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Cluster sampling MUSA methodology for user satisfaction analysis of an educational distance-learning platform

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Abstract

The subject of this paper is to provide a robust user satisfaction evaluation of an educational distance-learning platform with the use of multicriteria satisfaction analysis (MUSA), an innovative and consistent decision-making algorithm, which leads to analytical satisfaction charts and improvement action charts. The educational platform evaluated is Moodle. MUSA algorithm criteria used for the purposes of the present analysis are: (1) technical dimension, (2) possibilities of teachers, (3) possibilities of participants, (4) pedagogical dimension, and (5) automated functions. The originality of this re-search is the fact that MUSA algorithms criteria weights are calculated both for the total number of participants in the present study and for smaller sample subgroups, which represent various levels of satisfaction (above average grade represents overall satisfied users and below average grade represents overall dissatisfied users), age, gender and identity (teachers or university students). The selected cluster sampling leads to differentiated criteria weights and action diagram in MUSA algorithm. The selected methodology is a crucial step for the optimization of the existing user satisfaction algorithm and leads to more robust and valid results. As a result, the modified method is called cluster sampling MUSA algorithm (CSMUSA) and leads to an enhanced decision-making procedure, which is considered fundamental for the constant improvement of any educational platform and software and could be implemented by software companies during the design process.

Keywords: CSMUSA algorithm, user satisfaction evaluation, cluster sampling, weight criteria, distance learning educational platforms, decision making process

INTRODUCTION

In the last few decades, the idea of the fulfillment of the client has ascended as an essential methodology for the advancement of a wide range of items and administrations. Companies have connected the clients' fulfillment to their general degree of success. In addition, different scholars and scientists have emphatically recommended that customer or client fulfillment is a fundamental component for the creation of an important advantage. During the recent years of the COVID-19 period, many different researchers have inferred that the product's or alternately administration's transformation to client needs and changing inclinations is a basic precondition to their long-term progress (Morris et al., 2022). The outcomes got by customer fulfillment investigation analyses might actually formulate a strategy creator setting based on the motivation and satisfaction of service or product users (Nguyen et al., 2016). In addition, some studies have concluded that user satisfaction or fulfilment leads to quality (Ebrahimi et al., 2023; Leninkumar, 2017) while others disagree and conclude the opposite (Mishimar, 2023; Perotti et al., 2020). Concerning customer satisfaction, there are various quantification attempts and multiple definitions in modern literature (Zahidi et al., 2014). A more traditional definition (Vaezi et al., 2016) suggests that customer satisfaction has an immediate connection with the emotional judgement of the user by various encounters in educational settings. Numerous research have proposed different aspects and attributes for customer/user satisfaction. Customer satisfaction implies that the client's needs are fulfilled, product or service characteristics are viewed as satisfactory and so the experience of the user/customer is generally positive. According to Vaezi et al. (2016) there are

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Contribution to the literature

- This study significantly contributes to the current literature by proposing an innovative methodology, the Cluster Sampling MUSA Algorithm (CSMUSA), for the robust and precise evaluation of user satisfaction in distance learning platforms.
- This unique approach takes into account differentiated criteria weights based on user segmentation, providing a more detailed analysis for software optimization.
- By applying this methodology to the widely used platform, Moodle, this work provides new insights for educational software design, enhancing understanding of user satisfaction, and offering valuable tools for the continued improvement of remote education in response to global shifts in learning modalities.

different meanings of customer fulfillment/satisfaction, which are signified by the subject of interest and the explanation level. The most important fulfillment factors incorporate among others the product/service performances, the client encounters, the client reliability and so on.

In addition, the quality of the service relies upon two principal aspects: perceived and expected services. Over the course of the past ten years, much research have uncovered a strong link between customer satisfaction and the quality of service (Alvarez et al., 2019). The emphasis on the scholastic area administrations assessment and client fulfillment and educational software has been a significant subject of examination during the last 10 years. For instance, Lupo and Buscarino (2021) have created a quantifiable systemic methodology to assess customer satisfaction for scholarly e-administrations (the college's site, Moodle platform, and so on) with bases on the ServQual methodology. Chen et al. (2020) utilized a neural network methodology in order to survey customer fulfillment for online schooling platforms during the lockdowns of the COVID-19 pandemic in China. Zurita et al. (2019), though, have utilized 12 measurements to assess through an organized survey customer fulfillment for an instructive versatile application.

Hence, considering the extraordinary circumstances, which emerged in different educational frameworks from one side of the planet to the other as a result of the pandemic, which incorporate impulse reception of distance learning devices and programming, the scholarly area and the product business area genuinely should give an easy to involve and hearty instrument to gauge client fulfillment for instructive programming and stages. The purpose of this paper is the investigation of the enhancement of the existing multicriteria satisfaction analysis (MUSA) methodology, under the prospect of cluster sampling, in order to minimize possible calculation errors. The proposed methodology will be named CSMUSA and its basis is the division of the total sample in satisfaction levels, which will in turn produce differentiated criteria weights to be incorporated in the overall algorithm. such a methodology with the use of MUSA algorithm. The case study of the present research is a widely used (both in Greece and worldwide) e-learning platform, namely Moodle.

