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Selected Papers on the Practice of Educational Communications and Technology - Volume 2

Presented Online and On-site during The Annual Convention of the Association for Educational Communications and Technology

Editors
Michael Simonson, Ph.D.
Fischler College of Education and School of Criminal Justice
College of Health Care Sciences
Nova Southeastern University
Davie, FL

Deborah Seepersaud, Ed.D.
Instructional Designer/Adjunct Faculty
Extended Learning
Academic Affairs
Barry University
Miami Shores, FL

Preface

For the forty fourth time, the Association for Educational Communications and Technology (AECT) is sponsoring the publication of these Proceedings. Papers published in this volume were presented online and onsite during the annual AECT Convention. A limited quantity of these Proceedings were printed and sold in both hardcopy and electronic versions. Volumes 1 and 2 are available through the Educational Resources Clearinghouse (ERIC) System. Proceedings volumes are available to members at AECT.org.

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REFEREEING PROCESS: Papers selected for presentation at the AECT Convention and included in these Proceedings were subjected to a reviewing process. All references to authorship were removed from proposals before they were submitted to referees for review. Approximately sixty percent of the manuscripts submitted for consideration were selected for presentation at the convention and for publication in these Proceedings. The papers contained in this document represent some of the most current thinking in educational communications and technology.

Michael R. Simonson
Deborah J. Seepersaud
Editors

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and
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Editors
Michael Simonson, Ph.D.
Professor
Instructional Technology and Distance Education
Fischler College of Education and School of Criminal Justice
Nova Southeastern University
Davie, FL

Deborah Seepersaud, Ed.D.
Instructional Designer/Adjunct Faculty
Extended Learning
Academic Affairs
Barry University
Miami Shores, FL

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Learning Analytics Feedforward: Designing Dashboards According to Learner Expectations and Lecturer Perspectives.

Mustafa TEPGEC
Hacettepe University
Faculty of Education
Ankara, TURKEY

Fatma Gizem KARAOGLAN YILMAZ
Bartin University
Faculty of Science
Bartin, TURKEY

Ramazan YILMAZ
Bartin University
Faculty of Science
Bartin, TURKEY

Sema SULAK
Bartin University
Faculty of Education
Bartin, TURKEY

Furkan AYDIN
Kahramanmaras Sutcu Imam University
Vocational School of Higher Education
Kahramanmaras, TURKEY
Halil YURDUGÜL

Hacettepe University
Faculty of Education
Ankara, TURKEY

Abstract

Learning analytics provide valuable information for learners and instructors by combining and analyzing learners' historical data during the learning experience. The most common way of employing this information is in the form of learning analytics dashboards (LADs). This study primarily aims to propose LADs design based on the perspectives of various stakeholders. The secondary aim of the study is to propose the concept of 'learning analytics feedforward'. After an iterative and formative design process, the LADs were developed in two different interfaces: a course-related dashboard and a topic-related dashboard. Each dashboard element is classified according to whether it contains feedback or feedforward. The development of LADs based on learner expectations and lecturer perspectives is described in detail.

Keywords*: learning analytics, feedback, feedforward.*

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1. INTRODUCTION

With the spread of technology, the interest in online learning environments is increasing. The desire to obtain meaningful results from the digital data left by learners in online environments and the efforts to improve learning environments reveal the need for learning analytics. Learning analytics is based on data resulting from the user's interaction with information and communication technologies. For example, recorded log data is potential data for event learning analytics with timestamps about viewing certain resources, completing essays and quizzes, or discussion messages viewed or sent (Gašević et al., 2016). Learning analytics is considered an interdisciplinary field within the fields of educational technology, pedagogy, machine learning, business intelligence, artificial intelligence, and statistics as a new field of study (Guenaga & Garaizar, 2016; Siemens, 2013, Chatti et al., 2012). The aim of learning analytics is to improve learning, teaching, and learning environment by using educational data (Clow, 2013). Moreover, learning analytics is expressed as measuring, collecting, analyzing, and reporting data about students and their contexts to optimize learning and learning environments (Siemens, 2013).

The use of learning analytics has been increasing in recent years and is frequently preferred especially for the creation of individualized learning environments. In this process, learning analytics indicators are important in terms of monitoring students' success-failure situations and monitoring their behaviors in the process. In addition, recommendation and guidance feedback based on learning analytics (also known as learning analytics feedback) by instructors in this process will provide various benefits to students. The most foreseen benefit of the learning environment is the improvement of the communication between the instructor and the student. In addition, the instructor can give more effective feedback based on the knowledge gained in the process. The log data consists of the students' own behaviors, and feedback can be provided on the behavior of the students, such as which lesson and when they watch, where they hang out, where they do it right. Siemens (2013) states that learning analytics will affect existing education models and provide new insights on learning and teaching. He further indicated that in order to accomplish this goal, firstly it is necessary to make a deep sense of the existing potential in education, and secondly to deal with the difficulties encountered in educational applications of learning analytics.

Instructors can obtain information about students' behavior, performance, learning processes and learning outcomes in the online learning environment which can be obtained by learning indicators. In addition, these reports can provide instructors with an insight into students' learning needs and learning deficiencies. Also, instructors can have a foresight about whether to intervene with the student based on the learning analytics results in the process. Furthermore, how and when this intervention will take place is decided based on these results. To do so, creating personalized learning environments with learning analytics can be utilized as useful tools to provide personalized feedback. In this context, learning analytics can also be administered as an evaluation tool regarding the instructional design process, and it can provide input for the next cyclical processes of the instructional design process.

Recent research results yielded that providing tips, advice, and guidance about learning behaviors by using learning analytics in the process of creating personalized learning environments and improving instructional design processes is recommended (Jivet, Scheffel, Specht, & Drachsler, 2018). Thanks to the learning analytics based recommendation and guidance feedback, students will be able to recognize their own learning deficiencies and will try to tackle them by knowing where they have shortcomings and mistakes. The

recommendation and guidance feedback utilized are based on learning analytics. These feedbacks given in the process are suggestions based on learning analytics.

Feedback is considered the key element in formative assessment (Carrillo-de-le-Pena et al., 2009). However, feedback alone is not sufficient for formative assessment. Similar to instruction, formative assessment is often sequential (Hattie & Timperley, 2007). Each new sequence exponentially increases the possibilities for the next. Therefore, a feedforward approach is needed in addition to feedback.

1.1. Learning analytics feedforward

The concept of feedforward is as old as feedback. Björkman (1972) defined feedback and feedforward as different operators serving the same purpose. In both operators, task-related information is provided by evaluating current performance against a specific target. Both can have supporting functions in providing information and policy making in the teaching process. (Sengupta & Abdel-Hamid., 1993). It is a controversial issue to completely separate the concepts of feedback and feedforward. While some views on the meaning of feedforward consider this concept as responses to feedback or as a feature of effective feedback (Dulama & Ilovan, 2016; Faulconer, Griffith, & Frank, 2019; Hattie & Timperley, 2007), some view a computational strategy used to offer suggestions before a task or performance (Björkman, 1972; Hendry, White, & Herbert, 2016).

