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Research on Learning Behavior of "One Network One Platform" Based on Lag Sequential Analysis

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Abstract: In this paper, 255 students from Ningbo Open University who took the course "English for the Humanities 3" in the 2022 spring semester are taken as the research objects. Using the course learning data from "One Network and One Platform", the online learning behavior sequence is classified, coded, and the behavior transformation diagram is generated through correlation analysis and lag sequential analysis methods. The research shows that the sequence of learning behavior follows the logical order of curriculum teaching, and learning behavior positively affects the learning results; the online learning input of students has a strong performance orientation; the learning path design and process of the platform meet the learning needs of students. Therefore, the course teaching process should be designed scientifically to guide and stimulate students' online learning needs.

1. Introduction

In recent years, new online open courses and learning platforms, such as large-scale online open courses ("MOOC"), have sprung up worldwide, expanding the teaching space and time, enhancing the teaching attraction, stimulating the learning enthusiasm and autonomy of learners, expanding the benefits of high-quality education resources, and promoting changes in teaching content, methods, models, and teaching management systems and mechanisms. It will bring new opportunities and challenges to the reform and development of higher education [1]. Online learning is of great significance to teaching reform and personalized learning. However, online learning is a kind of self-driven autonomous learning based on constructivism. Compared with ordinary undergraduate students, adult students of open education have lower learning initiative and weaker learning ability. Therefore, their online learning process should be guided, analyzed and supervised. Learning behavior analysis, as a new technology in the field of education, uses different analysis methods and technologies to analyze the behavior data in the learning process, so as to discover the learning rules, understand the internal characteristics of learners, predict the learning effect, present the analysis results to teachers through visualization technology, so that learners can understand their self-learning situation, interaction with learning partners, and adjust the learning progress and learning methods, It is of great significance for students, teachers, educational administrators, educational researchers, educational decision-makers and system developers to enable teachers to discover the deficiencies in teaching[2].

2. Research Theory and Learning Platform

2.1. Learning Analysis Theory

Since George Siemens put forward the theory of learning analysis in August 2010, it has attracted extensive attention from many educational researchers at home and abroad who carried out relevant researches. The basic research of learning analysis theory mainly involves the definition of learning analysis concepts and connotations, and the design of learning behavior analysis models. George Siemens, a founding President of the Society for Learning Analytics Research, together with Gu Xiaoqing and Zhu Zhiting, and others in China elaborated on the concept of learning analysis. The core and connotations of learning analysis include three aspects: learning analysis object, learning analysis focus and learning analysis goal [3].

Learning behavior analysis methods and technologies mainly include educational data mining, statistical analysis, social network analysis, discourse analysis, content analysis, etc. Yang Xianmin and others analyzed the learning behavior through the lag sequential analysis method, found the learning preference and guided the design of learning activities. The application research of learning behavior analysis mainly involves the use of learning analysis tools to collect and analyze student behavior data, pay attention to students' learning needs and learning environment, and explore the relationship between online learning behavior and learning performance [4].

2.2. "One Network and One Platform"

The Open University of China started the construction of the "Open University Internet plus University Integrated Management Service Platform Construction and Application Project" (referred to as "One Platform") in January 2021; The launch of the "Open University Internet plus University Learning Network Upgrade and Application Demonstration Project" (referred to as "One Network") on January 20, 2021 is a major initiative in response to the Ministry of Education's strategic action on digital education. The launch and application of this platform provide comprehensive technical support and process records for online learning of open education. Ningbo Open University is one of the six branches that carried out the whole process pilot application of the platform in 2021. By the 2022 spring semester, all students, all majors and all courses of Ningbo Open University were piloted in the "One Network and One Platform". There are 23,573 students in the whole city, 798 courses in total and 138,364 course selection records.

3. Research Design

3.1. Research Methods

Lag Sequential Analysis (LSA for short) was proposed by Sackett in 1978 [5]. It is mainly used to test the probability of one behavior occurring after another and whether there is statistical significance [6]. In recent years, researchers in the field of educational technology began to pay attention to LSA and applied it to the analysis of learning behavior. LSA has a good application prospect in the field of learning behavior analysis, which can help researchers and teachers accurately grasp the potential behavior patterns of learners, explain the reasons why technology enhances learning effects from a behavioral perspective, and effectively guide the design and implementation of follow-up teaching and learning activities [7].

