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Predictive reasoning of senior high school students in handling COVID-19 data

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Received 03 November 2022 - Accepted 10 March 2023

Abstract

The purpose of this study is to describe the characteristics of predictive reasoning made by students in solving graph-related problems, particularly related to COVID-19. This is a descriptive qualitative study with data collected from a sample size of 25 senior high school students and analyzed using the *generalization-prediction task*. The result revealed that there are three types of students' predictive reasoning made based on (1) data observation, (2) data observation coupled with prior experience, and (3) data observation coupled with prior experience or knowledge. The experience used to make a prediction is obtained from personal life, classroom, and general knowledge about COVID-19. In conclusion, this study improves students' understanding and ability to reason with graphs and future studies can be conducted with different prediction tasks.

Keywords: predictive reasoning, COVID-19, data observations, prior experiences, knowledge

INTRODUCTION

A recent study conducted by Trends in International Mathematical and Scientific Study (TIMSS) discovered that students in many countries are generally incapable of solving mathematical problems (Mullis et al., 2019). Based on this analysis, it was further reported that Indonesia only scored 397, compared to the international average score of 500 (Mullis et al., 2015). Similarly, in 2018, the results obtained from Program for International Student Assessment (PISA) showed that the average score of Indonesian students in mathematics was only 379. This is quite low compared to the OECD average score of 487 (OECD, 2021). Based on the studies conducted by TIMSS and PISA, several countries are faced with the issue of poor-quality education, especially Indonesia. Assuming this is not resolved immediately, Indonesia and other countries in the low-performance category would face a serious problem with their human resources as they are not yet ready to tackle the dynamic challenges of the 21st century and the fourth industrial revolution.

Since the advancement of technology in the 21st century and during the fourth Industrial Revolution, people can readily acquire and access data or information through various mediums. According to

Nurjaman and Hertanto (2022), it could be information about education, politics, culture, social and health issues, especially COVID-19, which are still highly debated presently. Sorakin et al. (2022) stated that the COVID-19 pandemic had been fought against for almost two years. It was perceived as a significant obstacle for the entire world, and the pandemic triggered drastic changes in many spheres of life, including education (Bozkurt et al., 2022; Fauzi et al., 2020; Tilak & Kumar, 2022). Information about its advancements is readily available for personal and governmental decisionmaking (Goniewicz et al., 2020). Therefore, the capacity to predict the future is crucial, especially when working with COVID-19 data. In reality, Fauzi et al. (2020) discovered that only a few students were classified as high achievers in COVID-19 literacy. Similarly, Archila et al.'s (2021) study stated that the COVID-19 literacy scores of Colombian undergraduates are moderate. Assuming an individual cannot interpret, evaluate, or identify the pattern of data, they are likely to be scammed, misled, or make faulty decisions, which will ultimately have a greater impact (Okan, 2016).

Several studies have offered solutions to address these problems, enabling society to face the challenges of the 21st century and the industrial revolution 4.0. Furthermore, a learning strategy directed at higher order

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Contribution to the literature

- This study adds to the limited study on predictive reasoning in mathematics education.
- It demonstrates how students generate predictions using observations of facts, experience, and knowledge.
- It also demonstrates that prediction activities can enhance students' COVID-19 literacy and creative thinking.

thinking skills (HOTS) was implemented (Firmansyah et al., 2021; Khoiri et al., 2021; Sagala, 2019; Syarifah et al., 2019). The earlier-mentioned studies generally focused on using higher-order questions and failed to consider those in the form of prediction questions. It is of paramount importance to study predictive questions. Predictive questions motivate students to reason and provide them with opportunities to relate mathematical ideas to new topics taught in the class (Kim & Kasmer, 2007; Lim et al., 2010). It also tends to increase students' engagement in the classroom (Kasmer & Kim, 2011; Lim et al., 2010). Kasmer and Kim (2012) further stated that making predictions helps students visualize the problem, especially through graphs.