Feedforward was not investigated as commonly as feedback in educational research (Dulama & Ilovan, 2016). The lack of necessary environments for providing feedforward was one of the reasons why it was not widely used in the past. However, in recent years, feedforward has gained attention by the use of educational data mining algorithms based on machine learning in learning environments (Knight, 2020; Meredith, 2020; Sedrakyan, Malmberg, Verbert, Jarvela, & Kirschner, 2020).

When it comes to operational definitions of feedback, the focus is always on current performance or target performance. However, there is a need for proactive approaches in the context of formative assessment. It is necessary not only to focus on current or target performance, but also to take into account possible performance. If possible performance is predicted accurately, prevention of learners from drop-out will be more easier and intervention to learning experience will be more meaningful.

The study primarily aims to propose a learning analytics dashboard design based on the perspectives of various stakeholders. The secondary aim of the study is to propose the concept of learning analytics feedforward (LA feedforward) to the educational researchers. As mentioned before, although it is not frequently used in educational research, the concept of feedforward has different functional definitions. For this reason, we recommend the use of the concept of learning analytics feedforward, just like the concept of learning analytics feedback (LA feedback). Thus, a common view will be formed when LA based feedforward is said.

2. METHOD

Within the scope of this study, a systematic data collection process was carried out for the dashboard design. This process was carried out on the basis of design-based research. Design-based research; new theory with iterative processes that do not have a fixed prescription (Barab, 2014, pp. 151), requires high cohesion and cooperation with the participants (Amiel & Reeves, 2008), is aimed at improving educational practices (Wang & Hannafin, 2005), and can be

adapted to other teaching contexts. It is a research method/framework that aims to develop applications (Barab, 2014, pp. 151). In this study, analysis, design and development phases were carried out. Although it is an iterative and formative design process, this study can be defined as quasi design-based research since there is no implementation phase.

2.1. Participants

The study was carried out in three phases with different participants. Figure 1 shows the distribution of participants at each phase by gender and education level.

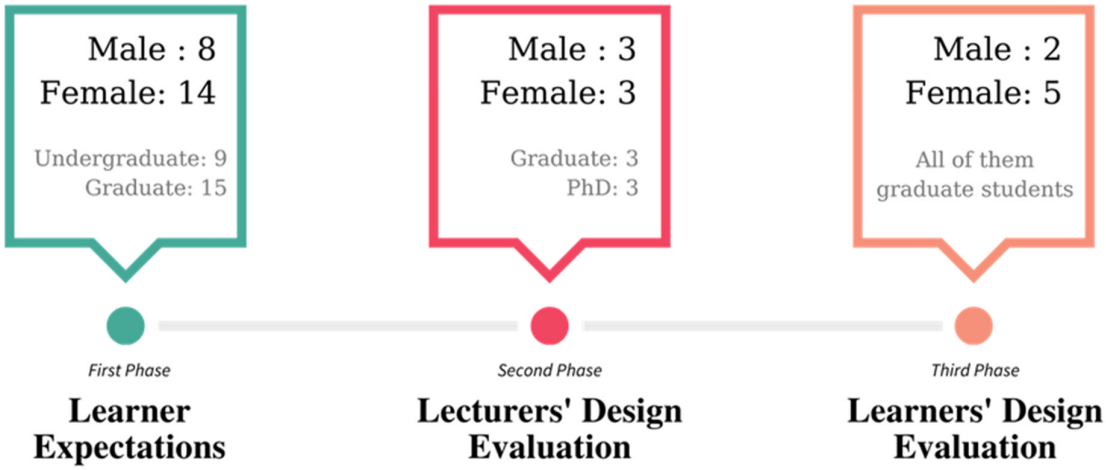


Fig 1. Phases of the study and participants

2.2. Data collection

In the first phase of study, an inclusive question was used to determine learner expectations from learning analytics. The expectations of 22 undergraduate and graduate students were obtained via a web-based form. This form includes only the below question:

"We need you to use your imagination. Suppose there is a Genie in the system, like Alaadin's Genie. If you had a maximum of 3 wishes (information you want to see based on your system interaction data), what would you wish from this Genie?"

A draft design for dashboard elements was created based on these expectations. The lecturers' perspectives on the draft design were gathered in the second phase of the study. Draft design form was sent via e-mail and six of eight lecturers participated. Draft design form includes this information:

1. Purpose and scope of feedback/feedforward to be presented,
2. Metrics/variables needed to present feedback/feedforward,
3. Details of the metrics/variables calculations or visualization components,
4. Appropriate data visualization graphs/charts to present feedback/feedforward,
5. Area for the lecturer comments,
6. Lecturers rating area for evaluating the information chunk from 1 to 5.

Lecturers gave their opinions for each dashboard element containing the above information, which was created according to learner expectations. Additionally, the lecturers can suggest a

new dashboard element in the above format. This form was revised as a result of the opinions of the lecturers.

The revised draft design form was presented to the students in the third phase of the study. The dashboard elements in the draft design were rated by seven graduate students who also took part in the first phase. The students on the other hand were not provided with metrics, detailed explanations and a comment area. Students only rated it from 1 to 5. Elements rated as 4 or 5 by all students were the elements to be included in the dashboard to be developed.

2.3. Environment

The aim of this study is to design a dashboard to be integrated into an existing MOOC system. However, in order to better understand some of the metrics and system components in the dashboard, Smart MOOC Integrated with Intelligent Tutoring (SMIT) is briefly introduced in this section.

SMIT was developed using HTML, JS, CSS, PHP, MySQL script and software languages. On the SMIT platform, the topics are presented as modules. Learners must take a mastery test to complete each module and the system decides that the relevant learner is master for that topic. Bayesian network method is utilized to determine the level of mastery. SPRT (Sequential Probability Ratio Test) was utilized in the estimation of mastery. When SMIT makes an authorized decision about the user, this is indicated to the user. When the system decides that the learner is not the master, the learner is directed to the relevant content and recommended to study the content. The user who is directed to the content decides that he/she is ready by browsing the learning materials, he/she can take the proficiency test until he/she is the master. When learners are not the master, they can also be directed to the intelligent tutoring system.

