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Mediation effect of scientific competency on relationship between inductive reasoning and domain-general and domain-specific problem solving

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ABSTRACT

This study investigated the role of scientific competency in mediating the relationship between inductive reasoning and problem-solving. Two types of problem solving, complex problem solving and science problem solving, were used to understand problem-solving mechanisms comprehensively. The participants were 1232 Indonesian high school students (M_{age} = 16.79 years; *SD* = 0.98; 36.6 % boys and 63.4 % girls). The MicroDYN test was used to measure complex problem-solving (CPS) along with science problem-solving (SPS). The other instruments were the inductive reasoning (IR) and scientific competency (SC) tests. The results indicated that SC mediated the relationship between IR with CPS and SPS simultaneously ($\beta = 0.35$, $SE = 0.07$, $p < .001$, $CI_{(95\ \%)} = [.24, 0.47]$; $\beta = 0.36$, $SE = 0.07$, $p < .01$, $CI_{(95\ \%)} = [.26, 0.47]$, respectively). Our conclusion is that IR is relevant in supporting the dynamics of problem-solving, and it is mediated by SC. Implications and recommendations for further research are discussed.

1. Introduction

The dynamic of problem-solving has generated academic debate due to the nature of the problem and its context-dependent approach. Jonassen (1997) explained that depending on the nature of the problem, there is a distinction between well-structured problems, which require the application of certain concepts, and ill-structured problems, which are situated in everyday practices rather than in a specified context. Well-structured problems are the core components of domain-specific problem solving that have a constrained problem situation. To solve these types of problems, problem solvers must implement cognitive processes that require the combination of skills and prior knowledge to understand the problem situation and apply the solution (Forbes & Fisher, 2018; Nokes et al., 2011; Seifried et al., 2020). Domain-specific problem solving is typically used for classroom learning and interventions, where the problems are presented by the subjects, such as mathematics, technology, and science (Chiu, 2022; Khalid et al., 2020; Song, 2018; Woo & Falloon, 2022). Ill-structured problems often require domain-general problem-solving skills that emphasise successful dynamic interactions in a general context and everyday task environment (Greiff et al., 2012, 2014; Lotz et al., 2016; Molnár et al., 2022). This approach presents familiar situations (e.g. cleaning, ticketing, and other daily tasks) and is closely associated with reasoning and

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decision making (Sonnleitner et al., 2013; Stadler et al., 2015). Domain-general problem solving does not necessarily require strong prior knowledge support; instead, it involves mental activities to acquire and apply knowledge during the task interaction. Thus, achievements in problem solving can only occur through the effective exploration and the integration of information from the environment (Fischer et al., 2012; Funke, 2010).

In order to explain the cognitive processes involved in solving a given problem, many studies have investigated the relationship between problem solving and a number of cognitive variables, such as inductive reasoning. They have revealed that students with high levels of inductive reasoning were more effective at solving general problems (Molnár et al., 2013; Sonnleitner et al., 2013; Stadler et al., 2015), whereas other studies have reported a significant connection between inductive reasoning and domain-specific problem solving (Molnár et al., 2022). To understand the problems and formulate solutions, students may need to select strategies, identify the relationship between variables, and consider cause and effect associated with inductive reasoning. Problem solving has also been shown to be strongly connected with knowledge-based performance (scientific competency and literacy) (see Bellová et al., 2018; Savitri et al., 2021) and knowledge achievement was shown to be promoted through the inductive reasoning process (Díaz-Morales & Escribano, 2013). Prior knowledge is found to affect the relationship between reasoning and problem solving (Weise et al., 2020). In contrast, the role of knowledge in problem solving is important but not necessary, especially in the scope of general domain (Greiff & Neubert, 2014; Shin et al., 2003). Nevertheless, the role of knowledge in inductive reasoning and its connection problem solving has not been extensively resolved. Hence, this study investigated the assumed mediation effect of knowledge-based competency in the relationship between inductive reasoning and problem solving.