LITERATURE REVIEW

Cluster Sampling

The concept of likelihood structure in arranged tests has been initially thoroughly explored discussed by Fisher (1938) (as cited in Suyari, 2013), who analyzes the impact of randomization in the determination of a section from the entire populace, which offers a substantial technique for estimating the measure of error committed. Simple random samples (SRS) are exceptionally difficult to accomplish as a general rule (because of defective testing outlines, non-reaction, etc.) and, regardless they are relatively imperfect approaches to getting a specific number of responses as far as field-work and voyaging costs, however such anomalies are missing in cluster sampling.

A further developed textbook on sampling is composed by Sukhatme (as referred in Rao & Fuller, 2017) in which a broad treatment of deduction has been given to various kinds of surveys. Gilbert (2006) analyzed the impact of cluster sampling in order to assess mortality rates in Iraq because of the attack of American soldiers and revealed that cluster sampling could be utilized to predict high mortality rate in events as famines, natural disasters and wars.

A thorough conversation of cluster sampling and regression analysis has been provided by Barrow et al. (2023). The authors employed a cluster sampling approach by pooling data from the 2019 to 2020 demographic and health surveys (DHS) of Gambia, Sierra Leone, and Liberia to investigate the uptake and determinants of childhood vaccination status among children under one year old. They utilized a multivariable logistic regression analysis to assess the predictors of vaccination uptake. Milligan (2004) examined the job of cluster sampling in extended program for immunization (EPI), where he has revealed how cluster sampling can be utilized to predict the immunization by vaccines inclusion, in cases when there is no updated household sampling background. In the same sense Ichimura et al. (2022) conducted a nationwide cross-sectional survey using a multistage cluster sampling procedure to analyze the factors associated with full immunization coverage among children aged 12 to 35 months in the Lao People's Democratic Republic (Lao PDR). They assessed the relationship between immunization coverage, demographic factors, and health service utilization through multivariate logistic regression analysis. Krapavickaitė (2022) conducted a study to examine the impact of changes in enterprises, such as joining or changing stratum, on the bias and variance of the estimator of the total in a sample business survey. The author proposed adjusted estimators and variance estimators to account for these changes and measured their influence using relative differences. The study highlighted the need for adjustment methods in cluster sampling to improve the accuracy of survey results in the presence of enterprise changes.

An analytical conversation of cluster sampling advantages has been shown by Jiang et al. (2023), where the effect of different parts of cluster sampling in respect to validity and reliability has been examined. Pham et al. (2018) conducted a cross-sectional survey using a three-stage cluster sampling method to investigate the coverage and factors influencing hepatitis B birth dose (HBV BD) vaccination in the Mekong River Delta Region of Vietnam. They examined the socio-demographic factors associated with HBV BD administration and assessed the reasons for non-immunization of neonates, highlighting the need for improved training, information dissemination, and protocols for timely HBV BD administration

A great discourse on the impact of assistant data on the fluctuation of cluster sampling has been conducted by Cuntrera et al. (2022), who have examined that the utilize of assistant data expels the additional variance coming from the variety within the cluster sizes. Additionally, it decreases the loss of effectiveness to the degree it decreases the conditional intra-class relationship given the covariates. Moreover, in case of cluster sampling, the researcher for the most part ought to adjust between the likely efficiency loss as compared to sampling of components and potential regulatory and operational profits that are critical in practice.

Crespi and Ziel (2022) conducted a review of cluster randomized trials focusing on cancer screening interventions published between 1995 and 2019. They examined the use of appropriate statistical methods for sample size calculation and outcome analysis, as well as the reporting of intraclass correlation coefficient (ICC) values. The study aimed to assess the adequacy of methodological practices and identify any persisting deficiencies in cluster randomized trials within the context of cancer screening. The authors concluded that while there have been improvements in the reporting of sample size calculations for cluster randomized trials with cancer screening outcomes, methodological and reporting deficiencies still persist. They emphasized the need for continued efforts to disseminate, adopt, and report the use of appropriate statistical methodologies in cluster randomized trials. Addressing these deficiencies will contribute to the overall quality and reliability of research in the field of cancer screening interventions.

Collins and Lu (2019) addressed the challenge of sampling from data streams, where the entire dataset is not available at once and elements can only be read once and in order. They proposed algorithm SR, an extension of Vitter's algorithm R, which enables cluster stratified reservoir sampling with optimal allocation. The authors demonstrated that the proposed method is asymptotically equivalent to classical stratified random sampling with optimal allocation, and implementation results showed its efficiency and potential superiority over algorithm R in the context of data stream mining. Wu et al. (2023) has illustrated that cluster sampling ought to be utilized only in cases when it is financially advocated or when decreased costs can be utilized to overcome misfortunes in accuracy and revealed that given a standard budget, the researcher may be able to utilize a greater sample with cluster sampling in comparison to other strategies.

