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Task and user-based Entropy-Rank Sum-TPOP integration proposal for usability evaluation of web applications

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ABSTRACT

The present study aims to determine the importance weights of the subjective and objective usability criteria based on task and user by considering these criteria simultaneously in the usability analysis of web applications. In this context, by proposing a Multi-criteria Decision Making approach including Entropy-Rank Sum (RS) – Technique of Precise Order Preference (TPOP) integration, the Multi-Dimensional Usability Analysis (MDUA) approach was advanced. The proposed analysis approach was applied on MOODLE software selected as a sample web application. The objective criteria in the sample application were measured using the Morae V3 program as a result of users performing their predefined tasks, and the subjective criteria were evaluated by determining the importance orders of the criteria for each user that affect the users' satisfaction. Subsequently, objective criteria weights were calculated by the Entropy method on task basis, and subjective criteria weights were computed by the RS method on user basis. In the last stage, the weights of the objective criteria and the weights of the subjective criteria that change according to the user are combined separately using the TPOP method. Thus, the most important subjective and objective criteria for improving the usability of MOODLE LMS were determined.

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1. Introduction

According to the latest “Digital 2021” report, it is estimated that there are 4.66 billion internet users worldwide. The time users spend on the internet is increasing every year. With the impact of the COVID-19 pandemic, which is a global crisis, the time spent on the internet in 2020 increased by 4% compared to the previous year and was determined as 6 h and 50 min on average. The pandemic has interrupted the education of nearly a billion people and online education applications over the internet have become savior tools. Again, in the future projection section of the same report, it is emphasized that due to the continuing impact of the pandemic, more emphasis is expected on online education applications, and competition will increase as industry giants such as Google and Facebook invest in online education applications (DataReportal, 2021). In a competitive environment, the issue of usability has

become even more important so that students and educators can access, use and be satisfied with online education applications via their web applications effectively and efficiently. As with other applications, the higher the usability levels of online education applications, the greater the commercial potential of the application (Juristo, 2007).

Generally, along with the search for the usability of web applications, studies on online education applications, in particular, have increased in recent years. In the study, subjective and objective usability criteria for the usability analysis of the Modular Object-Oriented Dynamic Learning Environment (Moodle), which is one of the popular online education applications and which is in the category of Learning Management System (LMS) (Cole and Foster, 2008), were discussed together and Multi-Criteria Decision Making (MCDM) methods were used in the analysis. In this context, a new Multi-Dimensional Usability Analysis (MDUA) approach has been developed.

Considering the studies evaluating the usability of Moodle LMS in the literature, it is seen that those survey methods or user tests have been applied. Again, in these studies, it was determined that the results were tried to be obtained from the perspective of students and instructors with different numbers of participants. However, no study was found in which the subjective and objective usability criteria were considered simultaneously in the usability

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analysis. Usability is not a simple phenomenon that can be evaluated only through surveys or user tests. It is important to consider the performance levels of the users along with their thoughts related to web applications' usability. Additionally, it has been determined that MCDM methods are not sufficiently utilized in the literature for the usability evaluation of Moodle LMS. In the literature, MCDM methods have been applied for usability analysis by considering a limited number of criteria. However, both objective and subjective criteria are important in usability analysis. Therefore, studies using MCDM for usability analysis are considered insufficient in the literature. Data obtained from user tests or satisfaction surveys can be adapted to MCDM methods.

Additionally, especially in user tests, it is seen that user performances change as the tasks performed change. This variability should also be reflected in the importance weights of the usability criteria. In this sense, it will be beneficial to weight the usability criteria on a task basis and to compare the web applications according to their usability levels. From the viewpoint of user satisfaction regarding web applications, it should not be forgotten that the usability criteria affecting the satisfaction level of each user may have different priorities. For this reason, it is necessary to evaluate the usability of the web applications by considering the priority of each user regarding the criteria affecting satisfaction, instead of trying to reach a collective result as in survey applications. In line with all these needs, it is considered that MCDM methods can be beneficial for the usability analysis of web applications, but the methods in question should be developed in line with these needs.

In this context, unlike usability analysis conducted in the literature so far, this study proposes a new MDUA approach for the usability analysis of Moodle LMS by simultaneously considering both objective and subjective usability criteria. Objective criteria were measured by the Morae V3 program by performing predefined tasks on Moodle LMS by users. Subjective criteria were evaluated as a result of the users ranking these criteria from important to unimportant. To increase the usability of Moodle LMS, the most important subjective and objective criteria were determined. In this context, the importance weights of the objective criteria were computed on a task basis, while the importance weights of the subjective criteria were identified on user basis. In real-life user tests, as the tasks performed by the participants differ, the values of measurable usability criteria (objective criteria) also differ. For example, the task completion time criterion may be short for one task and long for another task. Additionally, any user can complete the same task in a longer time, while the other user can complete it in less time. The tasks are chosen among the activities that the participants perform the most, and it is tried to ensure that the difficulty levels are similar for each task. However, the variability in the measurable criteria values that occur in different tasks shows that the user has problems in reaching the goal on the web application. In summary, as the tasks performed differ, the importance weights of the measurable usability criteria on a task basis also change. There is no other study in the literature that determines the criteria importance weights based on task and converts this into suggestions for improvement of the web application's usability. When viewed in terms of subjective criteria, the evaluations regarding these criteria vary from user to user. Each user reflects his or her own opinion on the importance of subjective criteria. For example, while the complexity of the web application is the most important criterion for one user, this criterion may be at the last for another user. In the literature, no study has been found that determines the importance weights of subjective usability criteria on a user basis. In this context, the weights of the objective usability criteria were computed by using the Entropy method, and the weights of the subjective usability criteria were calculated based on the user's thoughts, using the Rank Sum (RS) method. The

entropy method considers variability for objective criteria values (users' performance levels) for each task for different web applications. According to the Entropy method, if the users' performance levels for each task for each criterion for the related website differ, the relevant criterion should be considered in ordering the related web applications. Because such criteria facilitate the comparison of web applications and therefore their importance weights should be higher than the others for the Entropy method. If the performance values of users for the web applications for any objective criterion are close to each other, the relevant criterion does not have a distinctive feature in the ranking of the web applications in terms of usability. It is considered that the performance values for the web applications from the relevant criteria contain uncertainty. For this reason, the importance weights are lower than the others for the Entropy method. RS is a ranking-based weighting method. RS considers users' priorities for subjective criteria and RS transforms subjective criteria rankings into criteria weights. It can reflect users' opinions easily in criteria weights (Malczewski, 1999).

Since the weights of the objective criteria based on the task and the weights of the subjective criteria based on the user will differ, uncertainty arises in terms of importance weights. To model this uncertainty and to reach the final weights of both subjective and objective criteria, the Technique of Precise Order Preference (TPOP) method was implemented in the study. Although the TPOP method is relatively new, it has only been used in the literature to combine alternative rankings obtained from different MCDM methods. In this study, the TPOP method was applied for the first time in combining different criteria weights. TPOP considers an extended entropy computation for the results of different MCDM methods. In this study, TPOP focuses on entropy values for different objective and subjective criteria weights. In this study, objective criteria weights differ for different tasks and subjective criteria weights differ for each user. For this reason, TPOP was used for objective and subjective criteria separately. TPOP combined different objective criteria weights considering all tasks and different subjective criteria weights considering all users. Because the usability of web applications is examined in this study in two dimensions by considering objective and subjective criteria, the TPOP method was applied separately for both criteria dimensions.

Additionally, for the first time in this study, analyses were conducted for objective criteria using a three-dimensional initial decision matrix. The traditional initial decision matrix in MCDM methodologies has two dimensions consisting of alternatives and criteria. The proposed three-dimensional initial decision matrix in this study includes tasks, users, and objective usability criteria, and the Entropy method was performed for this three-dimensional initial decision matrix at first. In this respect, the study is original research that can contribute to the MCDM and web application's usability literature.

The reason why Entropy, RS, and TPOP were applied together as three different MCDM methods in the study is to show that the common results can be determined by the different methods. In the literature, there are many studies including more than one method to analyze usability for web applications. However, only the criteria weights or websites' rankings obtained from different methods are discussed in the conclusion sections of these studies. However, a single result can be obtained by combining the criteria weights or web applications' rankings obtained from different methods, and the effect of the different methods used on the final result can be determined. In this study, TPOP provides this flexibility. More than one MCDM method can be performed for usability analysis and the results of these methods can be combined via applying TPOP.

