Exploring the Navigation Patterns of Learners on an Educational Recommender System

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Abstract. In this study, the interaction of students with an educational recommender system has been analyzed based on log data. Considering the fact that it is quite a challenging task to measure and model how learning actually takes place, the main contribution of this paper is to provide insights into the learning processes of learners based on interaction data. Various types of factors about learners such as prior knowledge level, motivation level, and learning styles can affect their learning processes and the learning outcomes directly. These factors also affect the usability of educational systems among other system-related aspects. In this regard, analyzing the usage data of adaptive e-learning systems can provide valuable information about the effectiveness of recommendations and the learning processes of learners. With this motivation, we collected and analyzed the interaction data of a semantic web-based educational recommender system. The educational recommender system was used as a supplementary tool by 172 voluntary students who took the Digital Computer Design course of the Computer Engineering curriculum at a public university in Turkey. Different types of learning resources such as presentations, videos (for teaching theoretical subjects and demonstrating different examples), exercises, and quizzes have been used as learning materials. Users can directly access the learning materials in whichever order they prefer or may follow the recommendations of the e-learning system. We analyzed the system interaction data to provide descriptive statistics and insights on various aspects such as learning material usage patterns of learners, popularity of learning materials based on learning material types, success levels at quizzes, and whether the learners were likely to follow recommendations given as hints after wrong answers at quizzes. The results are promising; however, considering the limited application size of a single course, further studies should be conducted to support the findings.

Keywords: E-Learning · Recommender Systems · Student Behaviour · Navigation Patterns

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1 Introduction

Educational recommender systems aim to improve the learning processes of learners by observing their interaction with learning materials and guiding them to use other relevant learning materials [1–4]. In this regard, individual differences of learners such as prior knowledge level, motivation level, and learning styles are modeled to provide enhanced learning experiences to learners [5–8]. Monitoring the interaction of learners with recommended learning materials is important to assess if the recommendations are useful for the learners [9–11]. Since it is a challenging task to model and/or understand the learning process, evaluation of log data can provide meaningful insights about the learning processes of learners [12].

Semantic web technologies and ontologies are widely used for knowledge representation purposes to model learners and educational resources [13,14]. Individual differences of learners are often utilized to provide adaptation and/or personalization in e-learning systems [15,16]. The learner model ontologies and interaction data of learners with e-learning systems provide valuable data for recommender systems to operate on [17–20]. Various artificial intelligence methods can also be used for educational data mining to analyze the data collected by recommender systems [21–24].

In this paper, we collected interaction data by using a semantic web-based educational recommender system [25] that models individual differences of learners with an ontology based on previous knowledge levels and learning styles of learners. Then, we analyzed the collected data to provide insights into the learning processes of learners and enhance their learning experiences in future interactions.

The rest of the paper is organized as follows; Sect. 2 briefly discusses the related work, and Sect. 3 introduces the web-based educational recommender system and the course that provides the data analyzed in this paper. Section 4 presents and discusses the statistical findings obtained by the analysis of the log data of the utilized educational recommender system. Finally, Sect. 5 concludes the paper with a brief discussion of the findings, limitations of the study, and possible further work directions.

2 Related Work

The importance of recommendation systems in the field of education is increasing, and in order to improve the effectiveness of these systems, it is of great importance to understand the users' browsing behavior among learning materials. Some important studies on this subject are briefly discussed below:

Students' navigation behavior through learning materials was analyzed by [26], and the results of this analysis were used as a basis to determine students' skill levels and suggest appropriate problems to practice based on the skill levels of students. This approach aims to introduce an improved recommendation system to provide more personalized and effective learning experiences to students.

A recommender system for learning activities was developed by [27] by utilizing knowledge graphs. Knowledge graphs are employed to model relationships between learning materials, concepts, and learning objectives. These graphs define the learning path a student should follow to achieve a specific learning objective. The recommender system determines the most suitable learning paths, taking into account the student's current level of knowledge and learning objectives, and suggests learning materials based on these learning paths. This system demonstrates the potential of using knowledge graphs to optimize the learning processes of students and help them progress more effectively.