Jeelani et al. (2012) suggest that a common motivation for the use of cluster sampling is that reducing the interview costs given a settled budget would permit an expanded sample size. Accepting a settled sample size, the method gives more precise outcomes when the majority of variance within the populace is within the groups, not between them.

Finally, Rodrigues et al. (2021) conducted a study to determine the minimum cluster sampling size needed to estimate merchantable volume (MV) accurately and precisely in the Bom Futuro National Forest in the Brazilian Amazon. They evaluated different cluster sizes and found that a cluster size of 2,400 m² provided estimates of MV with the same accuracy as the original cluster size of 8,000 m², irrespective of the specific product being evaluated.

The present work is an attempt to show that cluster sampling is more efficient than simple random sampling for the use of MUSA algorithm in the evaluation of an educative platform. To the best of the researcher's knowledge, there has never been in literature any effort to enhance MUSA algorithm in any scientific topic with the use of systematic cluster sampling, as a result this reveals the originality of the present study. This attempt would potentially be a step towards the improvement of the existing MUSA algorithm and the altered methodology will be henceforward called as cluster sampling multicriteria satisfaction Analysis (CSMUSA).

Case Study Distance Learning Platform–MOODLE

Moodle is the most famous e learning platform and specifically LMS for a number of reasons.

Moodle platform is distributed as open source software through the GNU general public license. This means that the code can be downloaded from the Internet, its free and unrestricted use, as well as interventions, corrections and additions to the code. This way there is no purchase cost and restriction of licenses (Chang et al., 2022).

It is widespread throughout the world. Today there are thousands of installation facilities in 171 countries and the Moodle software is available in 75 languages. Among the organizations that use it are MIT, Yale, and other universities in America and Europe. In Greece, the platform has been installed in more than 45 education and training institutions, including the National Technical University of Athens and the Universities of Macedonia and Thessaly. Moodle (global Moodle community) global communication portal, which corresponds to http://moodle.org, has over 150,000 registered users. The extensive set of users around the world uses the new features of Moodle and provides feedback to their manufacturers. All new elements that meet the quality standards are contained in the new official editions of Moodle. Thus the collaboration of developers and ordinary users is equivalent to a very large quality control section of Moodle software (Anand & Eswaran, 2018).

Unlike other commercial LMS packages, which are tool-centered, Moodle platform is learning-centered and based on certain pedagogical principles. Thus, in addition to the educational material offered, great importance is given to the cooperation of the trainees in the construction of knowledge, the sharing of resources, communication through discussions and the exchange of ideas.

Its main features are (Mutawa et al., 2023), as follows:

1. Organization of the educational material according to the requirements that exist in each case (e.g., per week or per thematic unit).
2. Support for a wide variety of different types of activities (forums, journals, quizzes, resources, choices, surveys, and assignments).
3. Automatic registration of students through the Internet who then, as long as they have the appropriate rights, can enroll in the courses of their choice without the intervention of the course administrator.
4. Providing a high level of security.
5. Automatic grading of competitions with direct notification of the student.
6. Ability to create a personal profile for enrolled students.
7. Ability to electronically submit student work in the system. For these tasks there is the possibility of setting a submission deadline (deadline).
8. Ability to record and control the various types of student activities by the system administrator.
9. Support for more than 75 different natural languages, including the Greek language.

Many universities use this platform to offer online courses. There is also a portal of online university courses with a large number of courses based on the Moodle platform

MUSA Algorithm Applications for User Satisfaction Measurement

MUSA technique plays had a significant impact in the improvement of standard assessment models and it has been created to quantify and break down consumer loyalty (Bournaris, 2020; Drosos et al., 2020; Grigoroudis et al.,2000) . This strategy is utilized to assess a bunch of peripheral fulfillment capacities so that the general fulfillment model becomes as predictable as conceivable with client decisions. In this manner, the principal objective of the technique is to coordinate individual emergencies into a component of aggregate worth (Grigoroudis & Siskos, 2002). The reasons for MUSA's success can be traced to various applications to many sectors like agricultural marketing (Siskos et al., 2001), the banking sector (Grigoroudis et al., 2002), web quality (Grigoroudis et al., 2008) and the transport sector (Aouadni et al., 2014; Grigoroudis & Siskos, 2004). A strategy that incorporates individual client satisfaction standards into an all-out esteem work yet utilizes a virtual variable relapse procedure with extra requirements, was proposed (Joao et al., 2010). For similar info data, the consequences of the proposed technique are more reliable than those of MUSA, and the noticed contrasts permitted us to have a more profound information on the most proficient method to manage the data gave by participants in an overview.

