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Implementation of Sequential Pattern Discovery using Equivalent classes (SPADE) on MONSAKUN Media for Exploring and Digging for Information on German Language Learning

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Abstract. This study aims to utilize a log database of German Learning learning media using the sequential pattern method to explore useful information from the student's learning process when working on German Learning language problems. The algorithm used is Sequential Pattern Discovery using the Equivalent class (SPADE). Furthermore, this study uses an algorithm to identify the same learning patterns based on student learning activities when using MONSAKUN learning media. Moreover, the learning pattern that has been successfully obtained will be carried out by extracting information to analyze the same learning pattern based on the category of the student's ability to solve problems. Based on the results of the implementation and analysis that has been carried out on 20 German Learning language questions that have been successfully processed in the MONSAKUN learning media, six patterns of learning activities that vary on each question and level are produced, namely: pattern 1, pattern 2, pattern 3, pattern 4, pattern 5, and pattern 6. Each pattern requires further feedback and responses to optimize students' learning progress in Learning German Learning.

Keywords:
Pattern;
Exploration;
Learning;

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INTRODUCTION

The subject that is often found difficult by students during the learning process in class is German Learning. German Learning differs from other topics because it requires good conceptual reasoning(Byusa et al., 2022; Jääskä et al., 2022). In addition, the process also needs students to solve a problem with detailed steps, which can be solved with varied answers (Schoenfeld, 2016). Therefore, teachers are required to choose the right learning model so that learning German Learning is fun and, at the same time, triggers students' creativity in solving German Learning problems(Byusa et al., 2022; Görgen et al., 2020; Höyng, 2022). One alternative learning model that can trigger students to be actively involved in the learning process, especially German Learning material, is through a problem-posing approach.

The problem learning model is a learning model that requires students to solve problems presented under certain conditions by reformulating existing issues to find alternative solutions(Brammer et al., 2021; Tang et al., 2022). Problem-learning activities positively affect problem-solving skills because they require students to actively learn independently(Alp Christ et al., 2022; Brown, 2022). However, although learning activities with the problem can increase students' interest in Learning, teachers need to spend a lot of time providing assessments and instructing students to pose problems based on available information.

An interactive learning media based on the problem-posing learning model was created to help teachers guide students in making problems called Monsakun (Supianto et al., 2017; Supianto & Hafis, 2018). In addition, Monsakun is designed to carry out an automatic evaluation process for each student and receive feedback based on the assignment given, whether it is following the requested problem. In practice, learning media will require students to solve the issues presented in each task by compiling three simple sentences(Supianto et al., 2017; Supianto & Hafis, 2018). So, the activity integrates corrections according to the conceptual approach of the problem-posing learning model. Each sentence is implemented as a sentence card, where each sentence card is interpreted as a problem.

The use of Monsakun interactive learning media in learning activities has been carried out in previous studies. The researcher examined the student learning process in answering questions at Monsakun and also analyzed the student learning process in terms of the frequency of types of errors at each level when answering questions(Supianto et al., 2017; Supianto & Hafis, 2018). The analysis was carried out on student learning activities stored in a log data database. Then the researcher visualized log data to interpret students' thinking processes by identifying students' understanding and misconceptions about the structure of the problem at a difficult level.

In line with the research that has been stated, new research on education data known as Educational Data Mining (EDM) has become increasingly popular in recent years (Aldowah et al., 2019; Dabhade et al., 2021; Lemay et al., 2021). Especially data were related to recording student activities during Learning. The log data generated by the Monsakun learning media can be analyzed further because it contains a record of every action in the learning process as a sequence of student activities when working on questions. Investigation of the sequence of student learning activities using log data obtained four different types of learning patterns using web-based visualization techniques(Dabhade et al., 2021; Lemay et al., 2021). However, investigations to find learning behaviors that often occur in the student learning process have never been done before. Recognizing the same student's learning behavior during the learning process can make it easier for teachers to provide appropriate follow-up.

An appropriate EDM method is needed to find useful information in the log data to determine the learning behavior that students often do. Because log data contains a sequence of student learning activities, an EDM method, known as sequential pattern mining, is used to process the data. Sequential pattern mining is used to identify sequences of student behavior that are often carried out during the learning process(Adekitan & Salau, 2019; Ashraf et al., 2020; Daoudi et al., 2021). Previously, sequential pattern mining methods have been applied to learning media, such as identifying the paths that students usually use in group interactions to achieve success and examining the differences between the two groups in terms of student performance in learning concepts related to Learning.