The research is done based on the learning data of the course “English for the Humanities 3” in Ningbo Open University in the spring semester of 2022. The data is collected from the platform called “One Network and One Platform” of the Open University of China. This research uses the lag sequential analysis method to build a visual learning path, and explores the behavior sequence among online learning activities of four modules, namely “course guidance”, “teaching resources”, “unit learning” and “course interaction”. Finally, the results are presented in a visual online learning path map.

3.2. Research Objects

The research objects selected for this research are the learners of “English for the Humanities 3” in Ningbo Open University in the spring semester of 2022. The total number of students who selected this course is 270, belonging to 10 majors, and a total of 18 teaching classes. In this study, 255 learners (94.4% of the total number of students) were selected based on the criteria of obtaining valid final scores. The platform data will be counted from March 1, 2022 to August 1, 2022.

3.3. Research Process

3.3.1. Data Collecting and Pre-processing

The data provided by the “One Network and One Platform” of the Open University of China include the total number of course visits, the visits of each student, the visits to courses and the completion of each part of the content. Student visits data include the first time of entering the courses, the number of visits, the length of visits, the number of audio and video viewing, the rate of audio and video viewing, the length of audio and video viewing, the number of reference materials viewing and downloading, the rate of reference materials viewing/downloading, the number of online link viewing, the rate of online link viewing, the number of viewing of recorded and broadcast textbooks, the rate of viewing recorded and broadcast textbooks, the number of submitting times of assignments, the number of assignments submitted, the rate of submitting assignments, the number of online test submissions, number of tests submitted, online test submission rate, number of posts published (number of main posts/number of replies), discussion participation rate, roll call (arrived/absent/leave) and course completion. Among them, the number of visits, the length of visits and the degree of course completion can be regarded as representative indicators of each student's online learning data. The course content can be divided into four modules: course guidance, teaching resources, unit learning and course interaction.

Before the sequential analysis of students' learning behavior, it is necessary to determine the relationship between these learning activities and learning effects. Therefore, this study selected those three representative indicators of students' learning behavior and course comprehensive scores for Pearson correlation analysis. The results are shown in Table 1.

Table 1: Correlation (N=255).

	Scores	Number of visits	Length of visits	Course completion
Scores	1			
Number of visits	$.215^{**}$	1		
Length of visits	$.207^{**}$	$.710^{**}$	1	
Course completion	$.256^{**}$	$.627^{**}$	$.692^{**}$	1

Note: * * The correlation was significant on 0.01 level (double tail).

Table 1 shows that students' comprehensive scores are significantly positively correlated with the number of visits, the length of visits, and the degree of course completion, indicating that the more visits students have, the better their academic performance will be; the longer they visit, the higher scores they get; the higher the degree of course completion, the better the academic performance.

On this basis, this study further uses the lag sequential analysis method to investigate the sequence of learning behaviors that have a significant probability of occurrence on the platform, makes statistics on the student actions recorded in the course learning analysis table, and eliminates the types of sporadic actions that occur rarely. The effective data of each student's visit mainly focuses on 16 learning behaviors, including browsing “what to learn”, “how to learn”, “how to test”, “Teaching team”, “support services”, “assessment instructions”, “syllabus” and “expanding resources”, watching teaching audio and video, doing “conversation drills”, “practice while learning”, “writing training” and “unit self-test”, filling in the “student satisfaction questionnaire”, and participating in “headquarter Q&A” and “branch Q&A” as the research objects of this behavior sequential analysis.

3.3.2. Data Coding and Behavior Conversion Frequency Generation

When coding the learning behavior, in order to reflect the learning behavior and the category of the curriculum module, this study marks four modules in the curriculum content: course guidance, teaching resources, unit learning and course interaction as A, B, C and D respectively. The learning behavior in each module is marked with Arabic numerals in turn. The codes of the 16 learning behaviors in this sequential analysis are shown in the following table 2:

Table 2: Learning behavior code table.