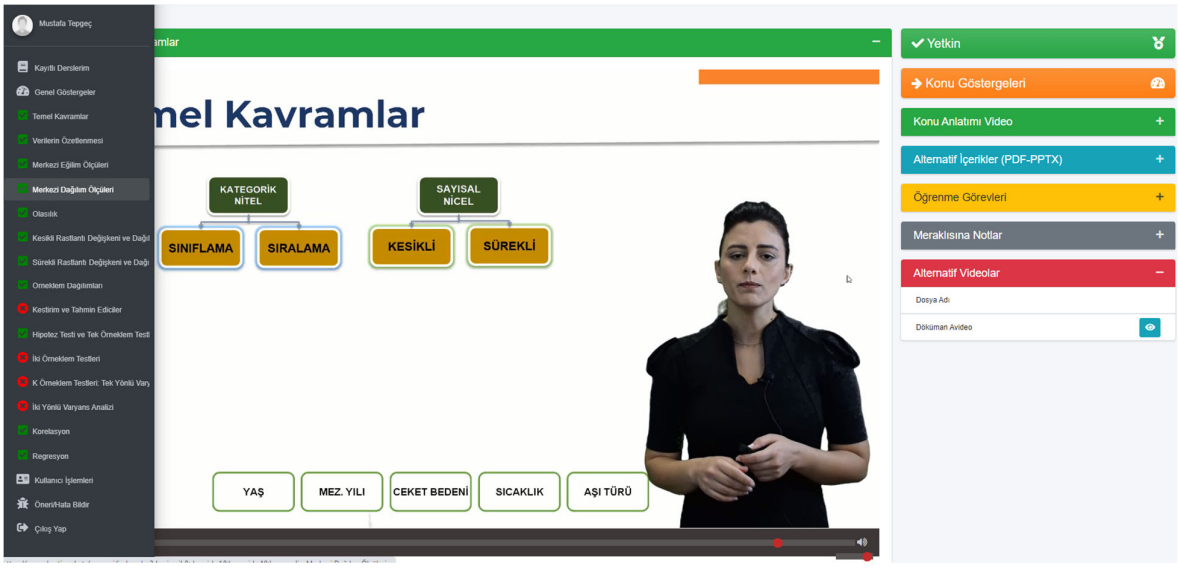


Fig 2. Screenshot of the learning environment

On the SMIT platform, the contents are presented in a highly enriched way. In addition to the topic video, presented in Figure 2, learners can reach alternative videos, written materials, presentations, and infographics from the section on the right. In addition, they can perform learning tasks and learn the topic in depth by going to the "notes to the curious" section. Moreover, learners can take notes while working on the content and view the indicators related

to the topic from the right column. Learners can view all the topics in the course and the course-related dashboard from the left column.

RESULTS

In this study, learning analytics dashboards (LADs) were designed gradually according to different stakeholders' opinions. In this section, the development of dashboard elements as well as the findings of the three-phase data collection process are presented.

3.1. Findings on learner expectations

In order to determine learner expectations from the learning analytics, a web-based form consisting of an inclusive open-ended question is presented. Students stated a maximum 3 expectations via this form. Consequently, the learners stated 36 information in total. However, not all of these expectations were considered during the design phase. Some of these are:

P2: "I couldn't understand the learning task, can you explain in detail?"

P22: "What should I do to be the best of the month??"

P1: "Can you provide material to maintain the permanence of what I have learned?"

Since every expectation recommended by the learners is not suitable for the features of the current system, nearly half of them were not used in the design phase. While the first comment above is about the feature of providing a more detailed explanation for the presented learning task, the second comment is about gamification elements and the third comment is about adaptively providing alternative content that already exists in the system to the learner. Within the scope of this study, since it is aimed to design LADs for an existing system, these comments were not evaluated during the design phase, since features that do not exist in the existing system cannot be added. Excluding these kinds of expectations, the remaining 19 information was analyzed in two categories as LA feedback and LA feedforward.

LA feedback provides information about the gap between learners' current state and targeted state by utilizing learning analytics. LA feedforward provides a prediction based on learners' past learning experiences and/or the learning experiences of others. 9 of learner expectations were evaluated as LA feedback and 10 of them were evaluated as LA feedforward.

3.2. Findings on design evaluation

A draft design form was developed corresponding with students' expectations from learning analytics. This design form was first presented to the lecturers. Lecturers rated dashboard elements that might be useful for learners, and also defined new dashboard elements that might be meaningful for learners to encounter in the current system. The 24 dashboard elements that the lecturers agreed upon were presented to the learners for final evaluation. Of these 24 dashboard elements, 15 contained LA feedback and 9 contained LA feedforward information. In addition, out of these 24 dashboard items, 15 were created based on learner expectations and 9 based on lecturer recommendations. Examples of presented information in the dashboard element, depending on whether they are from lecturer recommendations or learner expectations and whether they include LA feedback or LA feedforward, are shown in Table 1.

Table 1 Examples of LA feedback and LA feedforward

LA feedback	LA feedforward

Based on learner expectations	Trending material information Performance trend information relative to others	Prediction of success in the topic according to system interactions Information on when to complete the course
Based on lecturer recommendations	Mastery test performance information Log-in numbers information	Drop-out prediction information Next topic estimation

The learner views mentioned in the previous sections reflected the learners' expectations from learning analytics. Some of these learners (n=7) also participated in the design evaluation phase (third phase). The design evaluation form, which was developed according to the expectations of the learners at the first phase, was revised as a result of the lecturers' opinions. The revised design form was presented to these learners upon their design evaluation.

Unlike the form evaluated by the lecturers, the learners only rated scope and sample visualization of the dashboard element from 1 to 5. While the primary purpose of this phase is to provide the learner's views on the more concrete design, the secondary purpose is to identify the best among out of this information, since presenting 24 elements in the dashboard may result in negative learning outcomes. Hence, the elements that all 7 learners who participated in the research indicated 4 or 5 degrees out of 5 were included in the dashboard final design. Learners marked as 4 or 5 out of 5 for 12 elements out of 24 elements. Of these 12 dashboard elements, 8 were treated as LA feedback (later 3 of them revised as a single dashboard element), and 4 as LA feedforward.

3.3. Dashboard elements

In this section, the dashboard elements created as a result different stakeholder opinion will be introduced gradually. Since 3 of the agreed 12 dashboard elements (LA feedback) are composed of related metrics, they are graphed as a single dashboard element. Therefore, of the 10 dashboard elements, 6 were LA feedback and 4 were LA feedforward. As a result, these 10 dashboard elements obtained by the researchers were integrated into the system on two separate pages as topic-related and course-related.

LADs are designed for MOOCs, which was developed from a project. There are many courses in MOOC platforms and each course has a syllabus in general. Each element of the syllabuses is treated as a topic. Therefore, the dashboard design in this study is configured separately as both course-related and topic-related.