The rest of the study was organized as follows. In the second part of the study, related studies for Moodle LMS's usability evalu-

Table 1
Usability studies on Moodle.

Studies	Method	Participants
(Graf and List, 2002)	Survey	1 (Expert)
(Melton, 2006)	Task base	4 (Student)
(Kakasevski et al., 2008)	Survey	84 (Student)
(Kirner et al., 2008)	Survey	30 (Teacher)
(Tee et al., 2013)	Interview	5 (Student) 5 (Teacher)
(Ivanović et al., 2013)	Survey	266 (Student) 43 (Teacher)
(Unal and Unal, 2014)	Survey	135 (Student)
(Senol et al., 2014)	Survey	413 (Student)
(Farmanesh et al., 2016)	Survey	12 (Student)
(Hasan, 2018)	Survey	155 (Student)
(Suner, 2018)	Survey	19 (Student)
(Aliyu et al., 2019)	Survey	137 (Student)
(Yorulmaz and Can, 2020)	Task base	18 (Student)
(Başaran et al., 2020)	Survey	2 (Expert)

ation and usability evaluation with MCDM are debated. In the third section, the proposed approach and its application for Moodle LMS are explained. In the fourth section, the results are mentioned, and in the fifth section, the proposed approach is discussed and research ideas that can be conducted in the future periods are included.

2. Related studies

With the widespread use of the web, the quantitative evaluation of web applications has also become a research topic. Pioneering studies such as WebQEM (Web Quality Evaluation Method) have emerged since the late 1990s. In the evaluation of web applications, software quality standards were followed and quality characteristics were standardized as usability, functionality, reliability, efficiency, portability, and maintainability (Olsina and Rossi, 2002). Some studies try measuring web applications in a way that includes all quality characteristics (Olsina et al., 2008). This study focuses only on the usability of web applications. Usability, one of the important quality characteristics, is defined as “the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use” in the ISO9241-11 standard (Bevan, 2001). In the literature, there are many studies on the usability evaluation of web applications. In this study, only usability studies conducted on the Moodle application or evaluated using MCDM methods were examined.

Table 2
Usability studies that implement MCDM approaches.

Studies	Method	Participants
(Tsai et al., 2011)	DEMATEL, ANP, VIKOR	16 (Expert)
(Storto, 2013)	DEA, Stepwise Regression Method	35 (Undergraduate Student)
(Cebi, 2013)	Delphi, DEMATEL	5 (Expert)
(Akincilar and Dagdeviren, 2014).	AHP, PROMETHEE	Academics, practitioners, and hotel's managers
(Nagpal et al., 2015a)	FAHP	1 (Expert)
(Nagpal et al., 2015b)	FAHP and FTOPSIS	3 (Website Designer)
(Nagpal et al., 2016)	FAHP, Entropy	100 (Undergraduate Student) 50 (Postgraduate Student)
(Kang et al., 2016).	Fuzzy Hierarchical TOPSIS and E-S-QUAL (an extended form of SERVQUAL).	3 (Expert)
(Ilbahar and Cebi, 2017).	Fuzzy KANO	147 (Student, Employee)
(Adepoju et al., 2019).	FAHP, Artificial Neural Network	–
(Chmielarz and Zborowski, 2018).	TOPSIS	721 (Student)
(Pamučar et al., 2018)	IRMABAC, IR-AHP	9 (Expert)
(Ostovare and Shahraki, 2019)	Delphi, Shannon Entropy, PROMETHEE, GAIA	–
(Khan et al., 2019)	PIV	–
(Liang et al., 2019)	TODIM, VIKOR methods with Pythagorean Fuzzy Entropy and Cross-Entropy methods	–
(Muhammad et al., 2021)	FAHP	176 (Students, Staff)
(Abbaspoor et al., 2021)	DEMATEL, ANP	–

ity studies conducted on the Moodle application or evaluated using MCDM methods were examined.

When literature was reviewed, it was seen that there are many usability evaluation studies on Moodle, an open-source, popular online education application. The summary of these studies was given in Table 1.

As seen from the studies focused on Moodle LMS usability in Table 1, there is no study using MCDM approaches to analyze this topic. However, MCDM approaches can provide many advantages for usability analysis in terms of determining usability criteria importance, ranking different items (such as areas, products, websites) in terms of their usability levels, etc. By using MCDM approaches multi-dimensional usability analysis can be performed.

When the literature is examined in terms of studies in which MCDM methods are used in the usability analysis of websites, it has been determined that studies on this subject have increased in recent years and this subject is the focus of attention of researchers. The MCDM methods found in the reviewed studies are: Decision-Making Trial and Evaluation Laboratory (DEMATEL), Analytic Network Process (ANP), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Data Envelopment Analysis (DEA), Delphi, Analytical Hierarchy Process (AHP) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), Fuzzy AHP, Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS), TODIM (a Portuguese acronym meaning Interactive MCDM), Interval Rough (IR) AHP, Multi Attributive Border Approximation Area Comparison (MABAC), Proximity Indexed Value (PIV), Geometrical Analysis for Interactive Aid (GAIA). These studies are summarized below in Table 2.

As seen from Table 2, the studies focused on usability evaluation with MCDM use a predetermined weighting approach to order criteria and a ranking approach to compare websites. However, in none of the aforementioned studies, user performances were measured according to task-based usability criteria, and the results obtained from the questionnaires applied for the satisfaction levels of the users were not reflected.

3. Material and methods

3.1. Participants and using tools

In the study, a total of 18 participants, consisting of the second, third, and fourth-year students studying in the industrial engineer-

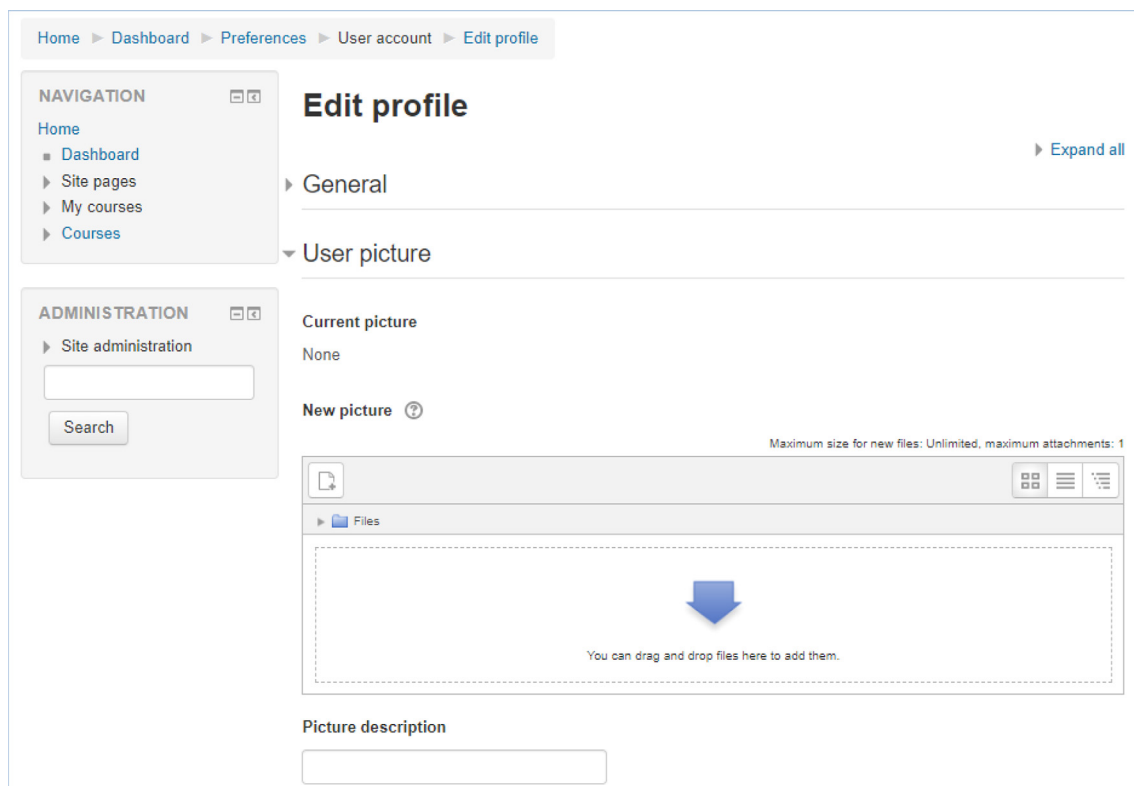


Fig. 1. Task 1: Changing the profile photo in Moodle.

ing department of a private university, were evaluated as the end-user group. Among the participants, 5 (28%) are male and 13 (72%) are female students. According to Nielsen (1993), 5 participants are sufficient to perform usability analysis and these participants can identify 75% of system errors. The students were selected from the second (5 people), third (6 people), and fourth (7 people) grades, who were not first-year students, had used the system for at least one year. Again, according to Nielsen (1993), to obtain reliable results at the level of approximately 90% in usability analysis; 13 participants are sufficient to evaluate the system. When

the number of participants increases, the number of detected errors does not significantly increase (Nielsen, 1993).