The ability to predict graphs is an extremely important skill for using technology in daily activities (Bragdon et al., 2019). However, students still find it difficult to make predictions based on graphs. For example, Bragdon et al. (2019) and Ozmen et al. (2020) stated that the students' ability to make a prediction based on graphs is still in low category. According to Ivanjek et al. (2016), those with extreme achievement could make predictions based on graphs. These studies focus on the difficulties in making predictions based on graphs, but they failed to deal with the reasoning aspect Kim and Kasmer (2007) and Russo et al. (2022) stated that predictions are an aspect of reasoning. It is evident that predictions and reasoning are inseparable, and this is referred to as predictive reasoning.

Several studies have been carried out on predictive reasoning. For example, Oslington (2018) stated that 10second graders use predictive reasoning at an average age of seven years and 10 months in classroom design studies. In a modeling activity based on actual data, students were asked to predict the highest monthly temperatures for the current year using the seasonal fluctuations realized through readings from the past six years. The reasoning strategies were documented throughout the lesson sequence by analyzing responses from written prompts, videos of interviews, and student-drawn graphs. Reasoning strategies are becoming increasingly sophisticated using TinkerPlots, providing students with opportunities to observe, represent, and reflect on data trends (Oslington, 2018, p. 20).

Oslington (2020) carried out a study designed on 46 third graders, who were asked to predict the maximum future monthly temperatures on a table of historical temperature data. The students' predictions were analyzed using two frameworks, namely awareness of mathematical pattern and structure (AMPS) and data lenses. Oslington (2020) stated that 54% of the students used the variability of the data in the table to predict the temperature in the range of monthly history. It was also reported that 83% of the students were at the idio-centric level. This finding shows the progress of students' predictive reasoning, considering the regular time ranges and patterns.

Furthermore, Oslington et al. (2021) conducted a oneyear longitudinal study to determine the changes in the predictive reasoning of 44 3^{rd} and 4^{th} graders in Australia. A hierarchical framework of structural statistical features was used to analyze the students' responses. Grade 4 students can make more reasonable predictions than those in grade 3 at 87% and 54%, respectively. This is due to their ability to provide data methodologies prediction based on extraction, clustering, aggregation, and observations or measures of central tendency, as well as to illustrate transnumeration in their diverse representations (71% vs. 19%). According to Oslington (2020), several students who drew their graph predictions reported that they generated the relationship by only studying the tables containing historical data. The ones who chose year as an independent variable show bivariate data coordination, but the resulting graphs had no visible relational components when the month was selected (Oslington et al., 2021).

Nevertheless, none of the earlier-mentioned studies explained the characteristics of predictive reasoning, especially concerning solving graph-related problems. Kim and Kasmer (2007) stated that this part of the prediction is still neglected by studies on mathematics education, compared to other reasoning aspects. The present study aims to describe the characteristics of students' predictive reasoning in solving graph-related problems, especially COVID-19 data. The study question is what the characteristics of students' predictive reasoning in are solving COVID-19 data. The answer aids this study in making certain contributions by helping students to solve predictive questions.

LITERATURE REVIEW

Prediction in Mathematics Education

Prediction complements other forms of reasoning, such as conjectures, generalizations, abducting, visualization, and imagination (Kasmer & Kim, 2012; Lim et al., 2010). The generalization of patterns and predicted outcomes are examples of the reasoning type known as prediction (Kim & Kasmer, 2007). Generally, a prediction is defined as a claim about a particular phenomenon or uncertainty. This tends to include educated guesses confirmed by sufficient data and arbitrary assumptions. Lim et al. (2010) stated that making predictions about mathematical concepts based on reasoning involves prior knowledge, patterns, or connections. The prediction may not always refer to a straightforward estimate. On the other hand, it is a complex process of connecting similar ideas. The students must have prior knowledge and link ideas from earlier explorations to make reasonable predictions.