Adaptive and personalized learning approaches were explored by [28] based on students' cognitive characteristics. Traditional educational methods often fail to consider that each student has different learning styles, skills, and needs. Therefore, a new learning approach aimed at enhancing learning experiences by understanding students' cognitive characteristics was introduced by [28]. Students' cognitive characteristics were assessed by using various tools, and methods, and used as an information source to provide adaptive and personalized learning content. The practical applications of this approach were discussed by examining how it can improve students' learning processes and enhance learning outcomes.

The main objective of [29] is to understand learning behavior patterns in social adaptive personalized e-learning systems. Students' learning behaviors in these systems were examined by combining social and personalized elements of e-learning. The use of various analyses and methods to understand student interactions and learning processes in such e-learning systems was discussed. Additionally, the impact of social interactions and personalized learning content on student success was investigated. Thus, this study aims to understand how the integration of social media and personalized learning technologies affects e-learning experiences.

It was aimed to utilize learning analytics to support both learners and teachers in [30]. The importance of using learning analytics tools to meet the needs of students and enhance their educational experiences was emphasized. Specifically, interactions and behaviors of students throughout their learning process were examined by adopting navigation among contents as a model. This model aims to understand how students navigate among learning materials and the impact of these navigation patterns on student success. Additionally, it may assist teachers in tracking students' progress and guiding their learning experiences more effectively.

It was aimed to predict student performance in higher educational institutions by utilizing video learning analytics and data mining techniques in [31]. It was sought to contribute to the exploration of new and effective methods for determining student success as digital technologies become increasingly integrated into education. Providing insight into how such analysis and predictions can be used to enhance teaching and learning processes in higher educational institutions was investigated.

3 The Educational Recommender System and Learning Materials Used for Data Collection

The semantic web-based educational recommender system utilized for data collection is presented in the following subsection. Then, the Digital Computer Design course is introduced and the learning materials prepared for this course are explained.

3.1 The Semantic Web-Based Educational Recommender System

The data used in this study is collected with a semantic web-based educational recommender system [25]. This recommender system was used as a supplementary tool to support Computer Engineering students at the Digital Computer Design course of a public university in Turkey. The recommender system was used by 172 voluntary students for two weeks and interaction data of learners with learning materials were collected from logs and used as the main data source to analyze the behaviours of learners.

The semantic web-based educational recommender system models individual differences of learners by using prior knowledge levels and learning styles. Learners were modeled with a learner modeling ontology that contains demographic information of learners, their grades at related courses, CGPA scores, and learner styles based on the Felder and Silverman learning style model [32]. A screenshot of the utilized educational recommender system is given in Fig. 1.

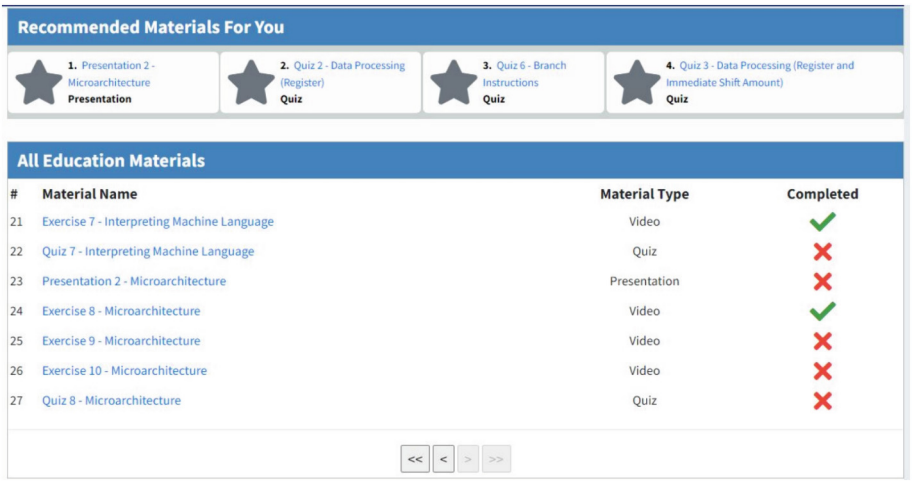

Fig. 1. A screenshot of the utilized educational recommender system [25]

This recommender system utilizes association rule mining to detect navigation patterns of learners [33]. In this regard, Frequent Pattern Growth (FP-Growth) algorithm [34,35], which is a popular algorithm that provides high

performance, is used by the recommender system to analyze log data and detect meaningful patterns among learning materials.