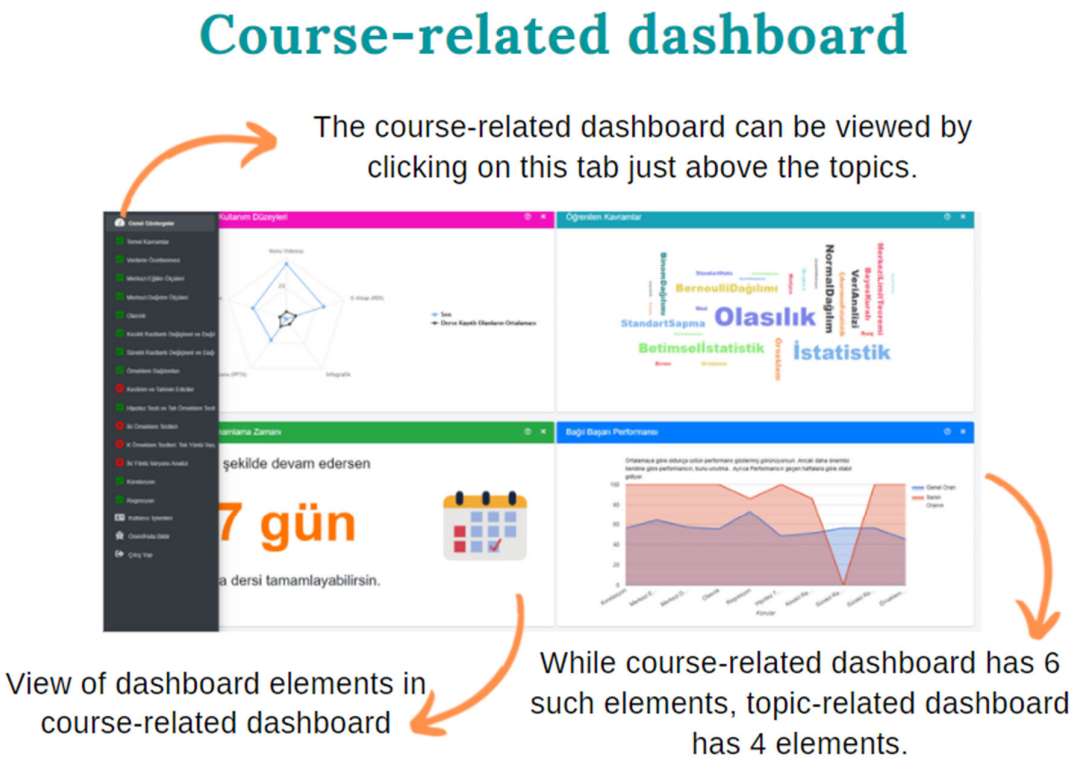


Fig 3. Screenshot of the course-related dashboard

Figure 3 shows a screenshot from the course-related dashboard. Topic-related dashboard is designed similarly, and dashboard elements on both pages are discussed separately in this section.

3.3.1. Course-related dashboard elements

As a result of the study, 6 (4 LA feedback, 2 LA feedforward) dashboard elements are determined and located under the course-related dashboard. In this section, each element to be included in the course-related dashboard, stakeholder opinions referring to this element, the metrics required for the information to be included in the element, the calculation methods, and visualization of these metrics will be presented.

Course-related element 1: Performance displays based on mastery test indicators

This dashboard element covers 3 different information and presents mastery testing performances to learners descriptively. Therefore, the information presented here is considered as LA feedback. The illustration and explanations of this element are given in Figure 4.

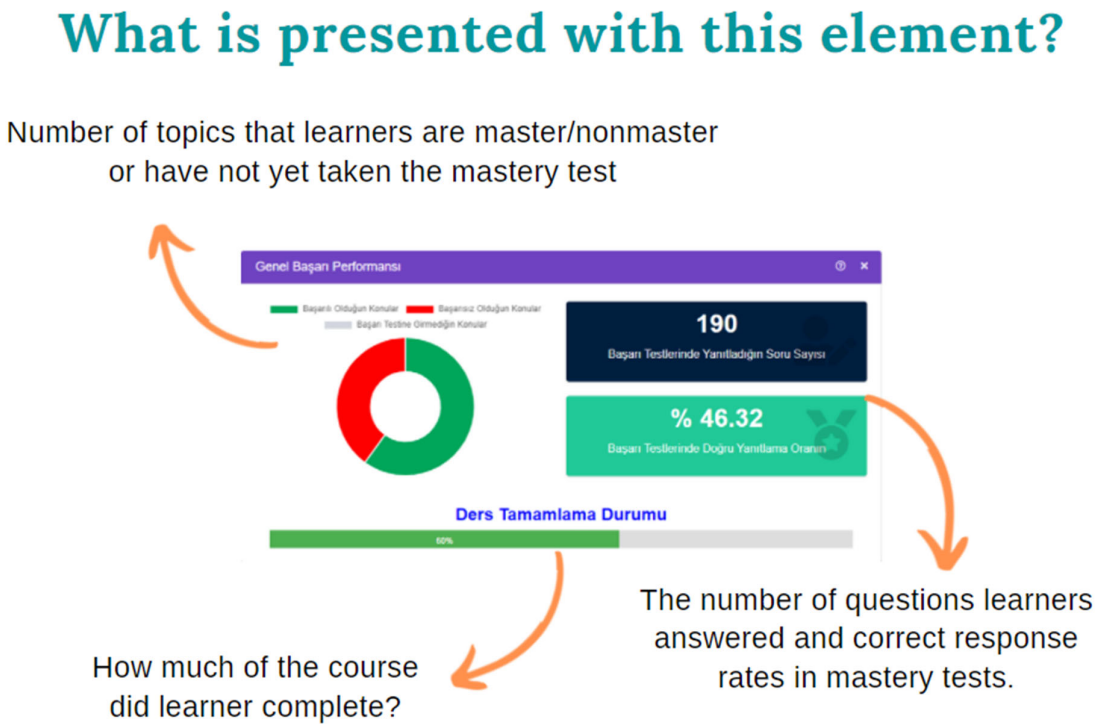


Fig 4. Course-related dashboard element-1

The dashboard element was created by consolidating 3 different information. While 2 information were recommended by the lecturers, 1 information was added based on the comment below.

P15: "How much progress have I made in this course according to interactions on the system?"

This dashboard element does not require any complex calculations. From this descriptive information, master/non-master/not taken metrics are presented as they are. Similarly, the number of questions encountered was obtained by adding the questions encountered in the mastery test in all topics, while the correct answer rate obtained by dividing the questions answered correctly by the number of questions encountered. The information in the progress bar under the element is obtained by dividing the topics of competence into the total topics.

Course-related element 2: Norm-referenced feedback and self-referenced feedback according to recent performance

Through this dashboard, the recent mastery testing performance of the learners is presented in comparison to the group and personal performance. The illustration and explanations for this element are shown in Figure 5.

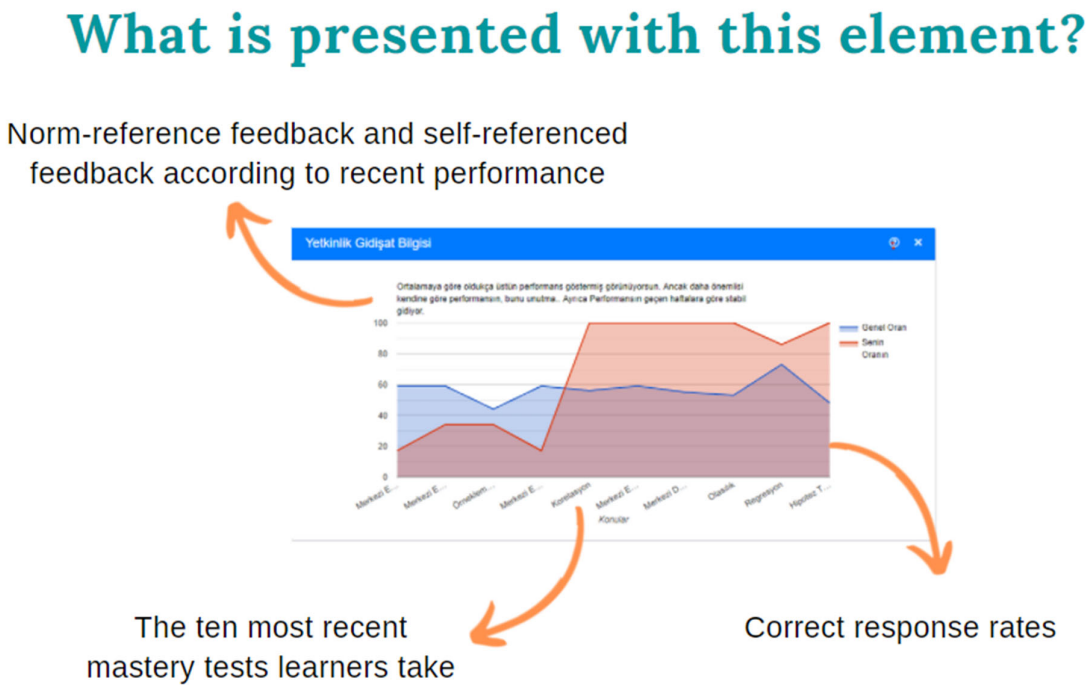


Fig 5. Course-related dashboard element-2

While the expectations of the learners were in the direction of norm-referenced feedback, self-reference feedback information was included in the design by the researchers. The comments of the learners for the related dashboard element are presented below.