Furthermore, unlike MUSA, they proposed the utilization of more than one regression strategy, beginning with a virtual variable relapse procedure that utilizes the least squares approach and afterward over and over applying a strong relapse technique like M. relapse. Further developed MUSA, for example, MUSA-INT (Angilella et al., 2014) additionally consider positive and negative cooperations between the rules, as well as the UTAGMS-INT multi-standards strategy. Furthermore, MUSA-INT considers a bunch of utility capacities that address consumer loyalty, taking on the vigorous ordinary relapse philosophy (Angilella et al., 2014).

METHODOLOGY

Introduction

For the purposes of the present research, a questionnaire of five criteria was distributed to 400 users of MUSA (teachers or university students). The criteria weights were calculated dividing the sample into clusters in respect to overall satisfaction, age and identity (teacher or university student). The survey took place in April 2022 and participants were residents in the island of Rhodes. The criteria selected on earlier studies (Avgerinos & Manikaros, 2018) for the educational software evaluation were, as follows:

1. ease of use,
2. efficiency,
3. efficiency, and
4. interactivity/ease of memory.

The above criteria that have been studied from a bibliographic point of view were enriched and reformulated in the present research in the following:

1. technical dimension,
2. possibilities of teachers,
3. possibilities of participants,
4. pedagogical dimension, and
5. automated functions.

The satisfaction responses of the participants follow a Likert scale (1-not at all satisfied, 2-a little satisfied, 3-moderately satisfied, 4-very satisfied, and 5-totally satisfied). The minimum possible overall grade is five points, and the maximum possible overall grade is 25 points. As a result, those participants whose grade is below 15 are considered as overall unsatisfied by Moodle and the rest are considered satisfied.

MUSA Algorithm Weight Calculation Methodology

This segment might be separated by subheadings. It ought to give a brief and exact portrayal of the trial results, their translation, as well as the experimental ends that can be drawn.

MUSA strategy follows the overall standards of prohibitive subjective investigation (ordinal relapse methods), utilizing straight programming procedures to address it (Grigoroudis & Siskos, 2000). It contains an added substance aggregate worth capacity Y^* and a bunch of some fulfillment capacities X_i^*, which are assessed in light of the assessments of all respondents. The essential condition of direct relapse investigation is as per the following:

$$Y^*=\sum_{i=1}^{n} b_i X_i^*, \sum_{i=1}^{n} b_i = 1, \quad (1)$$

where b_i is the heaviness of the i criterion and the capacities Y^* and X_i^* are considered normal to the span [0, 100], so that at the most minimal fulfillment level the worth of the function is 0 and at the most noteworthy 100. By entering a twofold blunder variable, the subjective regression investigation condition (1) takes the accompanying structure:

$$\tilde{Y}^* = \sum_{i=1}^{n} b_i X_i^* - \sigma^+ + \sigma^-, \quad (2)$$

Table 1. MUSA methodology variables (adapted from Grigoroudis & Siskos, 2009)

Variable	Description
a_i	Number of satisfaction levels for the i^{th} criterion
n	Number of criteria
X_i	User satisfaction for i^{th} criterion (i=1, 2, ..., n)
a	A number of levels of total satisfaction
y^m	Level y of total satisfaction (i=1, 2, …, n)
Y_i	Y overall user satisfaction
x_i^{*k}	k^{th} level of satisfaction for i^{th} criterion, k value of x_i^{*k} satisfaction level (k=1, 2, ..., a_i)
y^{*m*}	Value of satisfaction level y^m
X_i^*	Price function of X_i
Y^*	Price function of Y, value of satisfaction level y^m
x_i^k	k^{th} level of satisfaction for i^{th} criterion, k value of x_i^{*k} satisfaction level (k=1, 2, ..., a_i)

where $\tilde{Y}^*$ is the assessment of the collective worth capacity Y^* and σ^- and σ^+ are separately the underestimation and overestimation mistake each. The primary objective of the technique is to accomplish the littlest conceivable deviation between the worth capacity Y^* and the perspectives on the respondents Y, making a set out of various fulfillment points in the unique functions X_i^* and Y^*. **Table 1** shows MUSA methodology variables.

According to Grigoroudis and Siskos (2000) the evaluation of MUSA technique depends on the below stages:

1. Primer examination: At this stage the issue is distinguished, which will be investigated and will incorporate the definite assessment of the targets of the fulfillment study and a client conduct investigation and market climate will be performed (questionnaire and overview).
2. Utilization of the examination survey, the meaning of the parameters of the exploration and its conduct. Explicit significant attributes of the exploration will be recognized like the sort of examination, the example, and the cycle before it is directed.
3. Investigates: The data got from the examining will be dissected and will be measured by factual techniques and the multi-models MUSA strategy. There will likewise be an isolation investigation, where a different examination will be performed for client gatherings, in view of their qualities.
4. Suggestions and conclusions: At this stage we have the introduction of the outcomes and the ideas for explicit enhancements in the framework.