Module	Behavior	Code	Module	Behavior	Code
Course guidance	Browsing "what to learn"	A1	Unit learning	Watching teaching audio and video	C1
	Browsing "how to learn"	A2		Doing "conversation drills"	C2
	Browsing "how to test"	A3		Doing "practice while learning"	C3
	Browsing "Teaching team"	A4		Doing "writing training"	C4
	Browsing "support services "	A5		Doing "unit self-test"	C5
Teaching resources	Browsing "assessment instructions"	B1	Course interaction	Filling in the "student satisfaction questionnaire"	D1
	Browsing "syllabus"	B2		Participating in "headquarter Q&A"	D2
	Browsing "expanding resources"	B3		Participating in "branch Q&A"	D3

Input the contents of the table generated by the above coding steps into the lag sequential analysis tool GSEQ5, and generate the behavior frequency conversion table of 15 rows and 15 columns in Table 3. Each row in the table represents the previous behavior, each column represents the subsequent behavior, and the number represents the frequency of the subsequent behavior after the previous behavior. A total of 1,262 sequence relationships were generated in this study.

The data in the table represents the number of occurrences of the behavior sequence formed by the transformation of row behavior into column behavior. As the number 111 in the second column of the first row in Table 3 indicates, the total frequency of browsing “what to learn” (A1) followed by browsing “how to learn” (A2) is 111, that is, the total frequency of sequence A1A2 is 111. From Table 3, we can quickly find many behavior sequences, such as A1A2 (111 times), A2A3 (112 times), and A3A4 (110 times).

Table 3: Behavior conversion frequency table

	A1	A2	A3	A4	A5	B1	B2	B3	C1	C2	C3	C4	C5	D1	D2	D3
A1	0	111	0	0	0	0	0	0	0	0	0	0	1	0	0	0
A2	0	0	112	0	0	0	0	0	0	0	0	0	0	0	0	0
A3	0	0	0	110	0	1	0	0	0	0	1	0	2	0	0	0
A4	0	0	0	0	109	1	0	0	0	0	0	1	0	0	0	0
A5	0	0	0	0	0	58	2	8	13	3	1	3	21	0	0	0
B1	0	0	0	0	0	0	51	5	2	3	0	0	4	0	0	0
B2	0	0	0	0	0	0	0	49	3	0	0	0	2	0	0	0
B3	0	0	0	0	0	0	0	0	52	7	0	0	4	0	0	0
C1	0	0	0	0	0	0	0	0	0	71	0	0	3	0	0	0
C2	0	0	0	0	0	0	0	0	0	0	55	23	9	0	0	0
C3	0	0	0	0	0	0	0	0	0	0	0	56	2	0	0	0
C4	0	0	0	0	0	0	0	0	0	0	0	0	89	0	0	0
C5	0	0	0	0	0	0	0	0	0	0	0	0	0	45	47	56
D1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	2
D2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29
D3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

3.3.3. Residual Analysis and Sequence Transformation Visualization

The table contents were converted into standard scores, and the behavior sequences with standard scores of z-score>1.96 were screened out. These are significant behavior conversion relationships. Table 4 is the adjusted residual table.

Table 4: Adjusted residual table (Z-scores)