For the participants to test the usability of Moodle LMS more precisely, the system features that students use the most were observed and the tasks most representative of these features were defined. According to Nielsen (1993), to analyze the usability of software, the tasks to be performed must be chosen from among the activities mostly performed by the users (Nielsen, 1993). In the study, five different tasks were defined for students to perform. These tasks were determined as changing the profile photo (Fig. 1),

Bil124 - Advanced Programming Practices: View: User report

[Home](#)
[My courses](#)
[Bil124 - Advanced Programming Practices](#)
[Grade administration](#)
[User report](#)

User report - Bil124 - Advanced Programming Practices

[Overview report](#)
[User report](#)

Grade item	Grade	Range	Rank	Average	Contribution to course total
Bil124 - Advanced Programming Practices					
Quiz-1	60.00	0-100	2/10	35.71	15.00 %
Quiz-2	61.00	0-100	2/10	35.29	15.25 %
Quiz-3	45.00	0-100	1/10	22.14	11.25 %
Quiz-4	75.00	0-100	1/10	75.00	18.75 %

Fig. 2. Task 2: Seeing the grades in Moodle.

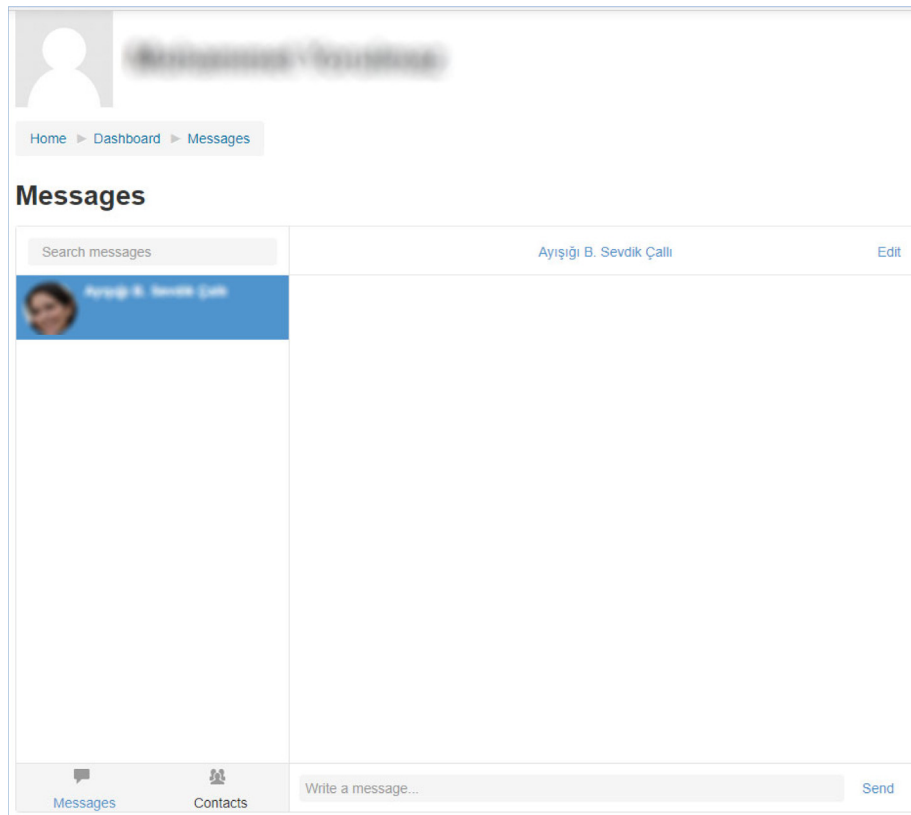


Fig. 3. Task 5: Sending a message to the instructor in Moodle.

downloading the lecture notes, uploading a file to the system, seeing the grades (Fig. 2), and sending a message to the instructor (Fig. 3), respectively. The link chain (Home > Dashboard etc.) at the top of the page of the sample screenshots gives an idea about the processing density. In the sample screenshots (Figs. 1–3), the user and author identities are blurred.

As hardware within the scope of the analysis; a computer with an Intel i7 processor, 8 GB of RAM, a Windows 10 operating system, and a microphone was used. Additionally, Moodle LMS 3.0 (version 3.3.4), Morae V3, Microsoft Edge, and MS Excel software were used as software. Before starting the analysis, the participant was informed about the purpose and content of the experiment. After the briefing, the experiment was started with the Morae software. During the experiment, the tasks are displayed as a window on the screen, one by one, thanks to the Morae software. After each participant completed five different tasks, they filled out the satisfaction questionnaire via Morae. Morae V3 package program used for tests, by recording user actions (duration, sound, screen, mouse movements); It can automatically provide standard measurement (such as mouse clicks, mouse movement distance, task time) data.

3.2. The proposed MDUA approach and its application

The proposed MDUA approach consists of six phases. The first phase is the identification of components for usability evaluation. The second phase is to measure objective usability criteria based on tasks by performing usability tests with Morae V3. The third phase is the determination of the weights of the objective usability criteria based on tasks using the Entropy method. The fourth phase is to combine the objective criteria weights obtained for different tasks with the TPOP method. The fifth phase is to obtain the weights of the subjective usability criteria on a user basis using RS. The sixth, the last phase, is to combine the subjective criteria

weights obtained for different users with the TPOP method. In the following sections, the implementation phases of the proposed MDUA for OCG and SCG are explained in detail and Fig. 4 shows the application steps of the proposed MDUA for these criteria groups.

3.2.1. Phase 1: Determining the components for usability evaluation

In this phase, the components of the usability assessment are determined as the participants, the usability criteria and the tasks to be performed by the participants. Usability criteria are considered performance criteria for websites, and in the study these criteria are divided into two as objective criteria group (OCG) and subjective criteria group (SCG). The values of the objective criteria group according to the users were obtained by using the Morae V3 program. The evaluations of the SCG were obtained as a result of the participants ranking the criteria in this group from the most important to the least important. In this study, $U_v; v = 1, \dots, V$ presents the users, $T_i; i = 1, \dots, I$ shows the tasks, $OC_l; l = 1, \dots, L$ define the objective criteria, $SC_p; p = 1, \dots, P$ presents the subjective criteria.

OCG includes mental workload (score) (OC_1), task completion time (second) (OC_2), the number of mouse clicks (OC_3), the time between two data entries (second) (OC_4), mouse movement distance (pixel) (OC_5). SCG consist of the level of willingness to use the system again (SC_1), the level of finding the system complex (SC_2), the level of finding the system easy (SC_3), the level of need for technical support while using the system (SC_4), the level of feeling safe while using the system (SC_5), the level of need for prior knowledge when using the system (SC_6), the level of good integration with the system (SC_7), the level of the inconsistency of the system (SC_8), system learning rate level (SC_9), the level of the cumbersomeness of the system (SC_{10}).