Sequential Pattern Discovery using Equivalent class (SPADE) is a sequential pattern mining algorithm that performs better in finding frequent sequences of transactions in sequential data (Gunawan, 2021; Nowak et al., 2020; Pushpalatha & Ananthanarayana, 2020). On the other hand, the SPADE algorithm has been modified to overcome the shortcomings of previous algorithms such as AprioriAll and GSP (Generalized Sequential Pattern)(Johnson et al., 2019; Ralla et al., 2019). Based on this background, this study proposes extracting information on the student learning process using the sequential pattern mining method from the Monsakun learning media log data. Then the algorithm used in this study is the SPADE algorithm. Therefore, this study poses a research question about how the patterns are generated by applying sequential pattern mining algorithms to obtain information on student learning processes in German Learning Learning Media.

METHOD

Monsacun Learning Media

Monsakun is designed as a tablet-based interactive learning media that applies a problem-posing learning model. The design of MONSAKUN aims to focus on learning activities that students dominate, where the teacher only acts as a facilitator(Aldowah et al., 2019; Dabhade et al., 2021). The task given to students is in the form of story questions in German Learning that contain German Learning words that are integrated into a sentence. Monsakun will automatically evaluate based on student answers. On the other hand, teachers can also monitor the activities carried out by students during learning activities at Monsakun, both while working and answering questions to find out the learning process of each student. The Monsakun learning media interface refers to the research consisting of three main components: a composition problem area, a sentence, and a diagnosis button shown in Figure 1; this research implements a mobile web-based.

Monsakun learning media is divided into two sides, namely the left side and the right side. The left side refers to the problem section of the composition area consisting of "requirements" and "card slots." When a student wants to work on a problem, the "requirements" section will display the name of the level, the number of questions, and the requirements that must be met to solve the problem. The presented requirements contain aspects requiring students to compose stories based on German Learning formulas that need to be formed. In this case, the "game slot" section serves as a place for compiling the story that will be included (Aldowah et al., 2019). There are three game slots that have been provided to form the right story according to the requirements given.

On the right side of the Monsakun interface, see the sentence games section. There are six sentence games that students can choose from to build the right story. However, not all sentence games can be used to create the right story sequence. Therefore, the presentation of the six-sentence games is intended as feedback in testing students' understanding(Dabhade et al., 2021). Finally, the diagnosis button section checks the correct placement of the three-sentence games students in the "game slot has prepared" area.

Figure 1. Example of implementation game german learning

The student learning process in Monsakun learning media is done by selecting sentence games and then arranging them in the game slot section. Students can choose sentence games according to their needs by inserting or removing them from the game slot (Aldowah et al., 2019; Lemay et al., 2021). Student activities at Monsakun are based on the arrangement of sentence games dragged into the game slot and the use of the diagnosis button. Monsakun will automatically save log data for analysis for every activity carried out by students.

The structure of the placement of the sentence games is arranged sequentially, and the sequence includes game 1, game 2, game 3, game 4, game 5, and game 6. However, its application to the sentence game section in the Monsakun system is made randomly. Figure 2 shows that the correct arrangement of sentence game combinations involves three correct sentence games, namely game 1, game 2, and game 3, depending on the type of story used in the problem. The kind of story in question is German Learning questions which are translated into sentences with addition and subtraction operations in German Learning. There are four types of stories used to define German Learning word problems, namely (1) combination (Combination), (2) addition (increase); (3) reduction (Decrease); and (4) comparison (.

The implementation of story problems in Monsakun for addition and subtraction operations is divided into three levels. The level reflects the extent to which students understand thinking when solving problems at Monsakun. Level adaptation refers to the research conducted by adjusting the number of levels in each question (Aldowah et al., 2019). To work on problems at each level, students must first understand the story type and then assemble it into correct German Learning sentences. For example, at level 1, shown in Figure 1, use forward-thinking problem-type questions. For this type of problem, the unknown picture in the problem is the final result of the calculation according to the given formula. An example of this type of question is "Make a guest picture about 'what is the picture in german language ...'". While at levels 2 and 3, they used reverse-thinking questions where the picture was unknown, while the final result was known beforehand. An example of this type of question is "Make a guess picture about 'what is the combination of the picture's name.