2. Domain-general and domain-specific problem-solving: an assessment approach

Domain-general problem solving is a skill set for adapting problems in contemporary society and everyday contexts (Greiff et al., 2014). It involves the individual cognitive capacity to understand and solve problem situations without obvious solutions (OECD, 2014), applies strategies to derive new information out of prior information to solve problems, and emphasises complex cognition to process information and to use working memory (Funke, 2010). It is characterised by the interconnectivity of unknown elements and dynamic changes over time and poses general rules or principles, relationships between concepts, and multiple criteria for solutions (Jonassen, 1997). Several cognitive and noncognitive skills are necessary to support domain-general problem solving, including evaluation of knowledge and information, reasoning, planning, self-regulation, and decision-making (Greiff et al., 2014). The assessment of domain-general problem solving is characterised by a non-routine interaction with a dynamic environment through the exploration and integration of information in a real-life problem-solving scenario (Greiff et al., 2015; Jonassen, 2000).

Complex problem solving (CPS) is one of the domain-general problem-solving approaches that contains several principles, including the connection between input and output variables, the dynamic changes and intransparency of the problems and multiple or contradictory goals (Weise et al., 2020). CPS is measured using the MicroDYN approach, which applies the linear structural equation framework to connect the input and output variables. In this test, the problem solver adjusts and manipulates the input variable in response to a change of the output variable, and the output variable can also influence itself or others (Greiff et al., 2012). This system allows test takers to demonstrate three aspects of problem-solving ability: (1) collecting information, (2) integrating and structuring information, and (3) making predictions (Kroner et al., 2005). These three problem-solving aspects are allocated to the two stages of the test: *knowledge acquisition* and *knowledge application*. During the knowledge acquisition phase, the test takers explore the system by manipulating the input variable and observing the changes in the output variables. They identify the connection between variables and simultaneously draw the relationship between variables in a causal model. In the knowledge application stage, the problem solvers are asked to reach the target goals of the output variable by positioning the right value in each input. The correct relationship model is given during the knowledge application phase to constrain the effect of the previous phase (Greiff, 2012; Greiff et al., 2015). The MicroDYN approach has been proven to provide good psychometric properties in terms of reliability and validity across different sample contexts, allowing for a convincing assessment for domain-general problem solving (Kretzschmar et al., 2016; Molnár et al., 2022; Schweizer et al., 2013).

Domain-specific problem-solving presents situations requiring personal knowledge and skills in the respective area (Beckmann & Goode, 2017; Funke et al., 2018). Mastering particular knowledge and its application becomes a necessary condition for solving domain-specific problems (Walker et al., 2016). As the typical problems in specific domains have clear elements, limited rules or principles, and prescribed solution processes (Jonassen, 1997), the complexity of problems can vary with the number of conflicting goals and interconnecting variables; by contrast, the solution depends on the individual's knowledge and expertise. Although domain-specific knowledge is beneficial, successful domain-specific problem-solving activities are also based on competence, cognitive processes, and strategies to apply knowledge (Weinert, 2001). The organisation of knowledge such that individuals recognise information and detect problems is essential to solution and decision-making. Domain-specific problem solving is mostly applied for learning and training purposes. It is integrated during learning intervention in particular subjects, such as science and mathematics (Cheng et al., 2017; Guven & Cabakcor, 2013; Li et al., 2020).

The research on domain-specific problem solving has been progressing since Pólya (1945) proposed mathematics pedagogy for solving mathematical problems. He provided a general outline for solving problems in mathematics into four heuristic components: (1) *understanding the problem*, (2) *devising a plan*, (3) *carrying out the plan*, and (4) *looking back* (Felmer et al., 2016). This framework presents a mental schema for summarising the relationship between information and the problem, and for generating solutions (Voskoglou, 2011). The other framework for domain-specific problem solving came from Seifried et al. (2020), which explains three phases of the problem-solving process: problem identification, making a plan and action, and stating the desired target.

Rausch and Wuttke (2016) identified domain-specific problem-solving as having different steps: (1) identifying information gaps and the action needs, (2) processing information, (3) making decision, and (4) communicating the decision. There are several theories of domain-specific problem-solving, and its main stages have similar processes. The initial stage requires knowledge and information processing to understand the problems, followed by planning for action or the solution. This process involves individual prior knowledge, skills and experience in the respective domain (Beckmann & Goode, 2017). Regarding educational assessment, several studies have examined domain-specific problem-solving with an adaptation from the Programme for International Student Assessment (PISA) problem-solving framework (Lin et al., 2015, 2020; Wake et al., 2016). The main cognitive process covered in this framework is explained as four stages: (1) exploring and understanding the information or problem situation, (2) representing the problem situation and formulating a hypothesis, (3) planning by setting goals and executing its sequential steps, and (4) monitoring progress and reflecting on the solutions. In the test format, the main approach of domain-specific problem-solving assessment involves the adaptation of this framework in a specific context, such as mathematics or science. Overall, the measurements of problem solving can be described by their complexity and context, whether in general or specific domains.