There are several benefits of making predictions in a math class. It provides an opportunity for students to realize and then overcome their misconceptions. Predictions help to draw their attention to the structural and relational aspects of mathematics and create opportunities for these students to experience cognitive conflicts, discover patterns and generalize specific cases, as well as expand the assimilation of certain conceptions. In addition, predictions can increase the students' engagement level (Lim et al., 2010; Thiel & George, 1976). For example, it helps students to engage in sense-making of a problematic situation and related concepts, and discussions on prediction tend to stimulate the use of multiple perspectives to approach an issue. This also helps to build links between topics and as a method to evaluate students' thinking (Kim & Kasmer, 2007).

Kim and Kasmer (2007) stated that prediction piques students' interests and elicits prior knowledge. However, prior knowledge is the total of all a person's knowledge at any one time, whether they are aware of it or not (Shane, 2000). It is also defined as knowledge before learning new information or concepts (Geofrey, 2021).

Meanwhile, few studies focus on prediction in mathematics education (Kim & Kasmer, 2007). Similar

studies have a different emphasis, for example, the present study provided three contrasting perspectives on predictions as mental actions, mathematical activities, and socio-epistemological practices to integrate diverse theoretical frameworks (Lim et al., 2010; Thiel & George, 1976). The conceptual underpinning of one's prediction, specifically schemes, is highlighted from a cognitive viewpoint, and this is perceived as a mental act. Based on a curricular perspective concerning mathematical activity, prediction illustrates various tasks taught in US mathematics courses (Thiel & George, 1976). Lim et al. (2010) stated that prediction is divided into four types as a mathematical task. This includes estimation-prediction, generalization-prediction, visualization-prediction, and concept-application prediction tasks. Generalizationprediction task entails making reasonable predictions by generalizing patterns.

Prediction skill is the acquired ability to use one or more rules to determine the outcome of a series of events without observation. This definition simply implies that a task designed to evaluate the predictive ability must have two characteristics:

- (1) a clearly identifiable rule or rules and
- (2) the description of the outcome of some event(Thiel & George, 1976).

The type of rule used in making predictions is based on three fundamental structures leading to concrete operations seen in children, as reported by Piaget (1971). These include

- (1) algebraic,
- (2) ordering, and
- (3) topological structures.

The ordering structure involves relationships type A<B, B<C * A<C, and it is also used to solve graphic problems. Furthermore, Molitor (1971) proved that all prediction items in its tests involve this relationship. An example of a prediction task is shown in **Figure 1**, which is categorized in the ordering structures.



Figure 1. Prediction tasks using graphs (Source: Authors' own elaboration)

Table 1. The classification of students' answers based on the rea	asons used when mak	ing a prediction	
Characteristics	Number of students	Selected participan	t Participant code
On data observation	18	1	S1
On data observation coupled with prior experience	4	1	S2
On data observation coupled with prior experience/knowledge	e 3	1	S3
Total	25	3	

Predictive Reasoning in Mathematics Education

Predictive reasoning is interpreted as a logical thought process of predicting future events by using past or present information to draw conclusions. In other words, reasoning relating to predictive problems is categorized as predictive reasoning. Oslington (2020) defined prediction as a daily statistical activity in which individuals apply past experiences and incomplete information to estimate, plan, or draw conclusions. In daily decision-making, predictive reasoning involves using chance events in the context of underlying causal variations. Lavoie (1999) stated that some of its functions are, first, a knowledge development process encourages students to build and deconstruct ideas. Second, predictive reasoning helps to develop the student's cognitive commitment or desire to verify whether their predictions are correct. Third, predictive reasoning allows students to resolve related issues based on their beliefs explicitly in the face of newly encountered ideas and cognitive conflicts. This is in addition to movement towards an alternative conceptual frameworks during the introduction and the application of terms and concepts. Fourth, active peer-to-peer discussions that contrast predictions promote the use and development of logical thought processes, make students' initial beliefs more explicit and enhance their cognitive commitments. Striving to put forward good arguments forces students to connect and organize their ideas, which has certain implications for constructivism and conceptual change.