P3: *"I am working but am I right? How is my performance compared to others?"*

P12: "*Hey genie, how am I compared to other users?"*

As it was deduced from the comments, the learners wanted to see the performance compared to the others. This performance information was created according to mastery testing. The last 10 mastery tests that the learner took and the correct answer rates are presented. Norm-referenced feedback is provided depending on three conditions. For these conditions, the standard deviation of the student's performance is defined. If it is greater than 1, determined as above the average, it is above the -1 determined as below the average and other conditions determined as at the average level.

Self-referenced feedback compares the student's performance on the last two tests to the prior three tests. If 2 of the last 2 test performances are lower than the average of the previous 3 test performances, it is reported that the trend is negative, and if it is higher, the progress is positive. Otherwise, the message that the status is stable.

Course-related element 3: Success predictions for all topics

Through this element, it is aimed to provide a success prediction for all the topics. As it turns out, this element is covered under LA feedforward. The illustration and explanations of this element are shown in Figure 6.

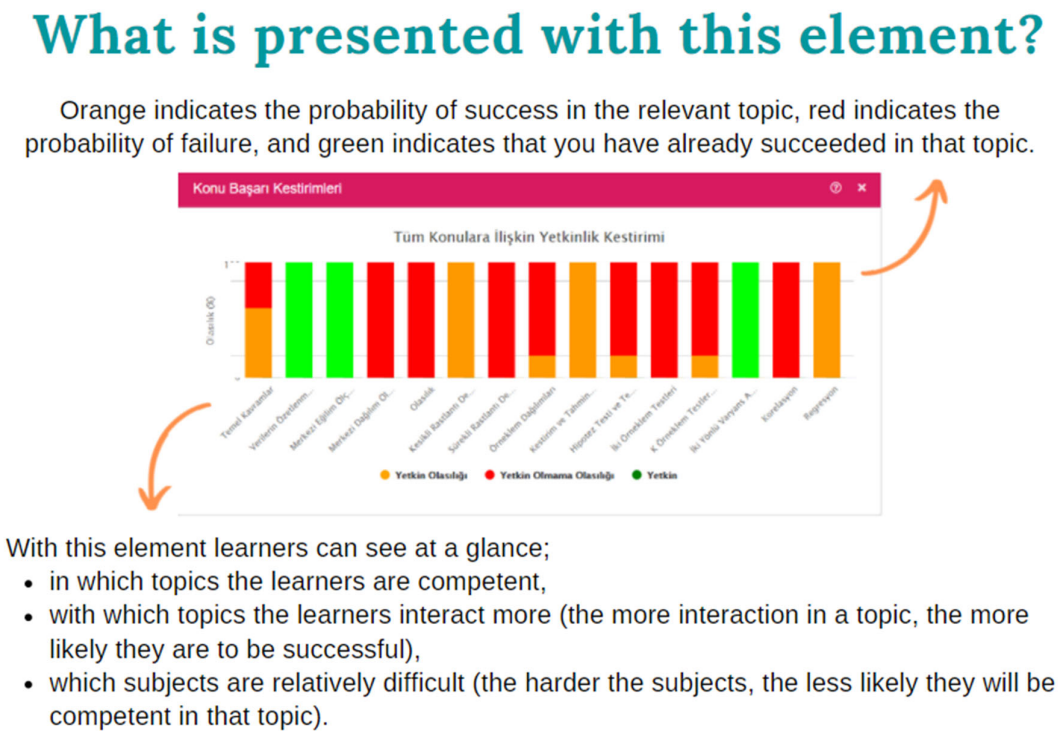


Fig 6. Course-related dashboard element-3

This dashboard element was created based on the expectations of 2 learners. In essence, learner expectations indirectly reflect this information. The comments of the learners for the related dashboard element are presented below.

P3: *"I have done so much right in this topic; will I be successful in the other topic or should I leave it here?"*

P13: *"Genie can tell my shortcomings and tell me the topics I need to focus on."*

As it mentioned in the comments, learners will have information about difficulty levels of the topics and the probability of being successful in topics according to their performance in a particular topic. In order to make this estimation, the correct response rate on all topics, the number of learning task views, and the number of course-related dashboard views were used. In addition, the duration of each topic-specific content, the number of video interactions (rewind, replay, note-taking) and the number of views on alternative content (pdf, pptx, infographic) were evaluated. Naive Bayes algorithm was used for predictions.

Course-related element 4: Course completion time prediction

In this dashboard element, the estimation on when the learner will complete the topic was presented based on their current performance. Thus, this element was evaluated under LA feedforward. The illustrations and the explanations related to this element are presented in Figure 7.

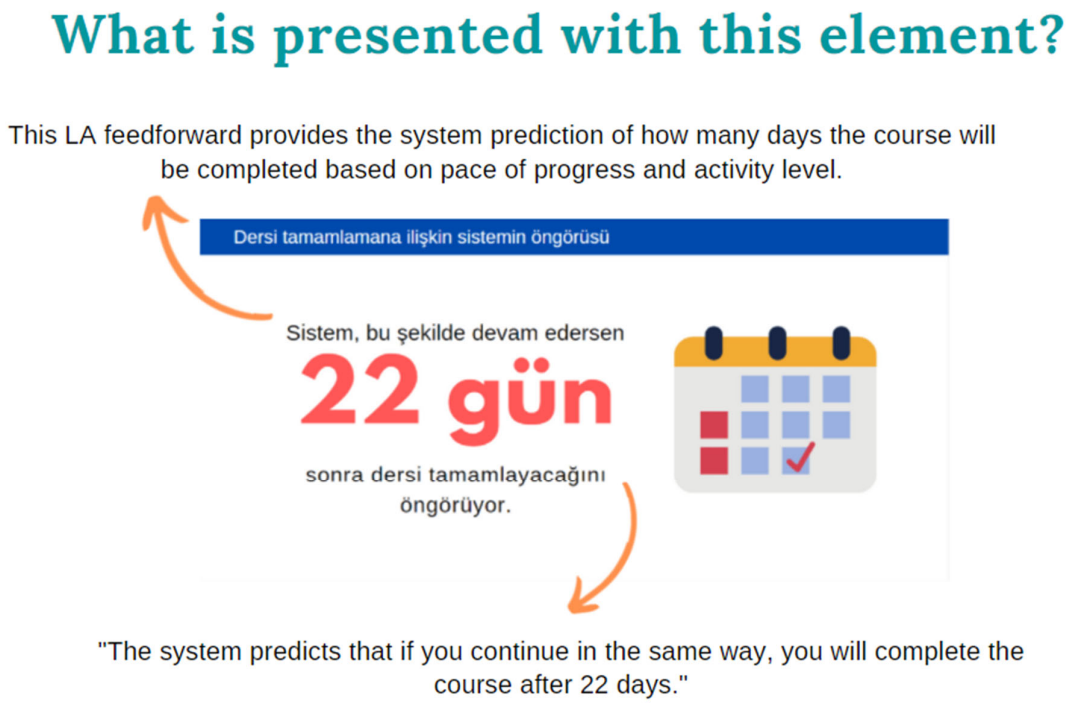


Fig 7. Course-related dashboard element-4

The learner expectations related to this element is given below.