3. Inductive reasoning and problem solving

The dynamic of the problem-solving process is explained in association with intelligence aspects, including inductive reasoning. Inductive reasoning is connected to a cognitive process of detecting generalisations, rules, regularities, irregularities, and diversity. It involves prediction-making about new situations or objects based on prior knowledge (Hayes et al., 2010; Hayes & Heit, 2018). An inductive reasoning task has similar properties that allow an individual to rule a set of elements with general operations such as classification, analogy, matrices, and incomplete series. It combines objects or conditions (attributes and relationships), resulting in several cognitive processes, including generalisation, discrimination, cross-classification, recognising relationships, differentiating relationships, and system construction (Klauer & Phye, 2008). Haverty et al. (2000) explained that the inductive process stimulates individuals to engage in data collection, pattern identification, and hypothesis generation, which is essential for solving problems. Inductive reasoning plays a critical role in organizing information, helping individuals find connections between components and generalize the problem conjecture. It supports problem-solving strategies by controlling and manipulating variables to understand the problem situations (Schwichow et al., 2016). Inductive reasoning facilitates building concrete mental models to transfer experience in problem-solving strategies, perceiving knowledge, and applying knowledge in similar problem situations (Christie & Gentner, 2014).

The relationship between problem solving and inductive reasoning has been shown consistently in many studies (Greiff et al., 2015; Molnár et al., 2013; Wu & Molnár, 2022). Christ et al. (2020) found a positive correlation between reasoning ability and CPS. Stadler et al. (2015) conducted a metaanalysis and revealed low to high correlations between reasoning and domain-general problem solving within different contexts. In addition, the connection between inductive reasoning and domain-general problem-solving remained moderate across grades in middle school (Molnár et al., 2013). Wu and Molnár (2018) also conducted interactive measurement of problem solving and found a predicting effect of inductive reasoning for problem solving ($\beta = 0.24$; $p < .05$). An explanation for this finding is associated with the conceptualisation of inductive reasoning which supports generating and testing hypothesis for solving a problem (Gilhooly, 1988). Inductive reasoning helps problem solvers build mental representation and find ways to solve the problem (Holyoak, 2012). It also helps individuals deepen their understanding of new knowledge and apply it in new problem situations (Wirth & Klieme, 2003). Thus, inductive reasoning potentially acts as a predictor of problem solving in supporting the capacity to provide solutions for complex problems.

4. Knowledge and competencies in problem solving

The dynamics of problem-solving are complex and, thus, cannot be explained only by a single component. Because problem-solving involves a series of cognitive operations, including intelligence and cognitive capacity (i.e. inductive reasoning) and other components related to the knowledge and cognitive process becomes necessary. Prior knowledge provides additional information about essential features of problems. Indeed, individuals with greater prior knowledge will more accurately encode the problem components, using problem-solving strategies that are more efficient than those with less prior knowledge (Booth & Davenport, 2013). When experiencing a novel problem, prior knowledge is activated to identify and understand the problem situation. If the activated knowledge is relevant to the problem, problem-solving strategies are applied efficiently to the respective problems (Crooks & Alibali, 2013). Furthermore, prior knowledge and competency are connected to memory organisation and cognitive schema, leading to domain expertise (Bartlett, 1995). Experts can apply stronger problem-solving strategies than nonexperts by using corresponding information in working memory and producing compatible cognitive rules. This condition can be promoted, reaching a certain level when fully automated, improving problem-solving efficiency (Lee et al., 2019). Concerning intelligence, the Elshout-Raaheim hypothesis explains that knowledge supports the connection between intelligence and problem-solving (Leutner, 2002). Specifically, the connection between intelligence and problem-solving can be strengthened with increased knowledge. Weise et al. (2020) investigated the moderating effects of prior knowledge on the relationship between intelligence and complex problem-solving. The results indicated that increased knowledge from task to task strengthens the correlation coefficient between these variables. These findings further support the role of knowledge in intelligence and problem-solving tasks and suggest that knowledge may mediate the connection between these abilities.