METHODOLOGY

Approach and Participants

This qualitative study employed a descriptive method, and it is aimed at producing a clearer and more detailed explanation of the characteristics or nature of predictions made by students to solve graph-related problems. The present study involves 25 Islamic State Senior High School students in Banjarmasin, South Kalimantan, who voluntarily participated.

Data Collection

The data was obtained from the participants through test and interview sessions, and predictive questions were asked. The participants were required to solve a generalization *prediction task*, making a generalized statement based on the patterns identified. The question given to the participants is shown in **Figure 1**.

The data obtained were classified according to the reasons mentioned by the participants when making the predictions. These were based on observation, prior experiences, or data coupled with prior knowledge or experiences.

Data Analysis

Data analysis focuses on the prediction problem given to the student, then the results or answers are grouped based on their reasons. Next, a student representing a category from each group related to predictive reasoning was observed. The results obtained were then used to identify the characteristics of predictive reasoning based on the reasons used.

RESULTS

In accordance with the participants' answers, there are three characteristics of predictions, namely

- (1) predictive reasoning based on data observation, denoted as S1,
- (2) predictive reasoning based on data observation of prior experience denoted as S2, and
- (3) predictive reasoning, based on data observation coupled with prior experience or knowledge.

The classification of students' answers is shown in **Table 1**.

The following are the interview results showing the characteristics of the participants' answers.

Predictive Reasoning Based on Data Observation (S1)

Predictive reasoning based on data observation was represented by a participant from the S1 category as shown in **Figure 2**.

Considering **Figure 2**, S1 made a prediction based on the data in the graph as they understood the problem by determining the number of COVID-19 cases from January to June. S1 understood the question, what was the predicted number of COVID-19 cases in July 2022, as shown in the following interview:

Q: What is a relevant question asked?

S1: From the graph, the number of COVID-19 cases in each month was deciphered, and the question asked was the predicted number of



Figure 2. Answers obtained from S1 based on data observation (Source: Authors' own elaboration)

COVID-19 cases in July 2022 because it was unknown.

Then, S1 analyzed by observing the graph, especially the number of cases from January to June, where there was always a decrease and no increase.

Q: Why was there always a decrease in the number of COVID-19 cases, and no increase?

S1: This is because from January to February, February to March, March to April, and April to May there were decreases in the number of cases by five, 10, five, and 10, respectively. Subsequently, in the following months, there was a decrease of five to 10 cases.

In accordance with the earlier interview session, it is evident that participant S1 finally discovered a pattern by saying, 'in the following months, there was a decrease of five to 10 cases respectively'. The pattern identified by S1 can be seen in their written calculations, - 5,- 10, -5, -10, ..., as well as from the stated reason in the arithmetic sequence, and this is shown in **Figure 2**.

Afterward, S1 drew a conclusion by applying the pattern used to predict the number of COVID-19 cases

for July. This is reflected in the following interview excerpt:

Q: Why was such a prediction made?

S1: It was because from January to February, the number decreased by five cases, and from February to March, the number decreased by 10. Therefore, in July, the number of cases decreased by 10, i.e., from 50 to 40.

Considering the earlier interview excerpt, subject S1 concluded that the predicted number of COVID-19 cases in city A in July 2022 is 40. Based on the answers provided by subject S1 and the responses in the interview, this prediction was based on *observing the information on the graph provided*. The subject used the information available from January to July, such as the number of COVID-19 cases, the changes every month, every two months, and its trends.

Predictive Reasoning Based on Data Observation Coupled With Prior Experience (S2)

Predictive reasoning based on data observation was represented by subject S2, as shown in **Figure 3**.



Figure 3. Answers obtained from S2 based on data observation couple with prior experience (Source: Authors' own elaboration)

Subject S2 predicted an increase in COVID-19 cases in July 2022 because many people ignore the health protocols, using the data shown in **Figure 3**. This initial prediction was made by analyzing **Figure 3**, as shown in the following interview excerpt:

Q: What information did you get from this question?

S2: The information from this question is the number of COVID-19 cases in city A from January to June 2022.

Q: What does the question determine?

S2: It predicts the number of suspected COVID-19 cases in July 2022.