3.2 Learning Materials of Digital Computer Design Course

Digital Computer Design course is one of the main hardware courses of the computer engineering curriculum [36]. It is closely related to the Logic Design course which is part of the previous semester of the curriculum. Even though there is not an official prerequisite relationship between these two courses, the topics covered in the Digital Computer Design course can be thought of as a continuation of the topics of the Logic Design course. Thus, the success levels of students at the Logic Design course can be a good indicator of the success levels of students at the Digital Computer Design course. That's why we used the grades of students from the Logic Design course to model previous knowledge levels of students.

Learning materials were prepared for two topics of the Digital Computer Design course; Machine Language Instruction Encodings and Microarchitecture; that were taught after the midterm exam. Therefore, we also used the midterm grades of students at the Digital Computer Design course to model the previous knowledge levels of students. Finally, we also used the CGPA scores of learners until the semester the Digital Computer Design course was taught as another data source. Thus, the knowledge levels of learners were determined based on three parameters; CGPA scores of learners, grades of the Logic Design course, and grades of the midterm exam of the Digital Computer Design course.

Four types of learning materials were prepared for the Digital Computer Design course. The statistics related to learning material types and the amount of available learning materials from each learning material type are listed in ascending order at Table 1.

Table 1. Learning Material Types and The Amount of Available Learning Materials from Each Learning Material Type

No	Learning Material Type	The Amount of Learning Materials
1	Presentation	2
2	Video	7
3	Quiz	8
4	Exercise	10

Two presentations were prepared as ".pdf" files for the two topics of the Digital Computer Design course covered by the educational recommender system. These two presentations are listed below:

- "Presentation 1 - Instruction Encoding"
- "Presentation 2 - Microarchitecture"

In addition to presentations, seven video files that cover the theoretical background of some important subtopics were prepared. We tried to focus on important aspects and keep the video lengths as short as possible, i.e. less than 10 min. The videos were named based on the subtopics they focused on, and listed below:

- "Video 1 - Data Processing Instructions (Immediate)"
- "Video 2 - Data Processing Instructions (Register)"
- "Video 3 - Data Processing Instructions (Register and Immediate Shift Amount)"
- "Video 4 - Data Processing Instructions (Register Shifted Register)"
- "Video 5 - Memory Instructions"
- "Video 6 - Branch Instructions"
- "Video 7 - Interpreting Machine Language"

Exercise videos that cover applied examples of some important subtopics were also prepared. We focused on the most important aspects and prepared more than one exercise video for some subtopics, while we decided not to include any exercise video for some subtopics as their theoretical videos were thought to be enough to cover those subtopics. We kept the exercise video lengths less than 10 min, too. The exercise videos were named based on the subtopics they focused on, and listed below:

- "Exercise 1 - Data Processing Instructions (Register)"
- "Exercise 2 - Data Processing Instructions (Register)"
- "Exercise 3 - Memory Instructions"
- "Exercise 4 - Branch Instructions"
- "Exercise 5 - Interpreting Machine Language"
- "Exercise 6 - Interpreting Machine Language"
- "Exercise 7 - Interpreting Machine Language"
- "Exercise 8 - Microarchitecture"
- "Exercise 9 - Microarchitecture"
- "Exercise 10 - Microarchitecture"

Eight quizzes were prepared to assess the knowledge levels of learners at each subtopic of the Digital Computer Design course covered by the educational recommender system. The quizzes are listed below:

- "Quiz 1 - Data Processing Instructions (Immediate)"
- "Quiz 2 - Data Processing Instructions (Register)"
- "Quiz 3 - Data Processing Instructions (Register and Immediate Shift Amount)"
- "Quiz 4 - Data Processing Instructions (Register Shifted Register)"
- "Quiz 5 - Memory Instructions"
- "Quiz 6 - Branch Instructions"
- "Quiz 7 - Interpreting Machine Language"
- "Quiz 8 - Microarchitecture"

The number of questions available at each quiz is listed at Table 2. A total of 20 distinct question types were distributed to eight quizzes based on the subtopics they are related to. We wanted the students to have a more focused experience at each quiz. Thus, we tried to keep the number of questions at quizzes at a relatively low amount.