While the OCG determines the effectiveness of the system, the SCG consists of criteria important to user satisfaction. Criteria in

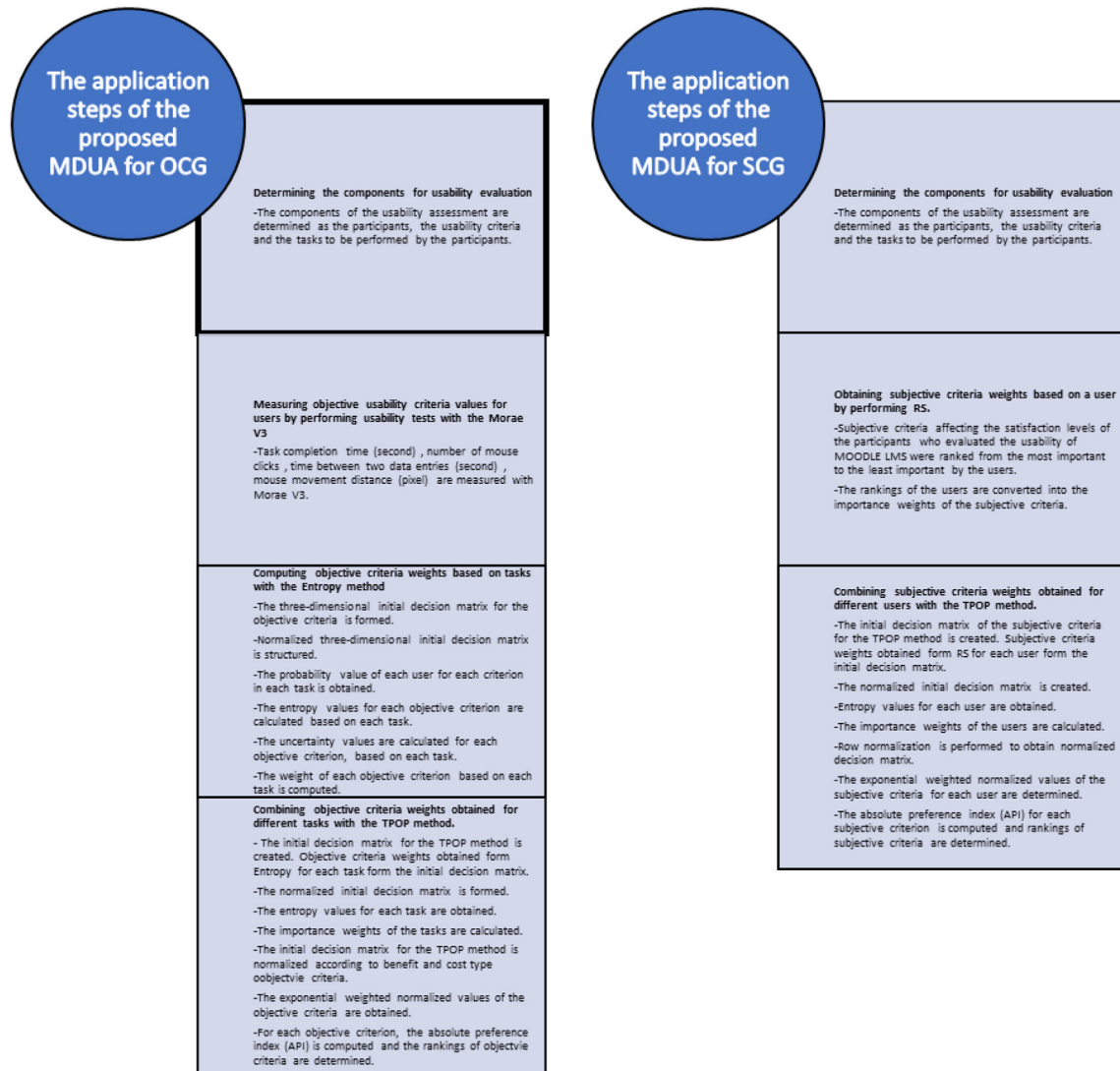


Fig. 4. The application steps of the proposed MDUA for OCG and SCG.

OCG were measured by the Morae V3 program except for the mental workload criterion. Mental workload criterion was measured by implementing The NASA Task Load Index (NASA TLX) scale. The NASA Task Load Index (NASA TLX) scale was applied to the participants to measure their mental workload after completing the five tasks. NASA TLX is a subjective, validated, and reliable, multidimensional assessment tool that rates mental (perceived) workload to evaluate the effectiveness or performance of a mission, system, or team. NASA TLX assesses mental workload in six sub-dimensions: mental requirements, physical requirements, time pressure, performance level, sense of failure, and effort level for the task performed. The scale consists of two parts. In the first part, six sub-dimensions are scored between 0 and 100 according to the task performed. In the second part, the six sub-dimensions are compared by considering the task performed. Here, a total of 15 pairwise comparisons are made. If each sub-dimension outweighs the other sub-dimension with which it is compared, this number is divided by 15, and weight is calculated for the relevant sub-dimension. Then, this weight is multiplied by the score value obtained from the first section to obtain a weighted score for each sub-dimension. The workload score is obtained by summing the weighted scores calculated for all sub-dimensions (Hart, 2006).

The SCG was created using the System Usability Survey (SUS). SUS is a survey used to evaluate the satisfaction dimension by measuring the success percentage of the web application users. SUS takes into account some statements about the usability of websites and uses a scale of 1–5 (1: Strongly disagree and 5: Strongly agree). The SUS is a simple, ten-item scale that covers subjective assessments of usability. SUS covers various aspects of system availability, such as support need, training need, and complexity, therefore it has a high level of validity to measure the usability of a system. (Bangor et al., 2008).

3.2.2. Phase 2: Measuring objective usability criteria values for users by performing usability tests with the Morae V3

At this stage, objective usability criteria were measured based on tasks with Morae V3 software. Measurements were made in the ergonomics and work-study laboratory of the engineering faculty of a university in Ankara-Turkey. Measurements were performed in a laboratory environment with the test observer and participant. Each participant was individually taken to the laboratory to perform the test, and a test observer was present in the laboratory during the test. The Morae V3 package program used for measurements can provide objective measurement data (such as

mouse clicks, mouse movement distance, and task duration) by recording user actions. Before starting the measurement, the participants were informed about the purpose and content of the test, and then the test was started with Morae V3. During the test, the tasks were viewed one by one on the screen by the participants as a window. As each user completed each task, objective criteria values were measured and recorded by Morae V3 on a task and user basis. These objective criteria values belong to criteria in OCG.

3.2.3. Phase 3: Computing objective criteria weights based on tasks with the Entropy method

In this stage, weights of the objective usability criteria based on tasks are computed with the Entropy method. First, the three-dimensional initial decision matrix for the objective criteria, defined as $[X]$, is formed as in Table 3. $[X]$ indicates the performance level of each user for each objective criterion while performing each task as three dimensions. Each element of $[X]$ is expressed as x_{vli} , $v = 1, \dots, V$; $i = 1, \dots, I$; $l = 1, \dots, L$. According to this, x_{vli} presents the performance level of v . user for i . task-related to l . objective criterion. For example, x_{111} shows when the first user performs the first task, the mental workload perceived by the related user is 90. This value was determined by applying the NASA TLX scale explained above.

After forming $[X]$, the normalization process is implemented as the second step. In this way, normalized three-dimensional initial decision matrix is denoted as $[N]$ is structured for OCG. The elements of $[N]$ are indicated as n_{vli} , $v = 1, \dots, V$; $i = 1, \dots, I$; $l = 1, \dots, L$ and calculated as in Eq. 1. n_{vli} shows the normalized performance level of v th user for i th task-related to l th objective criterion.

$$n_{vli} = \frac{\min_{\forall v} \{x_{vli}\}}{x_{vli}}, v = 1, \dots, V; i = 1, \dots, I; l = 1, \dots, L \quad (1)$$

where, $\min_{\forall v} \{x_{vli}\}$ presents the minimum normalized performance level for i th task-related to l th objective criterion among all users.

For the $x_{111} = 90$, n_{111} was computed as below by using Eq. 1.

$$n_{111} = \frac{\min_{\forall v} \{x_{v11}\}}{x_{111}}$$

$$n_{111} = \frac{70}{90}$$

$$n_{111} = 0.78$$

In the third step, the probability value (p_{vli}) of each user for each criterion in each task is obtained as in Eq. 2.

$$p_{vli} = \frac{n_{vli}}{\sum_{j=1}^V n_{jli}}; v = 1, \dots, V, i = 1, \dots, I, l = 1, \dots, L \quad (2)$$

In the fourth step, as given in Table 4, the entropy (e_{li}) values for each objective criterion are calculated based on each task, as in Eq. 3.

$$e_{li} = -k \sum_{v=1}^V p_{vli} \ln(p_{vli}), i = 1, \dots, I, l = 1, \dots, L \quad (3)$$

Here, k ; is the entropy coefficient and it is calculated as in Eq. 4.

$$k = -\frac{1}{\ln(V)} \quad (4)$$

Table 3
Three-dimensional initial decision matrix for OCG.