Furthermore, subject S2 related the months' changes to those infected by the pandemic and predicted an increase in cases. This is as quoted in the following interview:

Q: Why is the predicted number of cases increasing?

S2: The decrease in positive cases from April to June led to their negligence of the health protocols. For example, some desist from wearing masks when conversing with others. Some people also ignored the social distancing policy and started living as though they were in 2019, before the COVID-19 pandemic. In the end, there was an increase in the number of coughs, flu, and fever symptoms. Those that do not wear face masks with a weak immune system were easily infected, leading to an increase in the number of positive cases in July. Q: Besides paying attention to the data from April - June, is there any other information to analyze?

S2: Yes, ma'am, the line pattern

Q: Where did you get the line pattern?

S2: Usually, based on my experience when answering questions at school, an increase in the line pattern at the beginning, with a decrease in the middle pattern, will also increase it at the end and vice versa.

Subject S2 also tried to find a pattern from the above excerpt using previous experience. The subject concluded that the predicted number of *COVID-19* cases increased to 55. This is as quoted in the following interview:

Q: What is the approximate number of COVID-19 cases?

S1: In June, 50 cases were recorded, therefore, in July there will be an increase by five cases, culminating in 55 cases, based on the line pattern ma'am.

The predicted answer made by subject S2 was based on observation of the data in the graph, which was related to her experiences with the pandemic and when learning about patterns in class.

Predictive Reasoning Based on Data Observation Coupled With Prior Experience or Knowledge (S3)

Predictive reasoning based on data observation coupled with prior experience or knowledge represented by subject S3 is shown in **Figure 4**.



Figure 4. Answers obtained from S3 based on data observation couple with prior experience or knowledge (Source: Authors' own elaboration)

Figure 4 shows how subject S3 made a prediction based on data observation coupled with prior experience or knowledge. S3 started by looking at the graph and analyzing the information contained in making a prediction. The question asked in the graph is described in the following interview excerpt:

Q: What questions were asked, and did you have the right information?

S3: The information in the graph is about COVID-19 cases in city A in 2022. The graph shows that in January, February, March, April, May, and June, the number of positive cases were 85, 80, 70, 65, 55, and 50, respectively. However, the predicted number of COVID-19 cases in July 2022 is unknown, hence, the participant was asked to determine it.

Furthermore, S3 analyzed the variables by observing the monthly changes in the number of *COVID-19* cases and stated that it decreased each month. This is as quoted in the following interview:

Q: Why did the number of COVID-19 cases decrease?

S3: The decrease in the number of positive cases from January to February and from February to March by five and 10 was due to the adherence to the implemented health policy as shown in the line pattern, which continues until July.

Next, subject S3 analyzed a pattern by looking at the number of decreasing cases. This is as quoted in the following interview excerpt:

Q: Why was there a patterned decline?

S3: The patterned decline was due to a monthly decrease, which formed a repeating pattern of 5, 10, 5, 10, ...

Finally, S3 concluded by applying the pattern to July, where the predictive answer is required, as quoted in the following interview excerpt:

Q: Why did you predict 40 cases?

S3: I predicted this because after observing the graph from January to June, a pattern of 5, 10, 5, 10 was formed, which also applies to July. Therefore, the predicted number of cases would be 40 cases.

The subject concluded that based on prior experience, the prediction of the number of cases in July is 40. Therefore, there is a possibility of an increase because people are negligent with the health protocols, and the public response to COVID-19 is decreasing. This is in accordance with the interview with subject S3 as follows:

Q: And why is there a possibility of an increase?

S3: Data shows a decrease in the number of positive cases, with the possibility of unexpected spikes because people pay little attention to maintaining social distance and complying with health protocols. In addition, public activities have returned to normal, and large-scale activities attended by many people are held. This led to a decline in the line pattern, as shown on the graph, with the possibility of a spike due to the above-mentioned reasons.