Table 2. The Amount of Questions Available at Each Quiz

Quiz No	The Number of Questions
Quiz 1	3
Quiz 2	2
Quiz 3	2
Quiz 4	2
Quiz 5	2
Quiz 6	3
Quiz 7	3
Quiz 8	3
Total	20

4 Statistical Findings of the Educational Recommender System Usage by Learners

The data collected by the semantic web-based educational recommender system were analyzed to provide insights regarding the learning processes of learners, and the findings are presented in this section. First, the statistical findings regarding the usage of the recommender system by learners are given. Then, the success levels of students at quizzes are discussed. Finally, the interaction of learners with recommended learning materials based on hints after wrong answers at quizzes is analyzed.

The log data of the educational recommender system were analyzed to provide statistics about the learner-system interaction. The usage ratios of each learning material over 100% are listed in descending order at Table 3.

"Quiz 1 - Data Processing Instructions (Immediate)" is the most commonly accessed learning material with 16.57%. "Presentation 1 - Instruction Encoding" is the second accessed learning material with 12.93%. "Quiz 7 - Interpreting Machine Language" is the third accessed learning material with 4.97%; however, its usage percentage is quite low compared to the first two highly-accessed learning materials.

The first and the second highly-accessed learning materials account for 29.5% of the overall learning material access in total. Considering the fact that the recommender system has 27 learning materials in total, it can be concluded that

Table 3. A List of Most Commonly Accessed Learning Materials

Learning Material Name	Usage Ratio of the Learning Material
Quiz 1 - Data Processing Instructions (Immediate)	16.57/100
Presentation 1 - Instruction Encoding	12.93/100
Quiz 7 - Interpreting Machine Language	4.97/100
Quiz 2 - Data Processing Instructions (Register)	4.95/100
Quiz 6 - Branch Instructions	4.86/100
Exercise 2 - Data Processing Instructions (Register)	4.63/100
Exercise 4 - Branch Instructions	4.56/100
Quiz 8 - Microarchitecture	4.02/100
Quiz 3 - Data Processing Instructions (Register and Immediate Shift Amount)	3.72/100
Quiz 4 - Data Processing Instructions (Register Shifted Register)	3.7/100
Video 1 - Data Processing Instructions (Immediate)	3.1/100
Quiz 5 - Memory Instructions	3.01/100
Exercise 1 - Data Processing Instructions (Register)	2.58/100
Video 2 - Data Processing Instructions (Register)	2.32/100
Video 4 - Data Processing Instructions (Register Shifted Register)	2.3/100
Video 3 - Data Processing Instructions (Register and Immediate Shift Amount)	2.13/100
Video 6 - Branch Instructions	2.09/100
Exercise 8 - Microarchitecture	1.87/100
Video 5 - Memory Instructions	1.85/100
Exercise 9 - Microarchitecture	1.79/100
Exercise 3 - Memory Instructions	1.79/100
Presentation 2 - Microarchitecture	1.74/100
Exercise 7 - Interpreting Machine Language	1.72/100
Exercise 10 - Microarchitecture	1.72/100
Exercise 6 - Interpreting Machine Language	1,72/100
Exercise 5 - Interpreting Machine Language	1.7/100
Video 7 - Interpreting Machine Language	1.66/100

two of them dominated the others. However, the reason behind this domination can be easily observed when we check the contents of the first two highly-used learning materials. “Quiz 1 - Data Processing Instructions (Immediate)” is the first quiz learners can access and is involved with the first type of data processing instruction encoding. Thus, it is not surprising to see it at the top of the list

as learners could have probably wanted to test their knowledge level by starting with this quiz. The second most accessed learning material "Presentation 1 - Instruction Encoding" is the first of the two presentation files available at the system. Besides, it is the first learning material listed on the user interface. Thus, it can be expected for it to have a high level of user access as some of the learners might have wanted to start learning from the beginning and follow the order of the listed materials.

We can also analyze the usage ratios of learning materials based on learning material types. There are four types of supported learning materials in the recommendation system, which are stated at Table 1.