U_v	T_1	T_2	T_3	T_4	T_5	OC_1	OC_2	OC_3	OC_4	OC_5
U_1	x_{111}	x_{121}	x_{131}	x_{141}	x_{151}	90	88	85	87	85
U_2	x_{211}	x_{221}	x_{231}	x_{241}	x_{251}	70	68	65	67	65
U_3	x_{311}	x_{321}	x_{331}	x_{341}	x_{351}	82	80	78	81	79
U_4	x_{411}	x_{421}	x_{431}	x_{441}	x_{451}	75	73	71	74	72
U_5	x_{511}	x_{521}	x_{531}	x_{541}	x_{551}	88	86	84	87	85
U_6	x_{611}	x_{621}	x_{631}	x_{641}	x_{651}	72	70	68	71	69
U_7	x_{711}	x_{721}	x_{731}	x_{741}	x_{751}	85	83	81	84	82
U_8	x_{811}	x_{821}	x_{831}	x_{841}	x_{851}	78	76	74	77	75
U_9	x_{911}	x_{921}	x_{931}	x_{941}	x_{951}	81	79	77	80	78
U_{10}	x_{1011}	x_{1021}	x_{1031}	x_{1041}	x_{1051}	74	72	70	73	71
U_{11}	x_{1111}	x_{1121}	x_{1131}	x_{1141}	x_{1151}	89	87	85	88	86
U_{12}	x_{1211}	x_{1221}	x_{1231}	x_{1241}	x_{1251}	76	74	72	75	73
U_{13}	x_{1311}	x_{1321}	x_{1331}	x_{1341}	x_{1351}	83	81	79	82	80
U_{14}	x_{1411}	x_{1421}	x_{1431}	x_{1441}	x_{1451}	79	77	75	78	76
U_{15}	x_{1511}	x_{1521}	x_{1531}	x_{1541}	x_{1551}	86	84	82	85	83
U_{16}	x_{1611}	x_{1621}	x_{1631}	x_{1641}	x_{1651}	73	71	69	72	70
U_{17}	x_{1711}	x_{1721}	x_{1731}	x_{1741}	x_{1751}	80	78	76	79	77
U_{18}	x_{1811}	x_{1821}	x_{1831}	x_{1841}	x_{1851}	77	75	73	76	74
$\min_{\forall v} \{x_{vli}\}$	70	68	65	67	65	90	88	85	87	85

Table 5
Uncertainty values for OCG.

T_1					T_2					T_3					T_4					T_5				
OC_1	OC_2	OC_3	OC_4	OC_5	OC_1	OC_2	OC_3	OC_4	OC_5	OC_1	OC_2	OC_3	OC_4	OC_5	OC_1	OC_2	OC_3	OC_4	OC_5	OC_1	OC_2	OC_3	OC_4	OC_5
d_{1_1}	d_{1_2}	d_{1_3}	d_{1_4}	d_{1_5}	d_{1_1}	d_{1_2}	d_{1_3}	d_{1_4}	d_{1_5}	d_{1_1}	d_{1_2}	d_{1_3}	d_{1_4}	d_{1_5}	d_{1_1}	d_{1_2}	d_{1_3}	d_{1_4}	d_{1_5}	d_{1_1}	d_{1_2}	d_{1_3}	d_{1_4}	d_{1_5}
0.001	0.023	0.020	0.022	0.027	0.070	0.042	0.091	0.024	0.054	0.001	0.016	0.023	0.034	0.020	0.001	0.014	0.029	0.011	0.013	0.001	0.016	0.008	0.010	0.027
$\sum_{i=1}^5 d_{1_i}$				0.093	$\sum_{i=1}^5 d_{2_i}$				0.282	$\sum_{i=1}^L d_{3_i}$				0.094	$\sum_{i=1}^L d_{4_i}$				0.068	$\sum_{i=1}^L d_{5_i}$				0.062

Table 6
Importance weights of objective criteria for each task.

T_1					T_2					T_3					T_4					T_5				
OC_1	OC_2	OC_3	OC_4	OC_5	OC_1	OC_2	OC_3	OC_4	OC_5	OC_1	OC_2	OC_3	OC_4	OC_5	OC_1	OC_2	OC_3	OC_4	OC_5	OC_1	OC_2	OC_3	OC_4	OC_5
w_{1_1}	w_{1_2}	w_{1_3}	w_{1_4}	w_{1_5}	w_{2_1}	w_{2_2}	w_{2_3}	w_{2_4}	w_{2_5}	w_{3_1}	w_{3_2}	w_{3_3}	w_{3_4}	w_{3_5}	w_{4_1}	w_{4_2}	w_{4_3}	w_{4_4}	w_{4_5}	w_{5_1}	w_{5_2}	w_{5_3}	w_{5_4}	w_{5_5}
0.012	0.245	0.218	0.234	0.291	0.247	0.149	0.324	0.087	0.193	0.008	0.169	0.247	0.367	0.209	0.013	0.207	0.424	0.158	0.198	0.016	0.254	0.135	0.165	0.431

Table 7

Initial decision matrix of objective criteria for TPOP.

OC_i	T_1 w_{1i}	T_2 w_{2i}	T_3 w_{3i}	T_4 w_{4i}	T_5 w_{5i}
OC_1	0.012	0.247	0.008	0.013	0.016
OC_2	0.245	0.149	0.169	0.207	0.254
OC_3	0.218	0.324	0.247	0.424	0.135
OC_4	0.234	0.087	0.367	0.158	0.165
OC_5	0.291	0.193	0.209	0.198	0.431
Total	1.000	1.000	1.000	1.000	1.000

$\ln(\tau_1) = \ln(0.012)$ was obtained as -4.397 . As the last implementation e_1 was calculated using Eq. 8 as 0.888.

In the fourth step, using the obtained e_i values, the uncertainty values (d_i) are calculated using Eq. 9 for each task.

$$d_i = 1 - e_i(9)$$

For example, $d_1 = 0.112$ was computed as $d_1 = 1 - 0.888$.

In the fifth step, to see the effect of each task on the usability evaluation of Moodle LMS, the importance weights (W_i) of the tasks are calculated as in Eq. 10, Eq. 11, Eq. 12, and Eq. 13.

$$s_i = \frac{d_i}{\sum_{k=1}^I d_k}, i = 1, \dots, I \quad (10)$$

$$s'_i = 1 + \sqrt{s_i} \quad (11)$$

$$S' = \sum_{i=1}^I (1 + \sqrt{s_i}) = I + \sum_{i=1}^I \sqrt{s_i} \quad (12)$$

$$W_i = \frac{s'_i}{S'} = \frac{1 + \sqrt{s_i}}{I + \sum_{i=1}^I \sqrt{s_i}}, i = 1, 2, \dots, I \quad (13)$$

For example, the computation steps of $W_1 = 0.197$ are given below.

Firstly, s_1 was computed as in Eq. (10).

$$s_1 = \frac{0.112}{0.627}$$

$$s_1 = 0.178$$

Then, s'_1 was computed by using Eq. (11) as $s'_1 = 1 + \sqrt{0.178}$; $s'_1 = 1.422$. Thirdly, S' was obtained as in Eq. 12 by the help of s_i and $I = 5$ (task number) as $S' = 5 + \sqrt{0.422 + 0.291 + 0.477 + 0.497 + 0.513}$ and $S' = 5 + \sqrt{1.909}$; $S' = 5 + 1.382$; $S' = 6.382$. Additionally, W_1 can be obtained directly without computing S' by using Eq. 13 as $W_1 = \frac{1 + \sqrt{0.178}}{5 + \sum_{i=1}^I \sqrt{1.909}}$; $W_1 = \frac{1 + 0.422}{5 + 1.382}$; $W_1 = \frac{1.422}{6.382}$; $W_1 = 0.223$.

s_i is the importance weight of each task under the uncertainty, and W_i given in Table 9 is the adjusted importance weight of each task. The uncertainty here is due to the similarity or close values of the importance weights of the objective criteria calculated for the tasks. According to the TPOP method, as the objective criteria weights for different tasks get closer to each other, it becomes difficult to determine which of the tasks performed is most effective

Table 8

Entropy values for tasks.

T_1	T_2	T_3	T_4	T_5
e_1	e_2	e_3	e_4	e_5
0.888	0.947	0.857	0.845	0.835

Table 9

Weight values for tasks.

T_1	T_2	T_3	T_4	T_5
W_1	W_2	W_3	W_4	W_5
0.223	0.202	0.231	0.235	0.237

on the usability of the website. However, as the weights of objective criteria for different tasks change, it becomes easier to distinguish the tasks from each other in terms of their importance levels. When similar criteria weights are in question, the entropy value of the relevant task also increases. An increase in the entropy value means an increase in the uncertainty in the criteria weights.