ANALYSIS RESULTS

Sample Features

The sample consisted of n=400 participants. n=340 of them were university students (85.00%) and n=60 of them were teachers (15.00%). From the total sample

Table 2. MUSA weight criteria for SRS, one level, & two level cluster sampling scenario

Scenario/criterion	Technical dimension	Teacher opportunities	Opportunities for participants	Pedagogical dimension	Automated functions
Scenario 1 SRS	**0.12115**	**0.04220**	**0.78719**	**0.01835**	**0.03091**
Scenario 2 males	0.00081	0.17551	0.63371	0.11519	0.07611
Scenario 2 females	0.00000	0.00000	1.00000	0.00000	0.00000
Scenario 2 final results	**0.00040**	**0.08644**	**0.81960**	**0.05673**	**0.03749**
Scenario 3 students	0.23117	0.35019	0.00004	0.00003	0.42028
Scenario 3 teachers	0.00000	1.00000	0.00000	0.00000	0.00000
Scenario 3 final results	**0.19649**	**0.39766**	**0.00004**	**0.00003**	**0.35723**
Scenario 4 satisfied	0.00000	0.00000	1.00000	0.00000	0.00000
Scenario 4 unsatisfied	0.00051	0.08570	0.77872	0.06134	0.07480
Scenario 4 final results	**0.00005**	**0.00857**	**0.92787**	**0.00613**	**0.00748**
Scenario 5 satisfied students	0.00000	0.00000	0.00000	1.00000	0.00000
Scenario 5 unsatisfied students	0.00227	0.06146	0.81588	0.04370	0.07594
Scenario 5 satisfied teachers	0.00078	0.51695	0.00012	0.00005	0.48059
Scenario 5 unsatisfied teachers	0.00000	1.00000	0.00000	0.00000	0.00000
Scenario 5 final results	**0.00048**	**0.10762**	**0.14279**	**0.68265**	**0.06615**

n=197 participants were male (49.25%) and n=203 participants were female (50.75%). In the university students group, n=165 participants were male (48.53%) and n=175 were female (51.47%). In the teachers' group n=32 participants were male (53.33%) and n=28 participants were female (46.67%). The average age of all 400 participants was 26.56 years (standard deviation [SD]=±10.63 years). The average age of the university students was 22.51 years old (SD=±2.81 years) and the average age of the teachers was 49.55 years old (SD=±9.31 years).

Overall n=314 participants gave a grade equal or over 13 (satisfied, 78.50%) and n=86 participants gave a grade lower than 13 (dissatisfied, 21.50%). Among university students n=270 participants gave a grade equal or over 13 (satisfied, 79.42%) and n=70 participants gave a grade less than 13 (dissatisfied, 20.58%). Among teachers n=44 participants gave a grade equal or over 13 (satisfied, 73.33%) and n=16 participants gave a grade less than 13 (dissatisfied, 26.67%).

MUSA Criteria Weights for Various Scenario

The following scenario were formulated for which the criteria weights were calculated.

1. Criteria weights for all participants (n=400).
2. Criteria weights for male participants (n=197) and female participants (n=203).
3. Criteria weights for university students (n=340) and teachers (n=60).
4. Criteria weights for satisfied users (n=314) and dissatisfied users (n=86)
5. Criteria weights for satisfied teachers (n=44) and dissatisfied teachers (n=16), for satisfied university students (n=270) and dissatisfied university students (n=70).

Scenario 1 is a typical SRS case. Scenarios 2, 3, and 4 are typical cases of one level cluster sampling. Scenario 5 is typical case of two-level cluster sampling. The results obtained will reveal the differences of MUSA criteria weights between typical SRS, one level cluster sampling (in respect to gender, title and satisfaction) and two level cluster sampling (in respect to satisfaction and participant title). The results obtained are shown in **Table 2**.

Table 2 revels significant differences among scenarios in respect to the various criteria weights. Scenario 1 (SRS scenario) reveals that the most important criterion among all 400 participants is "opportunities for participants" (0.787), whereas the same criterion for scenario 2 has weight 0.82, for scenario 3 has weight 0.00004 and for scenario 4 has weight 0.928 (single step cluster sampling scenario). Moreover, it is obvious that scenario 5 gives for the same criterion weight 0.143 (double step cluster sampling scenario). As a result, this analysis reveals that the existing MUSA methodology has a significant drawback that is, the sampling methodology may lead to unreliable weight criteria results, since the sample has not homogeneity. In this paper it is strongly suggested that multi step sampling clustering should be followed so as to create homogenous participant groups. A characteristic example in the results presented **Table 2** is related to corresponding weights for criteria "opportunities for participants" and "pedagogical dimension". The group "satisfied students" believes that the most important aspect of MOODLE is its pedagogical dimension (weight=1) and the unsatisfied students believe that its most important aspect is the opportunities it offers for the participants (weight=0.816). It is obvious that depending on the overall satisfaction level (satisfied or not) and the participants identity (student or teachers) his/her perceptions about the importance of each criterion change radically. Another example of subjective perception is the fact that dissatisfied teachers judge as most important criterion "teacher opportunities" (weight=1) and satisfied teachers judge