Support and Confidence in the learning process

Support is a criterion to determine how often itemsets are from the total transaction. A high support value indicates that the itemset is dominant(Dahiya & Dalal, 2022). Minimum support (min_sup) is the smallest support parameter determined by the researcher to trim the list of sequences obtained to get interesting and meaningful sequences. The support value of an item is determined using the formula in Equation 1. For example, based on the total existing transactions, how dominant are goods A and B purchased simultaneously, that shown in equation 1

$$support\ (A \rightarrow B) = \frac{sum\ o\ intransaction\ intemset\ (A \rightarrow B)}{Total\ of\ transaction} \quad (1)$$

Confidence is the criterion for determining the strength of the relationship between two items in the association rule(Geng et al., 2021). Minimum Confidence is the smallest parameter that must be met to determine the quality rule. The confidence value of the relationship between two items is determined using the formula in Equation 2. Suppose how often item B is purchased if people buy item A, then

$$Support\ (A \rightarrow B) = \frac{sum\ o\ intransaction\ intemset\ (A \rightarrow B)}{Totalantecedent\ A} \quad (2)$$

Sequential Pattern Mining

Sequential pattern mining is an EDM method used to find all data with a frequent occurrence sequence pattern from a combination of items (periodic sequence)(Peña-Ayala, 2014; Xie et al., 2018). The sequential pattern mining flow in the illustrated data is given a set of sequences, where each sequence consists of a group of items and is given the minimum support limit set by the previous researcher. There are two main approaches in sequential pattern mining methods: a priori-based and pattern-growth (Peña-Ayala, 2014; Xie et al., 2018). The growth-pattern approach takes less time and is more efficient than the prior-based approach. However, this study did not prioritize speed considerations because the log data used was less than ten thousand events, and the priority-based method was easy to learn and apply.

SPADE

SPADE is a sequential pattern mining algorithm that uses and a priori-based approach. SPADE uses the vertical data format when determining the sequential pattern of the sequence database(Gunawan, 2021; Pushpalatha & Ananthanarayana, 2020). This algorithm is based on candidate creation and testing to improve and refine the previous algorithm.

The steps of the sequential pattern mining process using the SPADE algorithm are as follows(Wang et al., 2022).

1. Search 1-sequence frequently

To find a frequent 1-sequence is to add data to be sorted by sequenceID (SID), eventID (EID), size, and item. Furthermore, all things (itemset) will be collected for each item in the database. Each item is then calculated into the SID pair that owns the item. Next, we will check the itemset whether the SID and EID (id-list) pairs have been formed. If an id-list is created, then a frequent 1-sequence is formed. The determination of frequent 1-sequence is based on whether the support value is more than or equal to the minimum support value.

2. Search for 2-sequences frequently

Next, it is to find frequent 2-sequences. Data is collected from the results of frequent 1-sequences. Then it will be checked against each frequent 1-sequence to determine whether it has met the minimum support limit. Then each frequent 1-sequence with other frequent 1-sequences will be combined. The merger aims to check whether the id-list has the same SID. If they have the same SID, it will be double-checked to ensure they have the same EID. If the id-list matches, then the id-list will be added to the frequent 2-sequence. To ensure the regular 2-order category, check whether the support value is more than or equal to the minimum support value.

3. Looking for frequent k-sequences

The next step is to find the next periodic sequence; the same process will be carried out by searching for frequent k-sequences. Frequent k-sequences are obtained by combining frequent (k-1)-sequences with the same prefix. For example, to search for 3-sequences, periodic sequences of 2-sequences with the same prefix will be combined. For instance, if there are 3-orders A, B, C, and D, the last item to be prefixed is A, B, C. To ensure the frequent k-sequence category check whether the support value is more than or equal to the minimum support value. The subsequent periodic sequence checking process will stop when no more frequent (k-1)-sequences can be rejoined, and no more frequent k-sequences can be found.

4. Rules

After all frequent sequences are found, the rules of the existing sequences will be determined. From the sequence obtained to form the rule, 1-sequence is not used because it only has 1 item. For example, in sequence A B, the form of the rule obtained is A => B. If the sequence length is more than 2 (k-sequence), the last item will be used as a consequent, while all items before the previous item are called antecedents. Rules that meet are then checked whether they are more than or equal to the minimum support and minimum confidence values. Next, determine the strictest direction to calculate the lift ratio value.