P14: "*According to the information I have before the course, Genie can predict how long it will take to complete the course."*

For this dashboard element learner expectations were revised based on current performance although previously learner expectations were based on prior learnings. The estimation regarding completion time was estimated utilizing metrics that are obtained by the time spent on mastery topic in the system, the time elapsed from the two component topics to the previous component topic, and the number of completed topics. k nearest neighbor algorithm was utilized in order to gather this estimation.

Course-related element 5: Concepts learned

In this dashboard element, learners are presented with the concepts they have learned according to the content of the topics they are competent in. This dashboard element is considered as LA feedback since it provides information regarding previous performance. The illustrations and the explanations related to this element are presented in Figure 8.

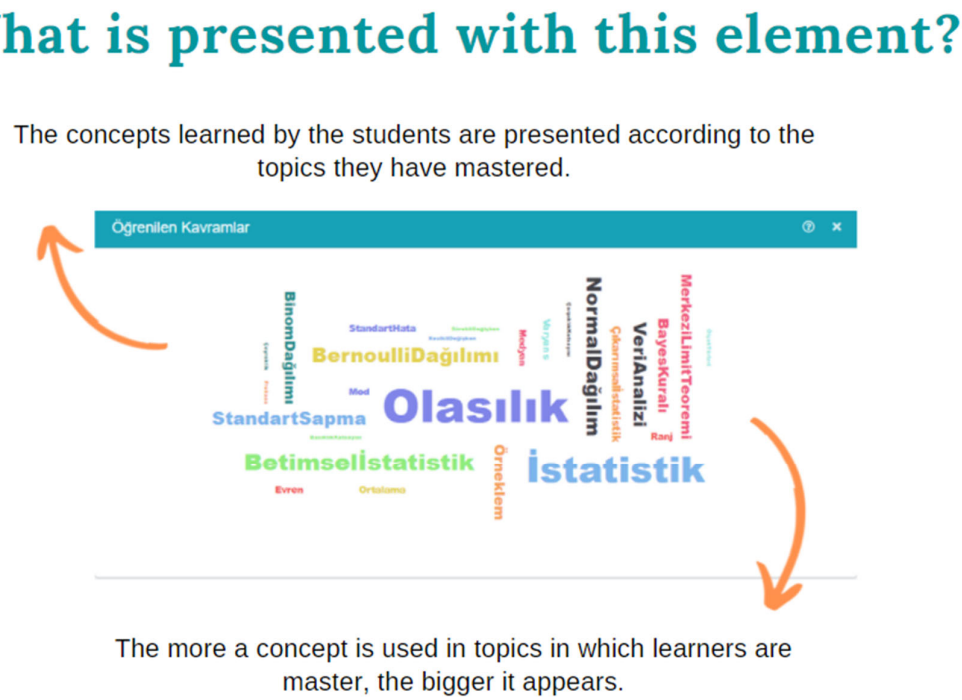


Fig 8. Course-related dashboard element-5

The learner expectations related to this dashboard element is given below.

P22: "*So, what I do know?"*

In order to create the word cloud, each topic and related concepts were paired based on instructor opinions. When the learner is competent in a particular topic, those concepts are added to the word with their weights.

Course-related element 6: Trending material types

The materials that learners are interested in the system are presented through this element. This dashboard element is considered as LA feedback. The illustrations and the explanations related to this element are presented in Figure 9.

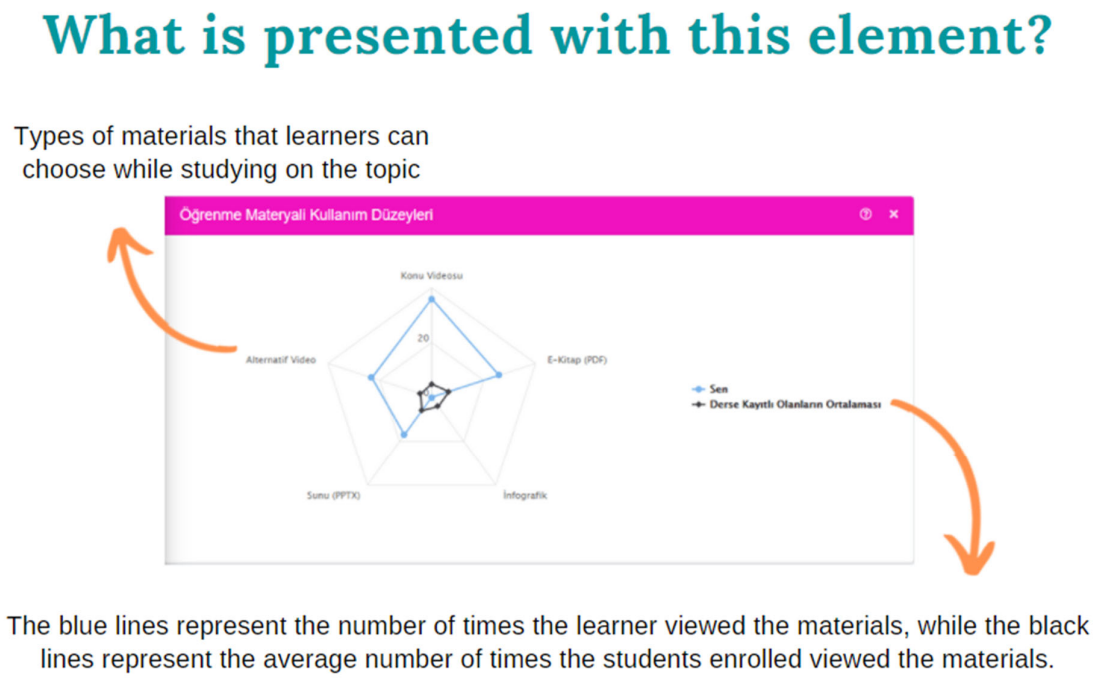


Fig 9. Course-related dashboard element-6

The learner expectations related to this element is given below.

P22: "*What type of content did I tend to most?"*

The material information that learners as well as others are interested is presented. The number of existing videos, alternative videos, presentations, pdfs, and infographic elements are given.

3.3.2. Topic-related dashboard elements

4 of the dashboard elements developed as a result of the study (2 LA feedback, 2 LA feedforward) can differ according to the topics. Therefore, this dashboard is not in the main menus of the system, but in the content of a topic and is customized according to the current topic.

Topic-related element 1: Roadmap of successful learners

Through this element, learners can view how successful people follow their topic content. With this element, the message "you can be successful if you follow a path like this" is presented secretly. Therefore, this dashboard element is also evaluated under the LA feedforward. The notation and explanations of this element are shown in Figure 10.