Table 3. Overall satisfaction levels for Moodle

Overall satisfaction level	5-8 grades	9-12 grades	13-16 grades	17-20 grades	21-25 grades
Label	Very unsatisfied	Unsatisfied	Neutral	Satisfied	Very satisfied
n	5	81	187	105	22
(%)	1.25%	20.25%	46.75%	26.25%	5.50%

Table 4. Demanding satisfaction levels for each criterion

Satisfaction/criterion	Technical dimension	Teacher opportunities	Opportunities for participants	Pedagogical dimension	Automated functions
Average grade	3.008	2.95	3.07	2.99	2.97
Grade (as satisfaction %)	50.38%	47.50%	53.25%	49.63%	48.63%
Normalized satisfaction levels (%)	7.52%	-50.13%	65.16%	-7.52%	-27.57%
Demanding satisfaction levels (%)	-0.38%	2.50%	-3.25%	0.38%	1.38%
Normalized demanding satisfaction levels (%)	-6.52%	43.48%	-56.52%	6.52%	23.91%

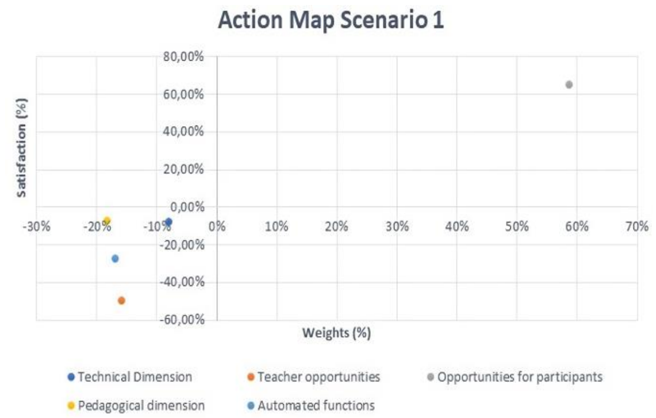

Figure 1. Action map for scenario 1 (Source: Authors' own elaboration)

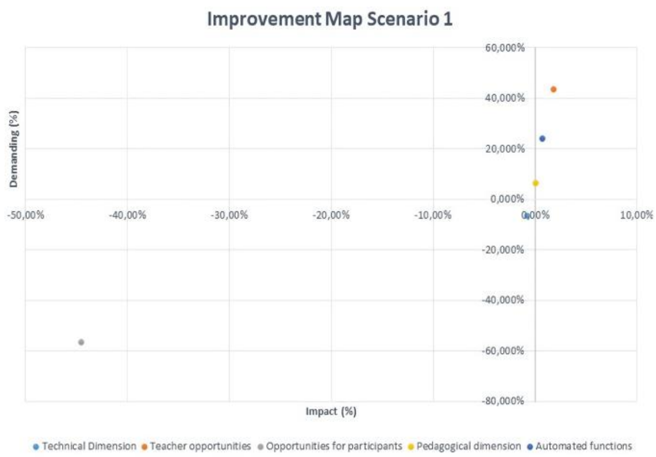

Figure 2. Improvement map for scenario 1 (Source: Authors' own elaboration)

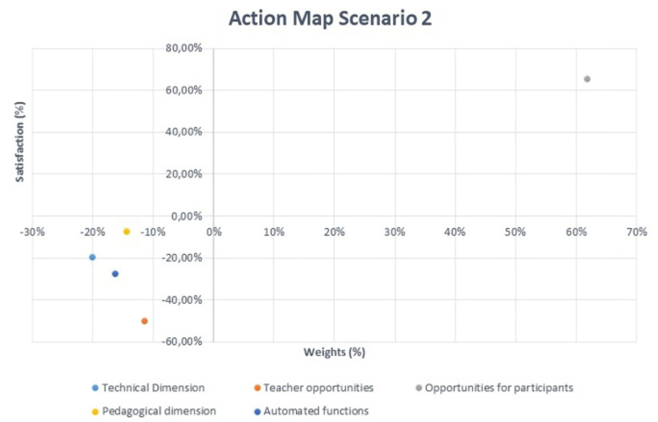

Figure 3. Action map for scenario 2 (Source: Authors' own elaboration)

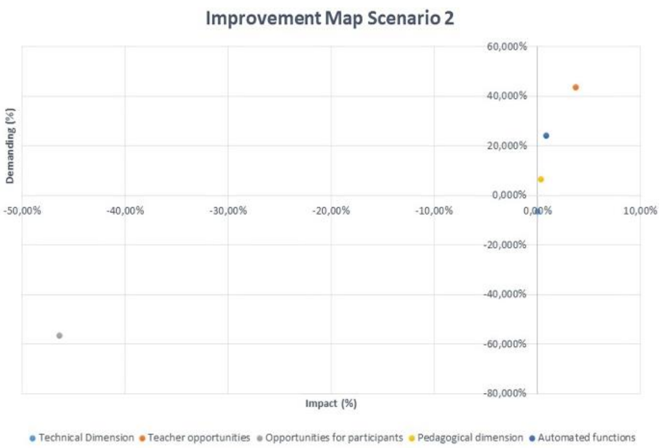

Figure 4. Improvement map for scenario 2 (Source: Authors' own elaboration)

as approximately equally important the aspect of "automated functions" (weight=0.481) and the aspect of "teacher opportunities" (weight=0.517).