In the fifth step, $[Y]$ is normalized according to whether the objective criteria are benefit and cost types and normalized decision matrix $[F]$ is obtained as in Table 10. Here, row normalization is performed as seen in Eq. 14. In the traditional TPOP method, the MCDM methods used in the initial decision matrix are in the columns and the alternatives are in the rows. The relevant matrix contains the preference indexes of the alternatives according to the MCDM methods. Therefore, in the traditional TPOP method, the benefit and cost type normalization is conducted according to whether the MCDM methods are used to consider the lowest or highest preference index in the alternative rankings. If an MCDM method determines the alternative with the lowest preference selection index as an alternative that should be selected first, cost-type normalization is used in the normalization of the preference indexes of the relevant MCDM method. In the opposite case, benefit type normalization is applied. Since all of the objective criteria considered in the usability analysis of Moodle LMS are the criteria whose values are desired to be as low as possible, cost-type normalization was used in the study. In Eq. 14 and Eq. 15, cost and benefit type normalization operations are presented, respectively.

$$f_{il} = \frac{w_{il} - \min_{\forall u} \{w_{iu}\}}{\max_{\forall u} \{w_{iu}\} - \min_{\forall u} \{w_{iu}\}}, i = 1, 2, \dots, I, l = 1, 2, \dots, L \quad (14)$$

$$f_{il} = \frac{\max_{\forall u} \{w_{iu}\} - w_{il}}{\max_{\forall u} \{w_{iu}\} - \min_{\forall u} \{w_{iu}\}}, i = 1, 2, \dots, I, l = 1, 2, \dots, L \quad (15)$$

where, f_{il} shows the normalized weight value of l th objective criterion for i th task, $\min_{\forall u} \{w_{iu}\}$ is the minimum weight among all criteria and $\max_{\forall u} \{w_{iu}\}$ is the maximum weight among all criteria for the i th task.

In the sixth step, for each task given in Table 11, the exponential weighted normalized values of the objective criteria (h_{il}) are obtained as in Eq. 16.

$$h_{il} = \exp(f_{il} + W_i) \quad (16)$$

In the last step, for each objective criterion given in Table 12, the absolute preference index (API) (API_i) is obtained as in Eq. 17.

$$API_i = \sum_{l=1}^L h_{il}, l = 1, \dots, L \quad (17)$$

For example, $API_1 = 6.178$ was obtained by using Eq. 17 as $API_1 = 1.250 + 3.328 + 1.260 + 1.264 + 1.267$.

According to the TPOP technique, the alternative with the lowest API value is the alternative that should be preferred at the first rank. In terms of objective criteria, since the mental workload (OC_1) criterion has the lowest API value, in terms of the usability of Moodle LMS, first, the mental workload that occurs in users should be decreased.

Table 10
Normalized decision matrix for TPOP.

OC_l	T_1 f_{1_l}	T_2 f_{2_l}	T_3 f_{3_l}	T_4 f_{4_l}	T_5 f_{5_l}
OC_1	0.000	0.677	0.000	0.000	0.000
OC_2	0.835	0.261	0.450	0.471	0.573
OC_3	0.739	1.000	0.665	1.000	0.285
OC_4	0.795	0.000	1.000	0.353	0.358
OC_5	1.000	0.447	0.561	0.450	1.000

Table 11
Exponentially weighted normalized values of objective criteria for each task.

OC_l	T_1 h_{1l}	T_2 h_{2l}	T_3 h_{3l}	T_4 h_{4l}	T_5 h_{5l}
OC_1	1.250	3.328	1.260	1.264	1.267
OC_2	2.879	1.224	1.751	1.821	2.182
OC_3	2.358	3.328	2.145	3.437	1.267
OC_4	2.768	1.224	3.426	1.800	1.812
OC_5	3.397	1.224	1.550	1.271	3.445

Table 12
API and rankings for objective criteria.

OC_l	API_l	Ranking
OC_1	6.718	1
OC_2	8.269	2
OC_3	10.025	5
OC_4	8.787	4
OC_5	8.671	3

3.2.5. Phase 5: Obtaining subjective criteria weights based on a user by performing RS

At this stage, the weights of the subjective usability criteria are obtained on a per-user basis using RS. For this process, first, 10 subjective criteria affecting the satisfaction levels of the participants who evaluated the usability of Moodle LMS were ranked from the most important to the least important by the users. In this context, the most important criterion for any user is given a sequence number of “1”, and the least important criterion is given a sequence number of “10”. The rankings of 18 users are given in Table 13. Here, $r_{v(p)}$ presents the rank of p . the subjective criterion for v . user.

Table 13
Ranking of subjective criteria according to users.

U_v	SC_1 $r_{v(1)}$	SC_2 $r_{v(2)}$	SC_3 $r_{v(3)}$	SC_4 $r_{v(4)}$	SC_5 $r_{v(5)}$	SC_6 $r_{v(6)}$	SC_7 $r_{v(7)}$	SC_8 $r_{v(8)}$	SC_9 $r_{v(9)}$	SC_{10} $r_{v(10)}$
U_1	1	2	3	4	6	8	5	9	10	7
U_2	8	9	5	6	1	4	3	2	7	10
U_3	2	5	9	4	3	7	10	6	8	1
U_4	1	8	9	2	7	3	6	5	4	10
U_5	10	8	6	7	9	5	4	2	3	1
U_6	10	9	8	6	3	5	4	1	2	7
U_7	10	6	9	3	2	4	5	7	1	8
U_8	1	3	8	7	2	5	9	10	6	4
U_9	7	3	5	10	8	4	9	1	6	2
U_{10}	1	2	3	9	7	5	8	4	6	10
U_{11}	3	5	8	9	2	7	4	6	10	1
U_{12}	2	1	3	4	9	8	7	10	5	6
U_{13}	6	8	7	5	4	3	2	10	1	9
U_{14}	6	9	7	2	1	10	3	5	4	8
U_{15}	8	9	4	3	5	10	2	1	6	7
U_{16}	5	10	8	9	1	3	4	6	7	2
U_{17}	3	8	2	1	10	9	7	6	4	5
U_{18}	2	8	7	3	6	4	9	10	1	5

After obtaining the rankings of the users for the subjective criteria, the RS method is applied using Eq. 18 and the rankings of the users are converted into the importance weights of the subjective criteria. Here, w_{vp} given in Table 14 represents the weight of p th the subjective criterion for v th user. $r_{v(p)}$ presents the rank of p th subjective criterion for the v th user.

$$w_{vp} = \frac{P - r_{v(p)} + 1}{\sum_{j=1}^V (P - r_{j(p)} + 1)}, v = 1, 2, \dots, V; p = 1, 2, \dots, P \quad (18)$$

For example, the computation steps of w_{11} are given below by using $r_{1(1)} = 1$ and $P = 10$.

$$w_{11} = \frac{10 - 1 + 1}{112}$$

$$w_{11} = 0.089$$

3.2.6. Phase 6: Combining subjective criteria weights obtained for different users with the TPOP method

At this phase, since each of the 10 subjective criteria has different weights for each user, the TPOP method was applied to combine these different weights. The TPOP implementation was conducted as performed for objective criteria. Therefore, at this stage, the application is briefly mentioned and computation examples were not given. First, the initial decision matrix $[D]$ of the subjective criteria, which is the transpose of the matrix given in Table 14 for the TPOP method is created. $[D]$, shown in Table 15, is a matrix including the importance weights of subjective criteria according to users.

Secondly, $[D]$ is normalized using Eq. 19 and the normalized initial decision matrix $[C]$ is created. The element of $[C]$ is denoted as c_{vp} that presents the normalized weight value of p . the subjective criterion for v . user.

$$c_{vp} = \frac{w_{vp}}{\sum_{j=1}^V w_{jp}}, v = 1, \dots, V \quad (19)$$

In the third step, entropy values (e_v) for each user given in Table 16 are obtained using Eq. 20, due to the differentiation of subjective criteria weights according to the different users.

$$e_v = -\frac{1}{\ln(V)} \sum_{p=1}^P c_{vp} \ln |c_{vp}|, v = 1, \dots, V \quad (20)$$

Table 14

Weights of subjective criteria according to users based on rankings.