DISCUSSION

Based on the aforementioned findings, subject S1 engages in predictive reasoning through observations of the data, which starts by understanding the data contained in the graph. Subject S1 is aware of both the information inferred from the graph and the query posed.

Meanwhile, subject S3 used all the graph's data, including details on the months and the number of COVID-19 cases. Subject S1 used all the variables in the issue based on this information, which is in accordance with Kelly and Simmons, study. According to them, it is crucial to understand how all available data will affect predictions when forecasters add more precise data.

Subject S1 connected the monthly variables and the total number of COVID-19 cases, noting a decrease per month. Subject S1 established a relationship between the two variables and made a prediction based on the knowledge of the downtrend in the number of COVID-19 instances. According to Block et al. (2004) study, students form predictions by drawing links.

Subject S1 discovered a pattern in the monthly variable and connected the changes to the quantity of COVID-19 cases. The alterations were calculated by comparing the difference in the number of COVID-19 cases from month n+1 to n. By leveraging patterns in the arithmetic sequence series and monthly changes, subject S1 made a prediction. In addition, subject S1 employed the pattern discovered between January and June to forecast the number of positive cases in July 2022. In conclusion, 40 cases were obtained with Michalke's (2021) findings, predicted using patterns.

Subject S2, who used data observation and prior experiences to execute predictive reasoning, comprehended the issue by identifying the data contained in and queried by the graph. S2 further attempted to establish a link between the monthly variable and the quantity of COVID-19 cases. However, when identifying the pattern, subject S2 only noticed the trend in the graph from April to June while ignoring the

Table 2. Characteristics of students' pi	redictive reasoning	
Characteristics of students' predictive	Character description	
reasoning on reasons used		
Data observation	 Using all known variables 	
	• Making a connection between month variable & variable of number of cases	
	 Using graph trends 	
	 Using all the patterns in the graph 	
Data observation coupled with prior	 Using all known variables 	
experiences	• Making a connection between month variable & variable of number of cases	
	 Using graph trend patterns 	
	 Using some patterns in the graph 	
	 Using class experience 	
	 Using personal life experience 	
Observation+prior	 Using all known variables 	
experience+knowledge	• Making a connection between month variable & variable of number of cases	
	 Using graph trend patterns 	
	 Using all the patterns in the graph 	
	 Using personal life experience 	
	• Using knowledge	

changes that occur every two months. As a result, when making a conclusion, subject S2 assumed that there would be an increase in COVID-19 cases due to prior experiences and data observation obtained while generating a forecast. This is in accordance with Katarína and Marián's (2017) study, which used previous experiences and observations to anticipate future consequences. The experiences of subject S2 on how to deal with patterns were gathered from both personal and class lessons. According to Stillman, the prior experience can be categorized into three groups, namely academic, general knowledge of the outside world, and personal life experiences. Subject S2 utilized both prior classroom and personal life experience in making analyses.

At the problem stage, subject S3 recognized the information by employing predictive reasoning based on observations of the data combined with prior experience of knowledge. The next step was for subject S3 to establish a link between the two categories of data or variables. The participant noticed a pattern of a declining tendency in the graph and discovered a trend of monthly and bimonthly fluctuations in the number of COVID-19 cases. Subject S3 made predictions based on personal life experiences, such as encounters with persons in public who are careless with following health standards. Since more incidents have occurred because of people disobeying health standards, subject S3's response is also included in the indirect experience. This is in line with the study by Becker et al. (2017), who claimed that an indirect influence refers to a direct reallife impact of a circumstance, even when it does not personally affect an individual. Subject S3 also made a forecast from various news outlets based on the information regarding COVID-19. This first knowledge relates to a learner's attitudes, experiences, and components (Kujawa & Huske, 1995). The experience here comprises regular daily activities, a variety of life occurrences, and rich living experiences, both at the family and community levels. Additionally, subject S3 stated that the news on COVID-19 obtained via media reports qualifies as a vicarious experience. This is consistent with the study by Becker et al. (2017) that persons who engage with other people, such as family members or acquaintances, are classed as having a vicarious experience (Becker et al., 2017). Traits of students' predictive reasoning are shown in **Table 2**.