Further knowledge-based competency has been reported to be tied directly with problem performance. Chan et al. (2022) found that students with higher symbolic and algebraic knowledge performed better in implementing problem-solving strategies. The knowledge construction process was also found to moderately correlate with problem-solving in medical fields (Wang et al., 2013). Moreover, students' literacy and competency affected their ability to assess problem situations and use effective methods in problem-solving (Sumirattana et al., 2017). Cardenas and Rodegher (2020) explained that the success of problem-solving activities is supported by domain-relevant skills, which include factual knowledge and technical skills in a particular major. It improves the chances of achieving successful outcomes through a comprehensive understanding of problem situations and idea production. In the context of science learning, prior knowledge was associated with problem-solving (β = 0.16, $p < .05$), which helps students to obtain evidence, support investigation, gain control over variables, and analyse relationships between variables (Scherer & Tiemann, 2012). Hestiana and Rosana (2020) demonstrated that students' problem-solving ability simultaneously improved with their scientific competency level during a problem-based learning programme. Song (2018) also explained that students with high science knowledge and conceptual understanding effectively collaborate and solve problems during science learning. They can recognise important information or variables and provide a detailed analysis of the problems. Indeed, knowledge and competency potentially predict individual problem-solving performance. With the presence of other variables, such as reasoning skills, their effect on problem-solving performance is further enhanced.

5. The present study

An association among inductive reasoning, prior knowledge, and problem-solving ability has been suggested. Although the relationship between these factors has been extensively studied, the role of knowledge and inductive reasoning in domain-general and domain-specific problem solving remains unclear. Based on the Elshout-Raaeheim hypothesis concerning the influence of knowledge on the connection between intelligence and problem-solving (Weise et al., 2020), the role of knowledge potentially serves as a mediator in the relationship between inductive reasoning and problem solving. Because reasoning is also a part of intelligence (see Klauer et al., 2002; Stadler et al., 2015), the level of students' prior knowledge is predicted to strengthen the connection between reasoning and problem solving (Leutner, 2002). The mediating effect of knowledge is supported by some studies that have revealed the connection between inductive reasoning and domain-general and domain-specific problem solving (Molnár et al., 2013; Wu & Molnár, 2022). Inductive reasoning was found to have a positive correlation with knowledge competency (Wicaksono & Korom, 2023a), and knowledge is connected to domain-general and domain-specific problem solving (see Milbourne & Wiebe, 2018; Scherer & Tiemann, 2012; Shin et al., 2003).

The present study aimed to investigate the mediation effect of knowledge in the relationship between inductive reasoning and both domain-general and domain-specific problem solving. Complex problem solving (CPS) and science problem solving (SPS) were applied to measure domain-general and domain-specific problem solving. Analogy and series tasks were used to measure inductive reasoning. In addition, prior knowledge was derived from the scientific competency task, which refers to knowledge about science and science-based technology (OECD 2019). Two models of the relationship between inductive reasoning, scientific competency, and problem solving were proposed: (1) Scientific competency mediates the relationship between inductive reasoning and complex problem-solving, and (2) Scientific competency mediates the relationship between inductive reasoning and science problem-solving.

6. Methods

6.1. Participants

The participants were 1232 high school students from Java, Indonesia. There were 451 (36.6 %) male participants and 781 (63.4 %) female participants; mean age = 16.79 years (SD = 0.98). The students were selected from 12 public high schools in Java Province, Indonesia. The schools were randomly selected among all schools in the area, encompassing various ethnic backgrounds, including Javanese, Madurese, and Sundanese, among others. All 10th-grade students in the selected schools participated in this study. All students were in tenth grade and had passed the national requirement of compulsory education and had attended schools using the K-13 Indonesian national curricula, covering math and science (physics, chemistry, biology, and geography), social studies (economy and history), literature studies (Indonesian literature and basic English), physical education, art and religious study (BSNP, 2013).