U_v	SC_1 w_{v1}	SC_2 w_{v2}	SC_3 w_{v3}	SC_4 w_{v4}	SC_5 w_{v5}	SC_6 w_{v6}	SC_7 w_{v7}	SC_8 w_{v8}	SC_9 w_{v9}	SC_{10} w_{v10}
U_1	0.089	0.106	0.092	0.067	0.045	0.032	0.062	0.021	0.009	0.042
U_2	0.027	0.024	0.069	0.048	0.089	0.074	0.082	0.093	0.037	0.011
U_3	0.080	0.071	0.023	0.067	0.071	0.043	0.010	0.052	0.028	0.105
U_4	0.089	0.035	0.023	0.087	0.036	0.085	0.052	0.062	0.065	0.011
U_5	0.009	0.035	0.057	0.038	0.018	0.064	0.072	0.093	0.075	0.105
U_6	0.009	0.024	0.034	0.048	0.071	0.064	0.072	0.103	0.084	0.042
U_7	0.009	0.059	0.023	0.077	0.080	0.074	0.062	0.041	0.093	0.032
U_8	0.089	0.094	0.034	0.038	0.080	0.064	0.021	0.010	0.047	0.074
U_9	0.036	0.094	0.069	0.010	0.027	0.074	0.021	0.103	0.047	0.095
U_{10}	0.089	0.106	0.092	0.019	0.036	0.064	0.031	0.072	0.047	0.011
U_{11}	0.071	0.071	0.034	0.019	0.080	0.043	0.072	0.052	0.009	0.105
U_{12}	0.080	0.118	0.092	0.067	0.018	0.032	0.041	0.010	0.056	0.053
U_{13}	0.045	0.035	0.046	0.058	0.063	0.085	0.093	0.010	0.093	0.021
U_{14}	0.045	0.024	0.046	0.087	0.089	0.011	0.082	0.062	0.065	0.032
U_{15}	0.027	0.024	0.080	0.077	0.054	0.011	0.093	0.103	0.047	0.042
U_{16}	0.054	0.012	0.034	0.019	0.089	0.085	0.072	0.052	0.037	0.095
U_{17}	0.071	0.035	0.103	0.096	0.009	0.021	0.041	0.052	0.065	0.063
U_{18}	0.080	0.035	0.046	0.077	0.045	0.074	0.021	0.010	0.093	0.063

Table 15

Initial decision matrix of subjective criteria for TPOP.

	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}
SC_1	0.089	0.027	0.080	0.089	0.009	0.009	0.009	0.089	0.036	0.089	0.071	0.080	0.045	0.045	0.027	0.054	0.071	0.080
SC_2	0.106	0.024	0.071	0.035	0.035	0.024	0.059	0.094	0.094	0.106	0.071	0.118	0.035	0.024	0.024	0.012	0.035	0.035
SC_3	0.092	0.069	0.023	0.023	0.057	0.034	0.023	0.034	0.069	0.092	0.034	0.092	0.046	0.046	0.080	0.034	0.103	0.046
SC_4	0.067	0.048	0.067	0.087	0.038	0.048	0.077	0.038	0.010	0.019	0.019	0.067	0.058	0.087	0.077	0.019	0.096	0.077
SC_5	0.045	0.089	0.071	0.036	0.018	0.071	0.080	0.080	0.027	0.036	0.080	0.018	0.063	0.089	0.054	0.089	0.009	0.045
SC_6	0.032	0.074	0.043	0.085	0.064	0.064	0.074	0.064	0.074	0.064	0.043	0.032	0.085	0.011	0.011	0.085	0.021	0.074
SC_7	0.062	0.082	0.010	0.052	0.072	0.072	0.062	0.021	0.021	0.031	0.072	0.041	0.093	0.082	0.093	0.072	0.041	0.021
SC_8	0.021	0.093	0.052	0.062	0.093	0.103	0.041	0.010	0.103	0.072	0.052	0.010	0.010	0.062	0.103	0.052	0.052	0.010
SC_9	0.009	0.037	0.028	0.065	0.075	0.084	0.093	0.047	0.047	0.047	0.009	0.056	0.093	0.065	0.047	0.037	0.065	0.093
SC_{10}	0.042	0.011	0.105	0.011	0.105	0.042	0.032	0.074	0.095	0.011	0.105	0.053	0.021	0.032	0.042	0.095	0.063	0.063
$\sum_{p=1}^P w_{vp}$	0.565	0.554	0.550	0.544	0.567	0.552	0.551	0.552	0.575	0.566	0.557	0.567	0.549	0.542	0.557	0.549	0.558	0.545

Table 16

Entropy values for each user.

	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}
e_v	0.741	0.746	0.748	0.751	0.743	0.749	0.751	0.747	0.736	0.739	0.747	0.738	0.748	0.752	0.743	0.747	0.745	0.751

Table 17

Importance weights of users.

	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}
W_v'	0.0617	0.0616	0.0616	0.0615	0.0620	0.0607	0.0610	0.0616	0.0617	0.0632	0.0596	0.0622	0.0622	0.0621	0.0622	0.0604	0.0616	0.0615

In the fourth step, using the obtained e_v values, the uncertainty values (d_v) are calculated using Eq. 21 for each user.

$$d_v = 1 - e_v, v = 1, \dots, V \quad (21)$$

In the fifth step, to see the effect of each user on the usability evaluation of Moodle LMS, the importance weights (W_v) of the users are calculated as in Eq. 22, Eq. 23, Eq. 24, and Eq. 25, which are shown in Table 17.

$$s_v = \frac{d_v}{\sum_{j=1}^V d_j}, v = 1, \dots, V \quad (22)$$

$$s_v' = 1 + \sqrt{s_v} \quad (23)$$

$$S'' = \sum_{v=1}^V (1 + \sqrt{s_v}) = V + \sum_{v=1}^V \sqrt{s_v} \quad (24)$$

$$W_v' = \frac{s_v'}{S''} = \frac{1 + \sqrt{s_v}}{V + \sum_{j=1}^V \sqrt{s_j}}, v = 1, 2, \dots, V \quad (25)$$

In the sixth step, row normalization is performed for $[D]$ to obtain normalized decision matrix $[U]$ as in Table 18 using Eq. 26 or Eq. 27, depending on whether the subjective criteria are cost and benefit types, respectively. In this study, $SC_1, SC_3, SC_5, SC_7, SC_9$ are benefit type criteria while $SC_2, SC_4, SC_6, SC_8, SC_{10}$ are cost type criteria.

Table 18

Normalized decision matrix.

	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}
SC ₁	0.000	0.778	0.111	0.000	1.000	1.000	1.000	0.000	0.667	0.000	0.222	0.111	0.556	0.556	0.778	0.444	0.222	0.111
SC ₂	0.889	0.111	0.556	0.222	0.222	0.111	0.444	0.778	0.778	0.889	0.556	1.000	0.222	0.111	0.111	0.000	0.222	0.222
SC ₃	0.143	0.429	1.000	1.000	0.571	0.857	1.000	0.857	0.429	0.143	0.857	0.143	0.714	0.714	0.286	0.857	0.000	0.714
SC ₄	0.667	0.444	0.667	0.889	0.333	0.444	0.778	0.333	0.000	0.111	0.111	0.667	0.556	0.889	0.778	0.111	1.000	0.778
SC ₅	0.556	0.000	0.222	0.667	0.889	0.222	0.111	0.111	0.778	0.667	0.111	0.889	0.333	0.000	0.444	0.000	1.000	0.556
SC ₆	0.286	0.857	0.429	1.000	0.714	0.714	0.857	0.714	0.857	0.714	0.429	0.286	1.000	0.000	0.000	1.000	0.143	0.857
SC ₇	0.375	0.125	1.000	0.500	0.250	0.250	0.375	0.875	0.875	0.750	0.250	0.625	0.000	0.125	0.000	0.250	0.625	0.875
SC ₈	0.111	0.889	0.444	0.556	0.889	1.000	0.333	0.000	1.000	0.667	0.444	0.000	0.000	0.556	1.000	0.444	0.444	0.000
SC ₉	1.000	0.667	0.778	0.333	0.222	0.111	0.000	0.556	0.556	0.556	1.000	0.444	0.000	0.333	0.556	0.667	0.333	0.000
SC ₁₀	0.333	0.000	1.000	0.000	1.000	0.333	0.222	0.667	0.889	0.000	1.000	0.444	0.111	0.222	0.333	0.889	0.556	0.556

Table 19

Exponentially weighted normalized values for subjective criteria according to users.