As the first type of learning material, there are two presentations available in the recommender system. The usage ratio of "Presentation 1 - Instruction Encoding" is relatively high at 12.93% as it is the second highest used learning material, whereas the usage ratio of "Presentation 2 - Microarchitecture" is quite low at 1.74% as it is ranked as the 23rd highly-accessed learning material among the 27 learning materials available at the system (Table 3). There may be a lot of reasons that contributed to this finding. First of all, "Presentation 1 - Instruction Encoding" covers most of the available learning materials as 22 of the 27 materials are related to it, while "Presentation 2 - Microarchitecture" is involved with the remaining 5 learning materials. The second reason may be the order of the learning materials as "Presentation 1 - Instruction Encoding" is listed as the first learning material at the user interface.

Videos are the second learning material type supported by the recommender system, and their usage statistics can be seen in Table 3. "Video 1 - Data Processing Instructions (Immediate)" has the highest usage ratio with 3.1%. "Video 2 - Data Processing Instructions (Register)" and "Video 4 - Data Processing Instructions (Register Shifted Register)" are the second and the third highly watched videos with very close percentages at 2.32% and 2.3%, respectively. "Video 3 - Data Processing Instructions (Register and Immediate Shift Amount)" and "Video 6 - Branch Instructions" follow them with close ratios to each other at 2.13% and 2.09%, respectively. "Video 5 - Memory Instructions" is ranked as the 6th most watched video with 1.85% and it is the 19th most accessed learning material. Finally, "Video 7 - Interpreting Machine Language" is the least watched video with 1.66% and it is also the least accessed learning material on the overall list as it is the lowest ranked learning material at the 27th position. The reason for this last position can be related to the order of the subtopics as it is the video related to the last subtopic. On the other hand, learners could have liked to engage with other learning material types more than videos.

As the third learning material type of the recommender system, the usage statistics of exercises can be seen at Table 3. "Exercise 2 - Data Processing Instructions (Register)" and "Exercise 4 - Branch Instructions" are the most accessed exercises with 4.63% and 4.56%, respectively. They are followed by "Exercise 1 - Data Processing Instructions (Register)" at the third position with a 2.58% access ratio, while the rest of the exercises have quite close usage ratios ranging between 1.87% and 1.7%. It is an interesting finding to see "Exercise 1 - Data Processing Instructions (Register)" at the third position, because the

first presentation and the first video were at the top positions for their learning material type. This finding may be related to quizzes as some learners might have wanted to check some exercises after wrong answers to some questions of the related quizzes.

The fourth and final learning material type supported by the recommender system is quizzes. The access ratios for each quiz can be observed at Table 3. "Quiz 1 - Data Processing Instructions (Immediate)" is by far the most accessed quiz with 16.57% access ratio. It is followed by "Quiz 7 - Interpreting Machine Language", "Quiz 2 - Data Processing Instructions (Register)", and "Quiz 6 - Branch Instructions" at the second, third, and fourth positions with close ratios at 4.97%, 4.95%, and 4.86%, respectively. "Quiz 8 - Microarchitecture" is at the fifth position with 4.02% usage ratio, while "Quiz 3 - Data Processing Instructions (Register and Immediate Shift Amount)" and "Quiz 4 - Data Processing Instructions (Register Shifted Register)" are at the sixth and seventh positions with 3.72%, and 3.7%, respectively. Finally, "Quiz 5 - Memory Instructions" is at the last position with access ratio of 3.01%.

"Quiz 5 - Memory Instructions" is the least accessed quiz; however, it is ranked as the 12th most accessed learning material on the overall learning material access list. Since there are 8 quizzes in total, it is a valuable finding to see that 8 of the top 12 positions are filled with quizzes. That shows that quizzes are the most accessed and the most popular learning material type.

Average grades of students at quizzes are listed in descending order at Table 4. Learners were more successful at "Quiz 1 - Data Processing Instructions (Immediate)", "Quiz 2 - Data Processing Instructions (Register)", and "Quiz 3 - Data Processing Instructions (Register and Immediate Shift Amount)" with very close scores at 67, 66, and 66 over 100 points, respectively. The least successful quizzes were "Quiz 5 - Memory Instructions" and "Quiz 8 - Microarchitecture" with very close average scores at 49, and 51 points, respectively. It should be noted that the learners can take the same quizzes over and over again, and the average grades listed at Table 4 were calculated by taking into account each quiz activity.