Z	A1	A2	A3	A4	A5	B1	B2	B3	C1	C2	C3	C4	C5	D1	D2	D3
A1	0	34.87	-3.5	-3.46	-3.44	-2.45	-2.29	-2.49	-2.67	-2.96	-2.38	-2.94	-3.68	-2.09	-2.85	-2.91
A2	0	0	33.06	-3.63	-3.61	-2.57	-2.4	-2.61	-2.8	-3.1	-2.49	-3.08	-4.18	-2.19	-2.99	-3.05
A3	0	-3.69	0	32.44	-3.65	-2.15	-2.42	-2.64	-2.83	-3.13	-2.06	-3.12	-3.64	-2.21	-3.02	-3.08
A4	0	-3.63	-3.65	0	32.85	-2.11	-2.38	-2.6	-2.78	-3.09	-2.48	-2.69	-4.16	-2.17	-2.97	-3.03
A5	0	-3.59	-3.61	-3.57	0	23.82	-1.39	1.01	2.72	-1.9	-1.99	-1.88	2.16	-2.15	-2.94	- 3
B1	0	-2.66	-2.68	-2.65	-2.63	0	30.34	1	-0.95	-0.77	-1.82	-2.25	-1.5	-1.6	-2.18	-2.23
B2	0	-2.41	-2.42	-2.4	-2.38	-1.7	0	29.5	-0.05	-2.05	-1.65	-2.04	-1.91	-1.44	-1.97	-2.01
B3	0	-2.62	-2.64	-2.61	-2.59	-1.85	-1.72	0	26.82	1.32	-1.79	-2.22	-1.43	-1.57	-2.15	-2.19
C1	0	-2.86	-2.88	-2.85	-2.83	-2.02	-1.88	-2.05	0	30.76	-1.96	-2.42	-2.19	-1.72	-2.35	-2.39
C2	0	-3.14	-3.16	-3.13	-3.11	-2.21	-2.06	-2.25	-2.41	0	26.66	7.3	-0.58	-1.88	-2.57	-2.63
C3	0	-2.5	-2.52	-2.49	-2.48	-1.76	-1.64	-1.79	-1.92	-2.13	0	27.57	-2.05	-1.5	-2.05	-2.09
C4	0	-3.18	-3.2	-3.16	-3.14	-2.24	-2.09	-2.28	-2.44	-2.7	-2.17	0	25.87	-1.9	-2.6	-2.66
C5	0	-4.32	-4.35	-4.3	-4.28	-3.04	-2.84	-3.09	-3.31	-3.67	-2.95	-3.65	0	17.82	12.54	15.25
D1	0	-1.97	-1.98	-1.96	-1.95	-1.39	-1.3	-1.41	-1.51	-1.68	-1.35	-1.67	-2.26	0	22.25	-0.31

D2	0	-1.77	-1.78	-1.76	-1.75	-1.24	-1.16	-1.26	-1.35	- 1 . 5	-1.21	-1.49	-2.02	-1.06	0	20.12
D3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

According to Table 4, the occurrence probability of 20 behavior sequences has reached the significance level, namely A1A2, A2A3, A3A4, A4A5, A5B1, A5C1, A5C5, B1B2, B2B3, B3C1, C1C2, C2C3, C2C4, C3C4, C4C5, C5D1, C5D2, C5D3, D1D2 and D2D3. Among them, A1A2, A2A3, A3A4, A4A5, B1B2, B2B3, C1C2, C2C3, C2C4, C3C4, C4C5, D1D2, D2D3 reflect that students gradually participate in the learning process according to the online course arrangement sequence in each module.

In order to present user behavior sequences more intuitively, it is necessary to draw a behavior transformation diagram (as shown in Figure 1) based on significant behavior data. The arrow in the diagram represents the direction of behavior transformation, the number along with the arrow represents the Z value (adjusted residual value) of each behavior sequence, and the thickness of the line represents the significant level of behavior connection.

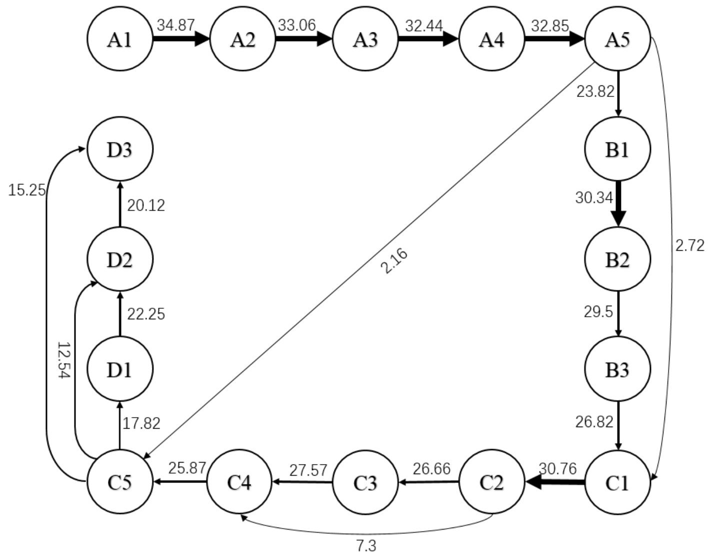

Figure 1: Behavior transformation diagram.