MUSA Satisfaction Levels, Action Maps, and Improvement Maps for all Sampling Scenario

The satisfaction levels (overall and for each criterion separately) for the whole sample are shown in **Table 3** and **Table 4**.

The corresponding action and improvement maps for MUSA algorithm for all sampling scenarios (SRS, single step clustering and double step clustering) are presented in **Figure 1** and **Figure 2**.

The most demanding aspect to be improved for scenario 1 is the teacher opportunities since it has the highest impact and most demanding satisfaction level.

It is clearly illustrated that the second scenario (one step cluster sampling in respect to gender) leads to approximately the same conclusion as scenario 1, which is that the most demanding aspect to be improved is the teacher opportunities, which has the highest impact and the most demanding satisfaction level (**Figure 3** and **Figure 4**).

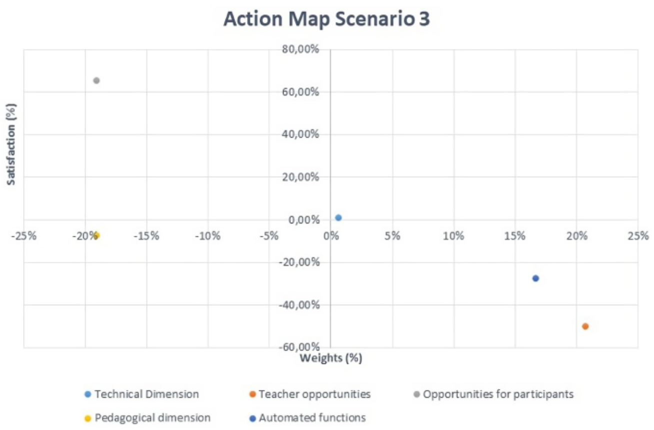

Figure 5. Action map for scenario 3 (Source: Authors' own elaboration)

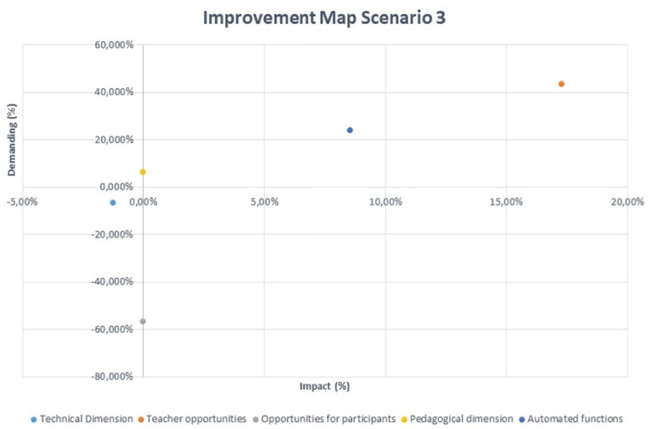

Figure 6. Improvement map for scenario 3 (Source: Authors' own elaboration)

The most demanding aspect to be improved for scenario 3 is the teacher opportunities since it has the highest impact and the most demanding satisfaction level. The only difference in respect to scenario 1 and 2 is that the teacher opportunities have significantly higher impact.

The most demanding aspect to be improved for scenario 3 is the teacher opportunities since it has the highest impact and the most demanding satisfaction level. The only difference in respect to scenario 1, 2, and 3 is that the teacher opportunities have significantly lower impact. It is clear that both SRS scenario and one level cluster sampling scenario led to the same conclusion. In all scenarios teacher opportunities is the most demanding aspect to be improved and also the first priority (**Figure 5** and **Figure 6**).

Figure 7 and **Figure 8** show action map for scenario 4 and improvement map for scenario 4, respectively.