The three subjects used all the data in the graph while making predictions, as evidenced by their answers. The graph includes statistics on the number of COVID-19 instances for January through July. Therefore, based on this data, the participants used all the variables found in the questions to be investigated to produce a downward trend pattern. However, only subjects S1 and S3 used all the patterns found in the graph to make predictions, while subject S2 used some. It is clear that subjects S2 and approach pattern recognition differently in S3 accordance with the various student experiences and mathematical models (Moss, 2017). The difference at the decision-making step is also evident, with S1 who merely created a forecast based on data observations without connecting it to previous knowledge. Subjects S2 and S3 made predictions using their prior life and classroom experiences and understanding of the COVID-19 pandemic. This indicates that not all subjects leverage existing COVID-19 data because students' knowledge of the pandemic is still considered low (Fauzi et al., 2020). Consequently, when applying predictive reasoning, subjects S2 and S3 had a wider range of more original justifications. This is in accordance with the study by Chua et al. (2008) that when people apply their past knowledge to a task, the ensuing answers typically have more options and lean toward creativity. The conclusions of subjects S2 and S3 were affected by their earlier experiences. This is consistent with the assertion made by Becker et al. (2017) that experience has various effects on a person's thought processes, such as imagining potential outcomes. Also, previous exposure can influence sensitivity to statistical regularities and artificial language.

This means that learning activities entailing prediction tasks can provide students the chance to reflect on their experiences, fostering creativity and enabling them to create an environment favorable to learning. To find anything and wrestle with concepts, learners should be accustomed to solving prediction problems. It can aid students in becoming independent thinkers by fostering their creativity and literacy.

CONCLUSION

This study assesses students' predictions regarding the COVID-19 pandemic based on various factors. The findings showed that the subject's predictive reasoning, based on data observation, involves known variables in the graph question. This includes connecting the monthly variable and the number of COVID-19 cases using graph trends and identifying all the patterns. The characteristics of the subjects, as revealed through data observation, showed that personal and class experiences were used to determine patterns. Additionally, when subjects used data observation and prior experience or knowledge, their predictions were informed by personal life experiences and general knowledge about COVID-19. This highlights that the reasoning behind predictions varies based on individual knowledge and experience, with those incorporating prior experience and knowledge able to produce more imaginative prediction.

Furthermore, by determining the characteristics of predictive reasoning, teachers can encourage students to optimize their knowledge and experience to generate creative predictions. They can also provide various alternative predictions to solve mathematical problems. In addition, by knowing the types of predictive reasoning, teachers are encouraged to use more prediction-task in teaching mathematics to improve students understanding. This study is only limited to the *generalization-prediction task*, with varying results obtained when a different prediction task is performed. Therefore, future studies need to examine students' predictive reasoning ability using other types of prediction-task.

Author contributions: All authors have sufficiently contributed to the study and agreed with the results and conclusions.

Funding: This study is funded by Ministry of Education, Culture, Research and Technology and Research in 2022 with contract number 092/E5/PG.02.00.PT/2022 and Universitas Negeri Malang with contract number 9.5.78 /UN32.20.1/LT/2022.

Acknowledgements: The authors would like to thank the Directorate of Resources of the Directorate General of Higher Education, Research, and Technology, the Ministry of Education, Culture, Research, and Technology of the Republic of Indonesia, for the study as well as publication funding for the Doctoral Dissertation Research program 2022 with contract number 092/E5/PG.02.00.PT/2022. The authors would also like to thank Universitas Negeri Malang, with contract number 9.5.80 /UN32.20.1/LT/2022 for funding this study.

Ethical statement: The authors of the study stated that at the time of its conduct, there were no established protocols in place at Islamic State Senior High School. The subjects participated voluntarily after providing informed consent, and the information collected was treated as confidential and used exclusively for the purpose of the study. It is important to note that the data collected cannot be used to identify the participants.

Declaration of interest: No conflict of interest is declared by authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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