In this study, rule formation was not implemented because it only looked for frequent sequence patterns. Therefore, applying the SPADE algorithm can quickly reduce the iterative processing time. However, the SPADE algorithm does not have a setting that allows the researcher to initialize the constraints in the desired order freely. Therefore, a modified version of the SPADE algorithm named CSPADE (Constrained Sequential Pattern Discovery using Equivalence class) is used in this study to facilitate the search for meaningful sequential patterns. The configurable limitations of the CSPADE algorithm include (1) length and width; (2) the minimum and maximum gap of the sequence, (3) the duration of occurrence of the entire series; and (4) adding and excluding items from the sequence. The implementation of the CSPADE algorithm uses the R programming language with the help of the R Studio software. Previously, a special library called "a rules Sequences" had to be installed first to provide functionality when searching for frequent sequence patterns.

Design

The methodology in this research is carried out systematically so that it can run well. The methodological stages in this research are in the form of a flow chart. The methodology flow chart can be seen in Figure 2.

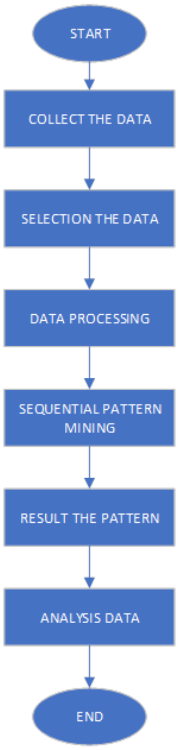

Figure 2. Flow chart of an implementation

Data Collection

Data collection is the first step in the methodology to find the data needed for research. Sources of data used in this study are secondary data sources. The data comes from a previous study conducted by Monsakun learning media when students work on questions(Aldowah et al., 2019; Dabhade et al., 2021). The data collected in this study was the participation of 23 students when working on questions in the form of log data. In addition, data on questions and answers were also collected in the form of documents. Collecting data was carried out on German Learning students at Universitas Negeri Malang using the German Learning version of the Monsakun learning media.

The form of log data collected is in JSON format and the category of sequential data. Each row contains attributes: student id, level name, question number, session id, processing time, work step, the operation performed, changed slot number, the game number used, answer sets, answer check, and error type that occurred and composition of the competency provisions for each of the proposed problems (constraints) that have been met. There are three levels with a total of 36 questions. Level 1 consists of 8 questions, level 2 consists of 8 questions, and level 3 consists of 20 questions.

Data Selection

The stages of data selection refer to the research analysis process to be carried out. All attributes collected in the log data are not all used. The identification of these attributes is related to the needs of the algorithm to be used. The algorithm requires input data from SID, EID, and items. The features used for SID are the id of each student, EID is the student's work steps when working on questions, and objects use the order of the question games used to solve the questions. The data of each student who has been selected will be categorized according to the number of questions and then selected based on their level. At the time of choosing EID data, data that has attributes that are not following the work of the questions will disagree. For example, the attribute step of working on a successful problem is repeated by students two times and does not match the session id.

Data Processing

Stages of data processing refer to the processing of data that has been previously selected so that it is ready to be used in research. The data will be adjusted to the SPADE algorithm input format. It aims to simplify the data processing process. The provisions of the SPADE algorithm format are SID, EID, size, and item. The implementation includes SID (student identity), EID (work step), size (number of combinations of question game arrangements), and item (order of question games used by students when processing Microsoft Excel (.xlsx) with the file name level2_asg2 .xlsx. After that, data conversion is carried out to match the processing format of the SPADE algorithm into text format (.txt) with the file name level2_asg2.txt. Each question number will be categorized based on each level to make it easier to find file names later.

Implementation

This research uses the mobile web to implement the system. The application can show in figure 3 and figure 4 in the mobile application. Figure 3 shows the game level at which the user must guess the picture. Figure 4 shows a game that the user must guess what kind of action at the figure.

Figure 3. Level 2 of the game German learning

Figure 4. Level 3 of the game German learning

RESULT AND DISCUSSION

Processing inquiry data

Successfully processed questions are based on the minimum support value to find frequent sequence patterns. A minimum support value of 0.1 is used in this study to find patterns that contain meaningful information in terms of analyzing the student learning process at Monsakun. The questions that were successfully processed at each level can be seen in Table 1. The data processing to identify frequent sequence patterns was obtained from the process of working on questions carried out by students. Three types of activities are carried out when working on questions, namely successful, not yet successful in completing, and not working on questions. The pattern of activities that are successful and those who have not succeeded in working on the questions can find out the pattern, while the questions that are not done by students cannot be processed because there is no work activity data.