Once more, in scenario 5, the most demanding aspect to be improved is teacher opportunities (higher impact and demanding percentage). The only difference of the two stage clustering sampling in respect to single stage clustering and SRS is revealed at the aspect of the pedagogical dimension, which has significantly higher

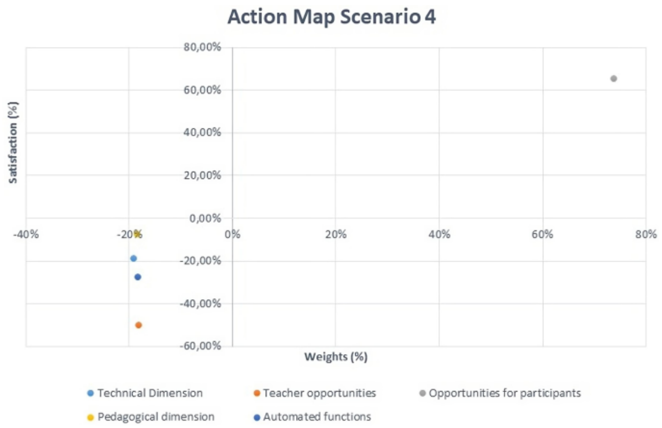

Figure 7. Action map for scenario 4 (Source: Authors' own elaboration)

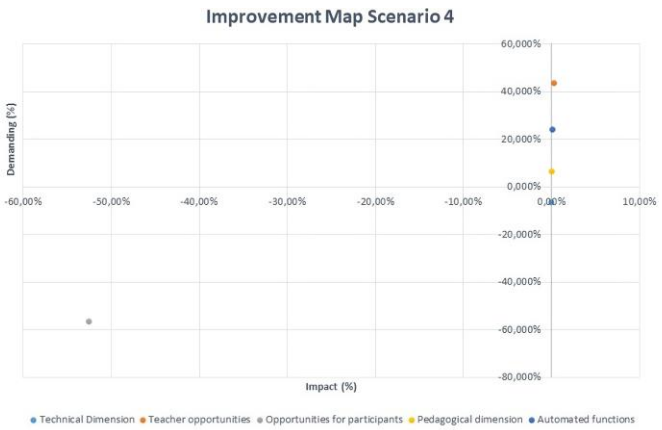

Figure 8. Improvement map for scenario 4 (Source: Authors' own elaboration)

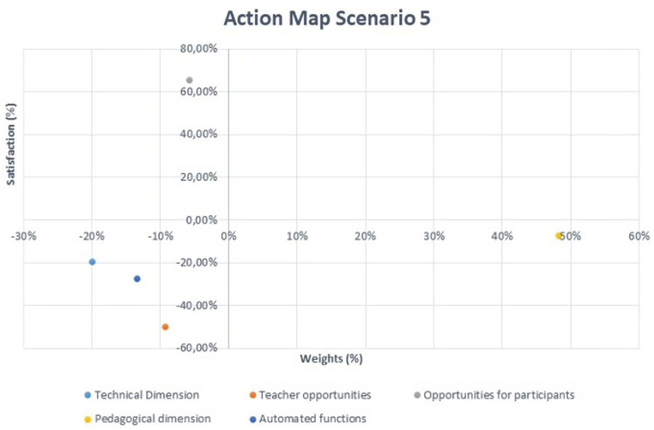

Figure 9. Action map for scenario 5 (Source: Authors' own elaboration)

impact and approximately the same demanding level (**Figure 9** and **Figure 10**).

CONCLUSIONS

The present paper revealed that MUSA algorithm produces significantly different weight criteria depending on the sampling methodology. Simple random sampling methodology in the present case study produced totally different weight criteria in respect to

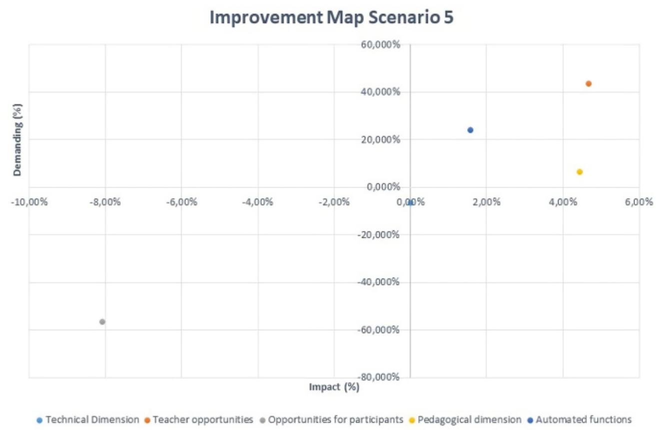

Figure 10. Improvement map for scenario 5 (Source: Authors' own elaboration)

single step clustering sampling scenarios and double step clustering scenarios. Nevertheless, the action diagrams in all scenarios led to approximately the same conclusion: the most demanding aspect to be improved for MOODLE (the platform under examination) is "teacher opportunities" dimension. This is a positive conclusion in terms of the accuracy and validity of the current SRS methodology, which used in literature for MUSA.

In any case, the slightly different action diagrams in all five scenarios suppose that clustering sampling methodology is a significant step towards improving the existing MUSA algorithm since it composes an overall sample through various homogenous samples. As a result, the present study suggests that in the future research is highly advisable to use the proposed modified algorithm (cluster sampling multicriteria satisfaction algorithm–CSMUSA) in order to minimize the possible sampling errors and lead to more accurate action diagram results.

The modified CSMUSA algorithm is expected to be highly reliable for the evaluation of any given software or platform and creates the necessary background for any future decisions of the software companies.

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