	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}	U_{13}	U_{14}	U_{15}	U_{16}	U_{17}	U_{18}
SC ₁	1.064	2.315	1.189	1.063	2.892	2.888	2.889	1.064	2.072	1.065	1.326	1.189	1.855	1.855	2.316	1.657	1.000	1.188
SC ₂	58.076	1.754	12.956	2.891	2.892	1.752	7.854	3.219	3.224	5.161	1.931	9.792	2.893	1.754	1.755	1.062	2.891	2.891
SC ₃	1.227	1.633	2.891	2.891	1.884	2.504	2.889	2.506	1.633	1.229	2.501	1.228	2.174	2.174	1.416	2.503	1.064	2.172
SC ₄	2.072	1.659	2.071	2.587	1.485	1.657	2.314	1.484	1.064	1.190	1.186	2.073	1.855	2.588	2.316	1.187	2.891	2.315
SC ₅	1.854	1.064	1.328	2.071	2.588	1.327	1.188	1.189	2.315	2.075	1.186	2.588	1.485	1.064	1.660	1.062	2.891	1.853
SC ₆	1.415	2.506	1.633	2.891	2.173	2.171	2.505	2.173	2.506	2.176	1.629	1.416	2.893	1.064	1.064	2.887	1.227	2.506
SC ₇	1.548	1.205	2.891	1.753	1.366	1.364	1.547	2.551	2.552	2.255	1.363	1.988	1.064	1.206	1.064	1.364	1.987	2.551
SC ₈	1.189	2.587	1.659	1.853	2.588	2.888	1.483	1.064	2.891	2.075	1.655	1.064	1.855	2.893	1.657	1.659	1.063	
SC ₉	2.891	2.072	2.315	1.484	1.329	1.187	1.063	1.854	1.854	1.857	2.885	1.660	1.064	1.485	1.855	2.069	1.484	1.063
SC ₁₀	1.485	1.064	2.891	1.063	2.892	1.483	1.327	2.071	2.587	1.065	2.885	1.660	1.189	1.329	1.485	2.584	1.854	1.853

Table 20

API values for subjective criteria.

	API _p	Rank
SC ₁	31.028	3
SC ₂	30.336	1
SC ₃	36.302	9
SC ₄	33.788	8
SC ₅	30.601	2
SC ₆	36.615	10
SC ₇	31.428	5
SC ₈	32.988	7
SC ₉	31.284	4
SC ₁₀	32.576	6

$$z_{vp} = \frac{w_{vp} - \min_{vj} \{w_{pj}\}}{\max_{vj} \{w_{pj}\} - \min_{vj} \{w_{pj}\}}, p = 1, \dots, P, v = 1, 2, \dots, V \quad (26)$$

$$z_{vp} = \frac{\max_{vj} \{w_{pj}\} - w_{vp}}{\max_{vj} \{w_{pj}\} - \min_{vj} \{w_{pj}\}}, p = 1, \dots, P, v = 1, 2, \dots, V \quad (27)$$

In the sixth step, the exponential weighted normalized values (o_{vp}) of the subjective criteria for each user in Table 19 are obtained as in Eq. 28.

$$o_{vp} = \exp(z_{vp} + W_v'), v = 1, \dots, V; p = 1, 2, \dots, P \quad (28)$$

In the last step, API (API_p) for each subjective criterion is given in Table 20 is calculated as in Eq. 29.

$$API_p = \sum_{v=1}^V o_{vp}, p = 1, 2, \dots, P \quad (29)$$

As seen in Table 20, the level of finding the web application complex (SC₂) was determined as the most important subjective criterion for the usability of Moodle LMS.

4. Discussion

In the study, a new MDUA approach is proposed by integrating Entropy, RS, and TPOP methods. Different objectives and subjective criteria were considered in the usability analysis simultaneously with the proposed MDUA approach. In the proposed MDUA, for the first time in the literature, the three-dimensional initial decision matrix was used, and the final weights of the criteria were obtained by considering the changes in the weights of usability criteria based on task and user. Additionally, the TPOP method was performed for the first time to combine different criteria weights.

According to the results obtained from the application of the proposed MDUA within the scope of the Moodle LMS usability evaluation, the most important criterion in the OCG emerged as the mental workload criterion (OC₁). This is because users want to easily reach the goals they want to achieve in Moodle LMS. In all web applications, the mental workload level of users will increase if designs are made in such a way that complex routes have to be followed for these purposes. Mental workload, also defined as cognitive workload, is the amount of mental work required for this user to reach his goal within a certain period. Mental workload emerges with the interaction between the stages that must be passed to reach the goal, the conditions in which these stages are conducted, and the skills and perceptions of the users. Accordingly, Moodle LMS must be designed in an easy-to-use manner for users with different skill levels. The second and third criteria in the OCG were determined as task completion time (OC₂) and mouse movement distance (OC₅). This order is also considered a logical order in terms of usability. The increase in mental workload in the use of Moodle LMS will lead to longer completion times of the tasks performed to achieve the goal. The longer the time, the longer the user will have to use the mouse at longer distances to reach the target. Since the change range of the mental workload criterion for tasks according to the TPOP method is higher than the other criteria, it has emerged as the criterion with the highest importance. Because the TPOP method is an entropy-

based approach, the wide range of variation means that the relevant criterion is more distinctive in terms of alternatives.

In terms of subjective criteria, it is seen that the level of finding the web application complex criterion (SC_2) emerges as the most important criterion. Accordingly, it is important for users that Moodle LMS has a simple and understandable design and ensures that the purpose is easily achieved. As can be seen, in the subjective and objective criteria groups, the criteria determined to be of the highest importance by the users overlap with each other. As the complexity of a website increases, the mental workload will increase. In the SCG, the level of feeling safe (SC_5) and the level of willingness to use again (SC_1) criteria are at the second and third importance level respectively. This order is also logical in terms of usability. The level of complexity of a website (SC_2) will also affect the level of the user feeling safe (SC_5) and willing to use it again (SC_1). When the user thinks that a website is complex, he or she thinks that he or she cannot achieve the purpose and may take wrong actions. This creates a feeling of insecurity for the user. Since the change range of the level of finding the web application complex criterion (SC_2) for users according to the TPOP method is higher than the other criteria, it has emerged as the criterion with the highest importance. Because the TPOP method is an entropy-based approach, the wide range of variation means that the relevant criterion is more distinctive in terms of alternatives.

5. Conclusion

As seen from the other usability studies conducted MCDM, this study has many differences compared to the others. First of all, this study uses real measurements for different users in terms of OCG. Secondly, the criteria prioritizations belonging to each user are considered in the analysis. Secondly, the performance levels of users for different tasks are included in the weighting criteria in OCG. Thirdly, differentiations between performance values of users for different tasks and differentiations between the rankings of criteria in SCG for different users are considered in ordering criteria. Finally, different rankings of criteria in OCG for different tasks and rankings of criteria in SCG for different users are combined to obtain a single ranking for OCG and SCG. These features have not been included in the studies in the literature in terms of website usability.

Additionally, this study has many novelties for methodological manners. TPOP was used to combine different rankings of criteria for the first time. A three-dimensional initial decision matrix was developed in this study. RS method was performed for usability at first. Both real performance values of users and criteria priorities of users were considered simultaneously for the first time.

For future studies, the importance weights of usability criteria for Moodle LMS can be determined by using different MCDM methods. Different LMSs can be compared with MCDM methods. In this comparison, the rankings of the LMSs that make up the alternatives can be obtained from the TPOP method. To fuse multi-complex-valued information as to performance values of users for different usability criteria while maintaining a high quality of the fused result by considering the usage of credible information sources like measurements and questionnaires, a generalized intelligent quality-based approach developed by Xiao can be performed (Xiao, 2021a). In this context, a vector representation of complex-valued distribution can be defined for measured performance values of users, as well as the definitions of compatibility and conflict degrees between complex-valued distributions. Then, the information quality measure of complex-valued distribution can be devised by leveraging the procedure of Gini entropy. Another future study option can be the generalized negation method proposed by Xiao. In this approach, a vector representa-

tion of complex-valued distribution for users' performance is structured. Then, an entropy measure is performed for the complex-valued distribution, called X entropy for different usability criteria. A transformation function to achieve the negation of the complex-valued distribution is used based on X entropy (Xiao, 2021b). These two approaches may have a more powerful capability to represent the knowledge, and uncertainty measure for performance values of users.

By reaching more users, evaluation results can be examined. This study, which is conducted for students, can also be applied to instructors. The proposed method can be applied to determine the most important criteria that affect the usability of web applications designed for different purposes.

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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