In addition, the feedback sent to the students during the learning journey helps them improve their weak points.

6. Conclusion

The authors of this paper proposed a new method for evaluating students during e-learning. The evaluation of participants was done under three dimensions: knowledge, skills, and interactions based on

Figure 5
Comparison between the proposed approach and traditional evaluation techniques



evidence theory and data fusion technique. Synchronous sessions and different types of assessments can give students a different belief evaluation during the learning journey. These evaluations are combined using a data fusion technique based on evidence theory. Finally, an overall evaluation of all students over the three dimensions can be done using the Pignistic probability. The proposed method seems to be sufficient to deal with more dimensions. In addition, using formative assessments enables educators to survey students' evaluations to improve the entire teaching methodology. In addition, this method can detect the complete uncertainty about the evaluation of students during the courses. Likewise, the implementation of this method is relatively simple. Results of four online courses at the Jinan University of Lebanon show the effectiveness of this approach.

To better monitor student evaluations, more dimensions like participation and attendance should be added to the proposed approach in the future. Furthermore, given the course's reliance on virtual learning systems, the proposed approach should be applied to more courses in different majors to evaluate its performance. Moreover, more comparisons with traditional evaluations should be done. Furthermore, this method will be extended to assist educators in detecting cheating on summative assessments.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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