Results at Level 1

Identification of the frequent sequence pattern of each question at level 1 shows various results. Like the interesting pattern produced in question number 2, there are 25 frequent sequences that can be seen in Figure 5, where 23 students successfully completed the problem.

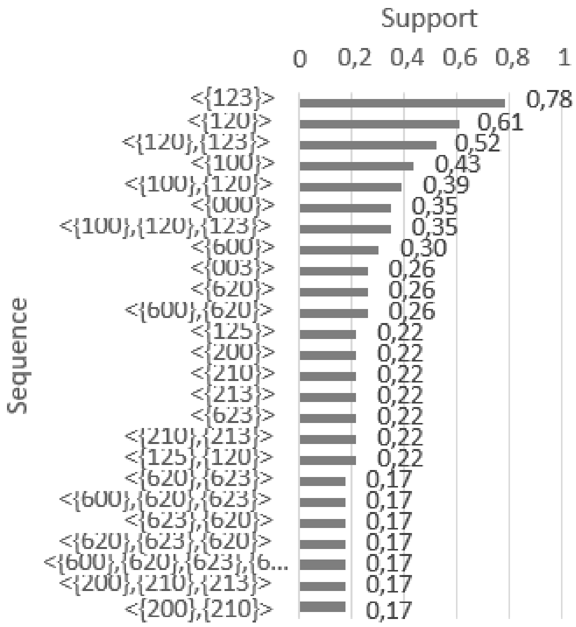

Figure 5. Sequence pattern level 1 question number 2.

The biggest support value is 0.78 in the order <{123}>. Based on this value, it can be interpreted that the success of 18 students in working on questions with a combination of <{123}>. Of course, the combination sequence <{123}> is the correct answer, so before getting the combination sequence, as many as 12 students have sorted the combination <{120,123}> first. In addition, as many as six students have used the combination sequence <{100},{120},{123}> when working on a problem that is defined as a perfect combination arrangement. In question number 2, level 1, it turns out that the correct answer combination is not only <{123}>, but also a variety of answers <{213}>. A total of 5 students answered questions with a combination of <{213}>. It is also known that the five related students have also ordered the mixture <{210},{213}> in advance. The combination order <{200},{210},{213}> was used by four students out of a total of 5 students who chose the previous <{210},{213}> combination order.

Results at Level 2

Identification of the frequent sequence pattern of each question at level 2 shows mixed results. Like the interesting pattern produced in question number 1, 12 periodic sequences can be seen in Figure 6, indicating that 18 students were successful when working on the questions, and one had not finished working on the questions.

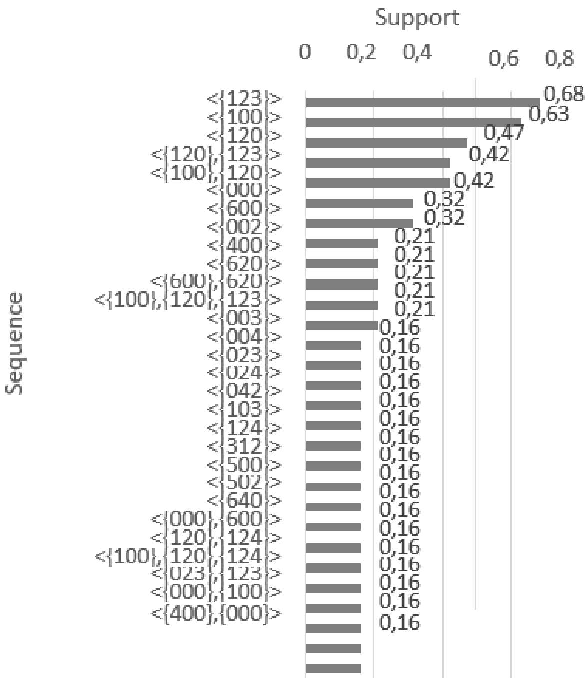

Figure 6. Sequence pattern level 2 question number 1

The biggest support value is 0.68 in the order <{123}>. Based on this value, it is determined that the success of 15 students in working on questions with the combination <{123}>. The order of the <{123}> varieties is obtained differently when answering the question. A total of 8 students previously arranged the combination arrangement to be <{120},{123}>, and as many as three students preferred to set the combination order to be <{023},{123}>. In addition, as many as four students have used the combination sequence <{100},{120},{123}> when working on a problem that is defined as a perfect combination arrangement. For example, in question number 1, level 2, it turns out that the combination of correct answers is not only <{123}>, but also the variety of solutions <{312}> made by three students.