Table 4. Average Grades of Learners at Quizzes

Quiz Name	Average Grade
Quiz 1 - Data Processing Instructions (Immediate)	67/100
Quiz 2 - Data Processing Instructions (Register)	66/100
Quiz 3 - Data Processing Instructions (Register and Immediate Shift Amount)	66/100
Quiz 4 - Data Processing Instructions (Register Shifted Register)	58/100
Quiz 7 - Interpreting Machine Language	55/100
Quiz 6 - Branch Instructions	54/100
Quiz 8 - Microarchitecture	51/100
Quiz 5 - Memory Instructions	49/100

Learners can check the correct answers after taking quizzes. If the answer to a question in the quiz is wrong, the recommender system guides the learners to suitable learning materials by giving them hints. The log data is analyzed to check if the learners followed the hints and clicked the suggested learning materials after each quiz. The results are listed at Table 5.

Table 5. Number of Clicks to Suggested Learning Materials After Each Quiz Based on Hints

Quiz Name	Number of Clicks To Suggestions
Quiz 1 - Data Processing Instructions (Immediate)	64
Quiz 2 - Data Processing Instructions (Register)	16
Quiz 3 - Data Processing Instructions (Register and Immediate Shift Amount)	19
Quiz 4 - Data Processing Instructions (Register Shifted Register)	7
Quiz 5 - Memory Instructions	2
Quiz 6 - Branch Instructions	16
Quiz 7 - Interpreting Machine Language	22
Quiz 8 - Microarchitecture	6

It is observed that users were the most likely to follow the hints after "Quiz 1 - Data Processing Instructions (Immediate)" with 64 clicks detected. Even though it is not certain whether the suggested learning material was clicked because of following the hints, based on recommendations at the user interface, or as a result of random navigation, there seems to be a correlation between usage ratios of quizzes and the number of clicks to suggested learning materials based on hints at the quizzes. "Quiz 1 - Data Processing Instructions (Immediate)" is at the top of both statistics, and "Quiz 7 - Interpreting Machine Language" is the second item on both of the lists. However, the number of clicks to suggested learning materials based on hints after taking quizzes is relatively low. Thus, we should point out that there is not enough interaction data to support the generalization of this finding. In this regard, the limited number of available log data is one of the main limitations of this study.

5 Discussion and Conclusion

In this paper, we analyzed the interaction data of learners with an educational recommender system to provide insights into how learners navigated through the system. The recommender system included learning materials prepared for a subset of topics of the Digital Computer Design course. The data used in this study was collected by utilizing the recommender system as a supplementary tool as part of the Digital Computer Design course of the Computer Engineering

curriculum at a public university in Turkey for two weeks during which the related subtopics were covered at the class.

The findings were discussed thoroughly to provide insights regarding the learning processes of learners. It is observed that learners were more likely to interact with quizzes than other types of learning materials. The fact that the recommender system was used as a supplementary tool and the students were already familiar with the subjects from the theoretical lectures might have been a factor in decreasing the popularity of other learning materials. In addition, there seems to be a correlation between quiz access ratios of students and the number of clicks to suggested learning materials based on the hints of wrong answers after taking quizzes; however, this finding needs to be supported by conducting new experiments with higher number of students, which is planned as future work.

In this regard, the study's reliance on data collected from a single course for a short duration is the main limitation of this study. Thus, the findings may have limited generalizability due to the specific context the data was collected. Even though the results are promising and in line with previous studies [21,29], the findings may not be representative of learner behavior in other educational settings or over longer time frames. Therefore, further studies should be conducted to support the findings of this study.

Future work directions can be discussed from learning design and system design perspectives. From the learning design perspective, instead of being used as a supplementary tool, the educational recommender system can be integrated with the theoretical lectures of the course to provide enhanced learning experiences. Feedback about the quality of the learning materials can be gathered and utilized to update them appropriately. In this regard, it is planned to work with learners more closely and also collect qualitative data by conducting focus group interviews. A comparison or control group against which to benchmark the observed navigation patterns could also be useful for achieving meaningful results in further studies.

From the system design perspective, the functionalities of the educational recommender system can be improved and new functionalities can be added. For example, instead of providing hints at the end of quizzes and checking whether the students followed the recommendations, the quiz feature can be enhanced to provide question-level interactions dynamically in case of a wrong answer. There are also plans to make technical adjustments to enhance the recommendation capability of the recommender system.

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