6.2. Instruments

6.2.1. Complex problem solving (CPS)-MicroDYN

We used a complex problem-solving approach with MicroDYN test, a computer-based task that uses a linear structural equation framework to assess domain-general problem solving (Funke, 2010; Greiff, 2012; Greiff et al., 2012). MicroDYN is designed to measure general complex problem-solving (CPS) and has demonstrated strong validity properties. For example, a study by Schweizer et al. (2013) showed that MicroDYN provides strong validity and reliability in the German context ($\chi^2(52) = 1.94$, CFI = 0.96, TLI = 0.98, RMSEA = 0.05, WRMR = 0.92; α = 0.83). This approach emphasises the connection between input and output variables that are related to general daily life topics (e.g. interactions between butterfly and flowers; or between gas and engine) and allows the test takers to experience dynamic interaction between the system and the presented problem (Greiff et al., 2013). MicroDYN items consist of two or three input variables, which can be connected to output variables (Wüstenberg et al., 2012). The test takers can manipulate the input variable and observe the impact on the output variables. There are two types of connection between the input variable when the input variable changes the value of the output variable or if the output variable affects itself (Wüstenberg et al., 2012).

Within the MicroDYN task, the test takers complete the test in two phases. First, the knowledge acquisition phase occurs when the test takers explore the system by changing and controlling the input variables and observing the effects on the output variables (Lotz et al., 2022). By exploring the system, test takers can find the connection between variables and draw their conclusions in a model. Second, during the knowledge application phase, they encounter a similar system with a specific target value (Fig. 1). The test takers control the system and reach the target value for all variables within four steps (Lotz et al., 2016). This study used 14 tasks: seven tasks in each knowledge acquisition and knowledge application phase.

6.2.2. Science problem solving (SPS)

An SPS test was used to measure students' domain-specific problem-solving ability. The test is constructed based on the theoretical consideration that problem solving is the ability of an individual to conduct cognitive processes to understand and solve problem situations (OECD, 2014). This test offers problem-solving tasks within the scope of science and has been analyzed in previous studies for its reliability ($\alpha = 0.73$) and validity ($\chi^2(52) = 1.99$, CFI = 0.98, TLI =0.98, RMSEA =0.03, SRMR = 0.04) (Wicaksono & Korom, 2023b). The component of SPS tasks is divided into two main phases: identifying problem and generating solution. The identifying problem task focuses on the ability to detect variables connected to the problem situation and find the main cause of the problems. A generating solution task mainly assesses the ability to plan and formulate a solution to the given problem. Each question is presented with information and data related to the problem situation in the test administration. Test takers identify the problem and formulate a solution based on their ability to organise and analyse the information and data (Fig. 2). The problem situations are presented within science phenomena that involve the topic of ecosystem, environmental issues, agriculture, conservation, and sport and energy. There are six items for identifying problem and five for generating solutions.

6.2.3. Inductive reasoning (IR)

The inductive reasoning test measures students' ability to discover rules, generalisations, and regularities by detecting similarities and dissimilarities of objects or matters (Csapó, 1997; de Koning et al., 2003). It includes series and analogy tasks with numerical and figural objects (Fig. 3). The series tasks aim to interpret a given phenomenon and provide a plausible meaning within a series of objects. The analogy tasks perceive and use relational similarities between two events or conditions (Adey & Csapó, 2012; Christie & Gentner, 2014). In this study, the inductive reasoning test comprises 32 items divided into four main task types: figure series, figure analogy, number analogy, and number series, and each task type contains eight items (Csapó, 1997; Pásztor et al., 2017, 2022). Due to the internal consistency and validity ($\alpha = 0.88$; CFI = 0.902, RMSEA = 0.038, and SRMR = 0.046) it has proven to be a suitable measure of inductive reasoning (Van Vo & Csapó, 2020).

6.2.4. Scientific competency (SC)

Scientific competency measurement assesses students' knowledge and cognitive disposition in managing scientific or science-related topics. The format of scientific competency tasks was adapted from the PISA scientific competency (OECD 2017), focusing on the ability to explain scientific phenomena and interpret and evaluate scientific data or evidence. Explaining scientific phenomena tasks assesses students' ability to recall information and understand science concepts (Fig. 4). Additionally, interpreting and evaluating scientific data or evidence tasks emphasise the ability to analyse the data, provide claims and arguments, and generate conclusions. The test was presented in multiple-choice format, with the core topics covering agriculture, ecosystem, environmental issues, and animal physiology and behaviour. The test comprises six items for explaining scientific phenomena and seven for interpreting and evaluating scientific data or evidence. The reliability ($\alpha = 0.72$) and validity (CFI = 0.96, TLI = 0.96, RMSEA = 0.03, SRMR = 0.06) of the test have been established in a previous study (Wicaksono & Korom, 2023a).