It can be seen from the above figure that the main line of students' behavior flows from A1-A2... to D2-D3 in turn, which means that after students log in to the platform, they first browse the content page of course guidance, then browse the teaching resource module, then complete the unit learning tasks, and finally participate in the course interaction activities. Most of the behaviors are carried out step by step according to the design process of the course platform, without reverse activities. This reflects the rationality and strong operability of the course network platform design. A5-C1 and A5-C5 reflect that students are eager to watch the teaching video content or directly try the unit test task after understanding the course support services; some students also enter the course question answering forum with questions after trying unit tests, and try to get help (C5-D2, C5-D3) through teacher-student communication and student-student communication, which reflects their willingness to input more efforts in order to achieve better performance and curriculum goals in testing activities. The appearance of C2-C4 sequence reflects that some students skip “learning while practicing” (C3) and directly enter “writing training” (C4) from “conversation practice” (C2). In the course platform, the forms of these three exercises are the same, and they are all objective forms of multiple choice questions or sorting questions. However, doing the exercises in “Learning and practicing" need to click the link to open another web page to operate and answer question. The answers are not shown immediately after submission; while "conversation practice" and "writing practice" is both done on the current web page, and the answers will be shown immediately after submission. This phenomenon shows that students are more inclined to complete exercises and assignments that are easy to operate and intuitively scored, which to some extent reflects students' unwillingness to choose tasks with higher cognitive challenges, and means that their persistence and concentration in learning may not be high.

4. Research Results

4.1. The Influence Mechanism of Learning Behavior on Learning Results

The examination of "English for the Humanities 3" adopts a combination of formative examination and final examination, with the scores accounting for 50% respectively. The formative assessment consists of two parts. The first part is to complete the self-test exercises of 8 units, accounting for 80%; the second part is teachers' comprehensive evaluation of students, which is included in formative assessment by 20%. Therefore, the scores of the eight unit self-test exercises in the course learning analysis data of the platform are part of the comprehensive course scores, which are necessarily proportional to the students' scores. Although other learning behaviors were not included in the curriculum assessment, the study found that students' learning behaviors were closely related to their grades.

First of all, Pearson correlation analysis was used to analyze the three representative online learning data of students' number of visits, length of visits, and course completion with their comprehensive course scores. The results showed that the three were positively correlated with their scores (see Table 1). It can be seen that the more time students spend participating in online learning on the platform, the more course knowledge they get from the platform, and the higher their final assessment scores, which fully demonstrates that online learning behavior has a positive impact on learning results.

Secondly, the statistics of the occurrence of single data of learning behavior is shown in the figure below (Figure 2). It can be seen that C5 (doing "unit self-test") has the highest behavior rate, reaching 100%, which means that all students have completed this activity. In addition, the incidence of other behaviors is below 50%, and the lowest D1 is only 18%. This comparison shows that the students' score-oriented learning objectives are very clear, and the high incidence of A3 (browsing "how to test") also reflects the students' high attention to the curriculum assessment results. Therefore, students' learning behavior can objectively reflect the assessment mechanism of the curriculum.

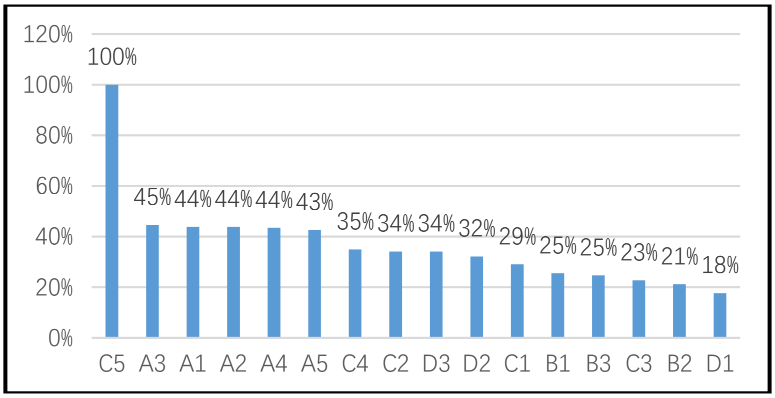

Figure 2: Incidence rate of learning behavior.