Results at Level 3

Identification of frequent sequence patterns for each question at level 3 shows mixed results. As the pattern generated in question number 2, there are 24 frequent sequences which can be seen in Figure 7 which shows the success of 9 students while working on the questions and 2 students who have not finished working on the questions.

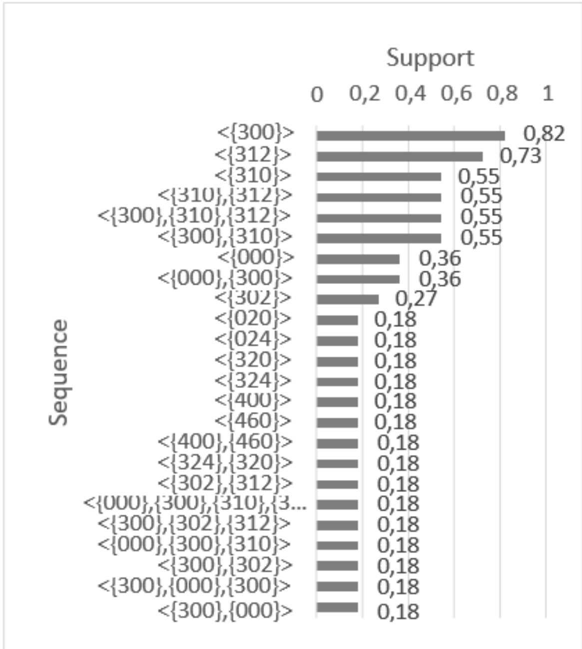

Figure 7. Sequence pattern level 3 question number 1

The biggest support value is 0.82 in the order <{300}>. Based on this value, it was determined that as many as nine students, when working on questions, often involved sentence game 3 for the first time in-game slot 1. The reason for choosing sentence game three was also proven by eight students who answered the questions correctly. using the <{312}> combination. The order of the <{312}> combinations is obtained when answering the question. A total of 6 students arranged the combination order from <{310},{312}> to the combination <{300},{310},{312}>. In addition, two students also began to arrange the combination order from <{302},{312}> to a combination of <{300},{302},{312}>.

Analysis of Student Learning Results

The analysis of the results obtained is based on discovering patterns that often appear in each question. This reflects the student's ability to work on the questions. The pattern of students during the learning process on Monsakun learning media is categorized into six types of patterns.

[1] Pattern 1 is a pattern with the correct order of sentence games <{100},{120},{123}>

[2] Pattern 2 is a pattern with the correct order of sentence games <{200},{210},{213}>

[3] Pattern 3 is a pattern with the correct arrangement of sentence games <{300},{310},{312}>

[4] Pattern 4 is a pattern with the correct arrangement of sentence games <{300},{302},{312}>

[5] Pattern 5 is a pattern with a work order involving one wrong sentence game

[6] Pattern 6 is a pattern with a work order involving two wrong-sentence games

Working on questions to solve questions with correct answers at levels 1 and 2 shows that most students, when working on questions, tend to use pattern 1. In contrast, at level 3, students tend to work on questions using pattern 3. correctly by involving game 1, game 2, and game 3. Although problem-solving at each level is similar, some students tend to solve problems using different patterns to answer questions correctly. This is shown in questions 1 and 2, where some students use pattern 2, while in questions 18 and 19, some students use pattern 4.

While working on the questions, some students enter the wrong sentence game in the arrangement of questions. The selection of the wrong sentence game causes the processing step to require a lot of processing steps on questions such as questions number 2, 3, 4, 11, 12, and 17, which use pattern 5, while 3, 4, 10, 11, and 17 use pattern 6.

CONCLUSION AND SUGGESTION

Based on the results of the implementation and analysis that has been done, it can be concluded that students' ability to solve problems varies greatly at each question and level. Six student learning patterns in German Learning media have been identified: pattern 1, pattern 2, pattern 3, pattern 4, pattern 5, and pattern 6. Each pattern requires different feedback to optimize student learning progress. Suggestions for further research are further analysis related to the types and types of learning processes so that the specific names of the patterns that have been identified can be known.

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