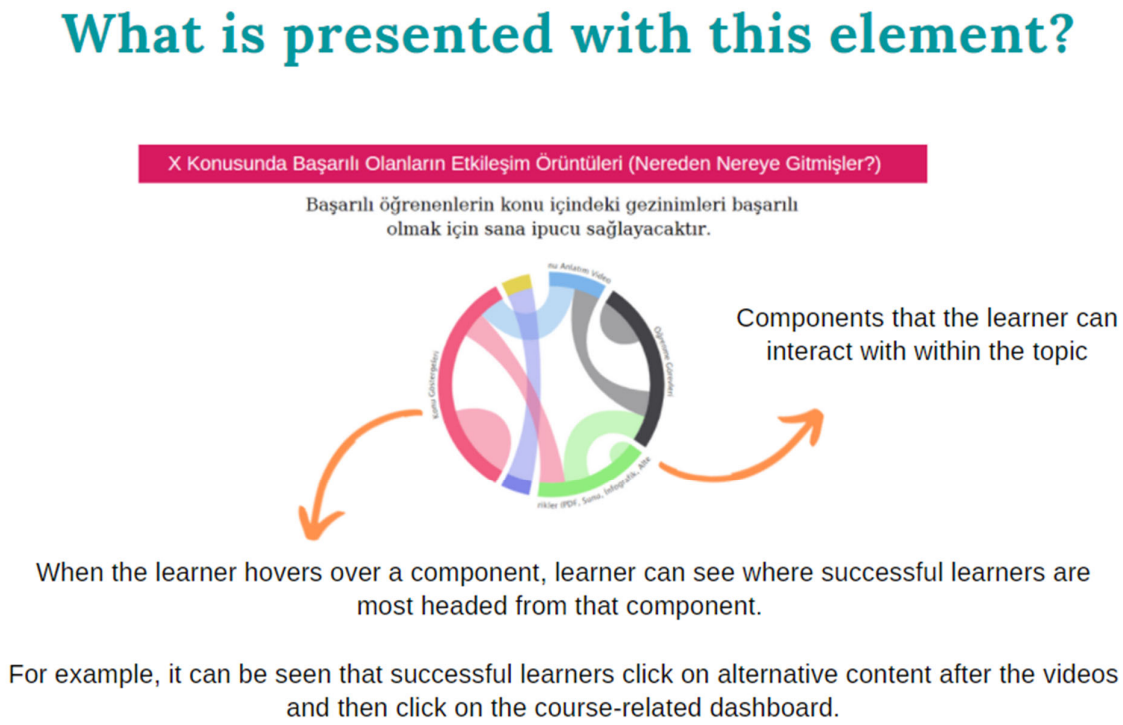


Fig 10. Topic-related dashboard element-1

The learner expectation associated with this dashboard element is presented below.

P1: "*What material will be most effective for me in my next learning?"*

Transition matrices have been created for this element. For example, information such as how many times successful learners have passed from the topic videos to the learning task on the relevant topic was displayed when hovering over the relevant component.

Topic-related element 2: Time spent on the topic

Through this element, the time spent by the learners is presented descriptively. Similarly, information about the average time spent by successful learners in the topic is presented. This dashboard element has been evaluated as LA feedback. The notation and explanations of this element are presented in Figure 11.

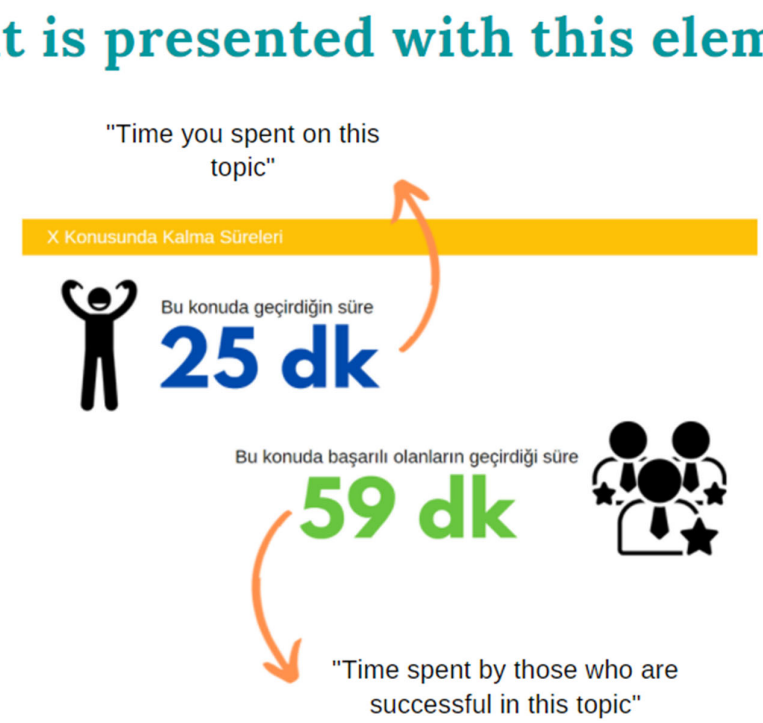


Fig 11. Topic-related dashboard element-2

The learner expectations associated with this dashboard element are presented below.

P1: "*How much time do I need to learn the next topic effectively?"*

P12: "*What is the average time I have to spend for each topic?"*

For this dashboard element, the time spent by the learners on the relevant topic and the average time spent by the successful ones are directly presented.

Topic-related element 3: Success prediction for the relevant topic

Through this element, the topic estimation in course-related 3 is presented under each topic-related dashboard. This display format is indicated in Figure 12.

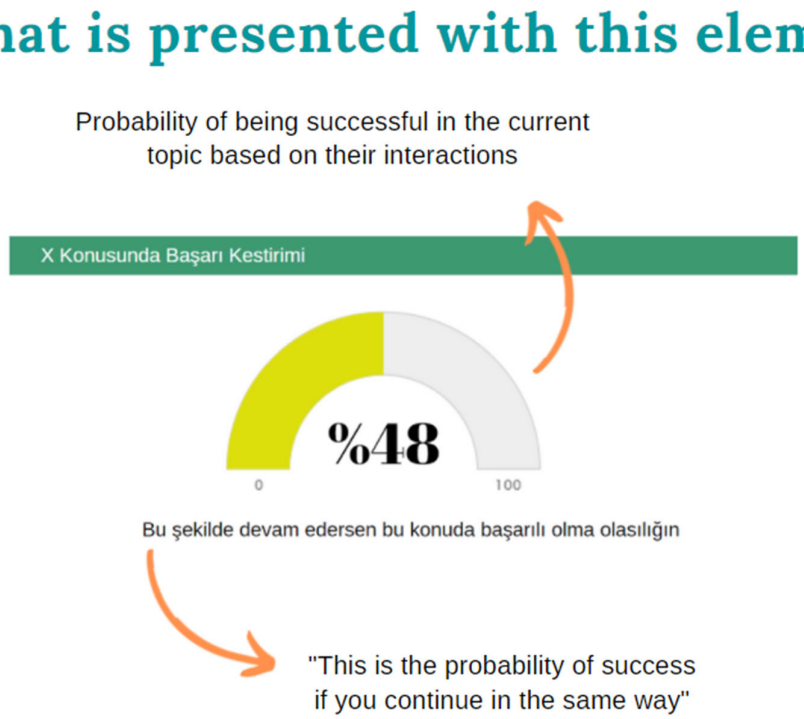


Fig 12. Topic-related dashboard element-3

The learner expectations associated with this dashboard element are presented below.