4.2. Verification and Enlightenment of Learning Behavior on Learning Platform

The design and development of the online courses of “One Network and One Platform” is basically around the resource design of knowledge points. The content arrangement of the online learning module of the “English for the Humanities 3” course in this study is consistent with the paper textbooks. The study on the sequence of learning behaviors found that students' learning behaviors showed a one-way flow (see Figure 1), and their learning order basically followed the logical sequence of curriculum teaching. In view of the fact that the students of this course are all part-time adult students of Open Education, their learning time is limited, and their learning ability and computer operation ability also have certain limitations. Such online course learning path design and process are very consistent with the learning needs of Open University students. The course platform has improved the learning efficiency of students to the greatest extent by reasonably guiding learning resources and activities, helping them successfully complete online learning content, and achieving better learning results.

However, students' high attention to course assessment and low incidence of non- assessment items (see Figure 2) also remind the platform designer how to attract students to actively participate in other projects and improve the visit rate and completion of various learning contents.

5. Conclusions and Suggestions

Learning behavior analysis is an important part of learning analysis. Through purposeful analysis of relevant behavior data recorded in the learning process, valuable information hidden behind the behavior data can be mined [7]. This research analyzes the learning behavior of “English for the Humanities 3” on the “One Network and One Platform” by using the lag sequential method. The following 3 aspects are found:

(1) The learning behavior has a positive impact on the learning results, and the learning behavior objectively reflects the curriculum assessment mechanism.

(2) The sequence of learning behavior basically follows the logical sequence of course teaching, and the design and process of course learning path are reasonable, which is convenient for students to use.

(3) The difference in the incidence of learning behavior reflects that scores are the main goal of students, that is, students' online learning input has a strong performance orientation.

In addition, the study also found some aspects to be improved:

(1) The low incidence and completion of non-assessment content is not conducive to students' expansion of learning. Tutors need to stimulate students' internal learning motivation, encourage them to participate in various learning activities more comprehensively, and obtain more complete learning experience. Teachers can guide students in the pre-class guidance, and the topics in the module can also be quoted in the tutorial class to attract students' attention to the module, but all this needs to be based on the useful and convenient design of the module. For example, the participation rate of C3 (“learning while practicing”) in Figure 2 is only 23%, because this exercise can only be completed by opening another web page, and students do not know the specific score after finishing, so students have a poor sense of experience. It is suggested to change this exercise to the current page operation mode, so students do not need to open another web page to do exercises. The scoring method is also set to score on the spot, and give correct answers and analysis, so that students can have a clearer and intuitive learning experience[9].

(2) The low degree of participation in the course interaction module also reflects the weak demand of students for learning and communication. It is suggested that the course forum and Q&A link have a clearer and more reasonable learning path, and that knowledge construction be effectively incorporated into the interaction activities, making it an important link for students'

online cognitive development. For example, the number of students' posts, replies, post clicks and likes can be included in the formative assessment results, which can not only increase the popularity of the forum, but also effectively share the relevant learning difficulties and experiences with more students. We can also organize students to share their life and learning experiences, introduce some hot topics, and attract more students to participate[10].

(3) The behavior transformation diagram (Figure 1) shows a one-way sequence from A1 to D3 as a whole, lacking interactive sequence activities, which reveals that students are more passive and mechanized in learning, and lack active learning. Teachers need to analyze relevant factors, guide students to in-depth studies according to their interests, attitudes, motivations and other variables, and use the resources of the platform to internalize knowledge.

An effective online learning participation model is a prerequisite to ensure that online learning really happens and deep learning occurs. Behavior sequence analysis shows that students' online learning needs guidance. Therefore, the focus of online course construction should not be simply resource construction, but should attach importance to the design and optimization of online learning paths, guide the design and development of resources and learning activities through the design of learning paths, provide online learning scaffolding for students with a more explicit and visual learning path, promote the formation of an effective online participation model, and achieve online learning and cognitive development [8]. Online learning is an important development direction of e-learning. Learning behavior analysis based on big data and learning analysis technology provides a new perspective and method for teachers to understand students' learning behavior and learning process. This research focuses on the open education English teaching practice, tries to tap the potential value of educational data, tries to show the current situation and main problems of online learning of open education students, and puts forward corresponding strategies to improve the use and operation ability of open education teachers and students on information technology, and ultimately improve the teaching quality.

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