P2: "*Can I be successful if I don't watch the video and only study the topic via pdf?"*

P17: *"Hey Genie, I only worked with infographics and presentations. Will I be able to succeed in this topic?"*

With the LA feedforward in Course-related 3, the calculations and the algorithm used are the same, and the representation of this information is different.

Topic-related element 4: Interactions for the relevant topic

In this section material interaction levels of the learners after taking the proficiency test on a topic are demonstrated. This information was considered as LA feedback. The illustrations and the explanations regarding this element are shown in Figure 13.

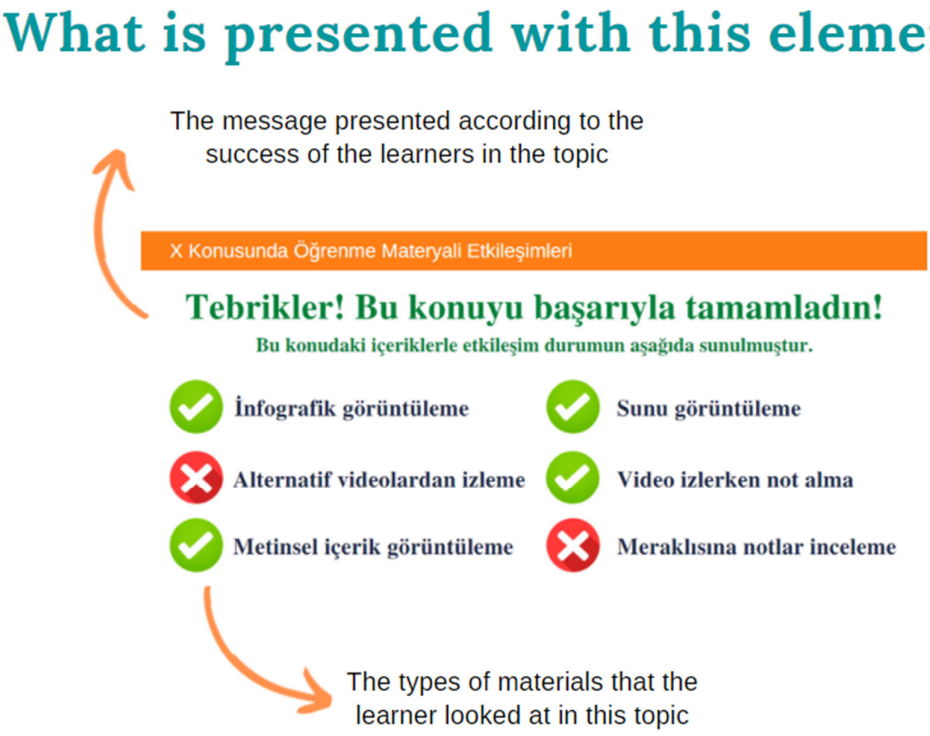


Fig 13. Topic-related dashboard element-4

The learner expectations related to this element is given below.

P17: *"*I interacted with content on many topics. What content do you think I am more successful?*"*

Learners can follow their level of mastery/non-mastery and their interaction with the related material. Hence, material interaction after taking the proficiency test can be followed by the learners.

In sum, 10 dashboard elements were generated as a result of a systematic design process. These elements were developed under course-related and topic-related sections. Four elements on the course-related dashboard were LA feedback and two of them were LA feedforward. While on the topic-related dashboard three elements were LA feedback and one element was LA feedforward. The design process can be revised based on application and evaluation. However, the ultimate aim of this study is to reveal a systematic design process as well as the dashboard design based on this process. Future studies will contribute for development and optimization of this design.

4. DISCUSSION and CONCLUSION

As a result of the systematic design process, it was determined that the expectations of students and lecturers from the learning dashboard were gathered under two main themes. First of all, it was agreed that the learning dashboard should be presented to visualize the current status of the students using the system. LA feedbacks, in which students' current situations are revealed depending on the system usage, are included in the learning dashboard. On the other hand, the future behavior and performance of the students has been tried to predict based on their current system usage behaviors and performances. These learning analytics indicators are also included in the learning dashboard as a LA feedforward.

The dashboard elements to be presented at the end of a systematic data collection and design process are structured on two separate pages as course-related dashboard and topic-related dashboard. MOOCs platforms are generally competency-based and have a modular structure. Therefore, the topic-related dashboard presented here is an example for other MOOC platforms.

As a result of the study, 10 dashboard elements were created, some of which consist of a single metric and some of which consist of many metrics. 6 of them were evaluated as LA feedback. The following information is presented with the dashboard elements evaluated as LA based feedback:

- Performance displays based on mastery test indicators
- Norm-referenced feedback and self-referenced feedback according to recent performance
- Concepts learned
- Trending material types
- Time spent on the topic
- Interactions for the relevant topic

Dashboard elements evaluated as LA feedforward are as follows:

- Success predictions for all topics
- Course completion time prediction
- Roadmap of successful learners
- Success prediction for the relevant topic

When researches on learning analytics are examined, most of the existing research until recent years included learning analytics reports based on descriptive statistics, aiming to determine the current behavior of students in the learning management system (Clow, 2013; Bakharia et al., 2016). Researchers emphasize that the benefit of reporting student data on LADs of learning management systems will be limited. The importance of interpreting these reports in a way that students can understand, making predictions about the future behavior and performance of the students, and making recommendations for students is emphasized (Jivet, Scheffel, Drachsler, & Specht, 2017; Jivet, Scheffel, Specht, & Drachsler, 2018). The importance of learning analytics indicators to be used for feedforward purposes, which will be included in LADs, becomes evident. In the study carried out by Leavy and Rheinschmidt (2010), a metric was developed to predict the success of the students in the online course. It was observed that there was a significant increase in the success of the students who took the course as a result of the lecturers following the student based on this metric and making interventions when necessary. Similarly, it has been demonstrated that learning analytics has the ability to accurately predict risky behaviors and improve students' learning performance and learning outcomes (Du, Yang,

Shelton, Hung, & Zhang, (2021); Herodotou, Rienties, Hlosta, Boroowa, Mangafa, & Zdrahal, 2020; Mubarak, Cao, & Ahmed, 2021; Namoun & Alshanqiti, 2021).

It is stated that in the studies carried out on learning analytics indicators, the opinions of students and instructors are mostly not consulted on which metrics should be used. Researchers especially emphasize the importance of student-centered learning analytics, which also includes student and instructor opinions (Muljana & Luo, 2021; Ochoa & Wise, 2021). With this research, learning analytics indicators that were decided to be utilized as feedback and feedforward in the learning analytics dashboard were determined based on student and lecturer opinions. For future research, obtaining data on the performance of this learning panel, determining the improvement process of the learning panel, and the effect of panel usage on the learning process and results of the students.

5. ACKNOWLEDGMENT

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