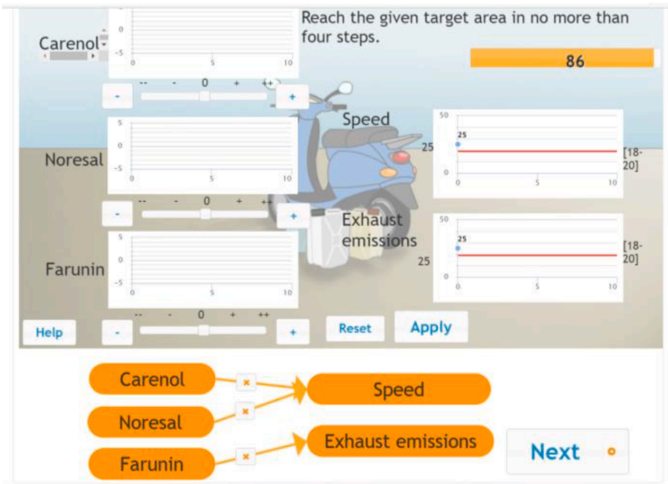

Fig. 1. A sample of the MicroDYN test in the knowledge application phase.
Note. It presents the problem situation related to gas and a motorbike. The test takers control and manipulate input variables (carenol, noresal and farunin) by adjusting the controller to its minimum (" - ") and maximum (" + ") value. The resulting effects appear in the output variables (speed and gas emission) graphically (red line) and numerically (18–20). The correct answer was assigned when the test takers correctly adjusted the input variables and reached all of the desired values on the output variables. The relationship model is displayed at the bottom of the figure.

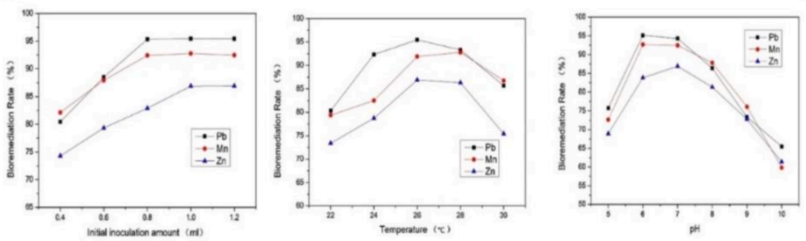

Figure 1. The bioremediation rate in different parameters

2. If the researcher introduced the microbial agent culture in the river E (T= 26°C, pH= 7.01). How is the bioremediation rate that can be predicted for water pollution?
   a. The bioremediation rate for Zn will reach 95%.
   b. The bioremediation rate for Zn will reach 85%.
   c. The bioremediation rate for Mn will reach 85%.
   d. The bioremediation rate for Mn will reach 80%.
   e. The bioremediation rate for Pb will reach 75%.

Fig. 2. Screenshot of SPS task on environmental issues.
Note. The test presented information related to the problem (i.e. heavy metal pollution) and some research data about the effect of microbial agents in decreasing pollution levels. Based on the research data, test takers generate a solution by formulating the optimal environment for microbial inoculation to minimise the number of pollutants.

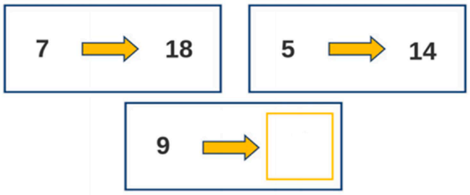

Fig. 3. Screenshot of inductive reasoning test with number analogy task.
Note. The test takers fill in the number that complements the previous prompt

11. How does fossil fuel consumption affect the increase in global temperature?
a. Fuel burning produces carbon dioxide, which becomes trapped in the atmosphere.
b. The heat from oil burning increases the surrounding temperature.
c. The heat from burning fuel decreases humidity in the air.
d. Gases from fuel burning trap water molecules, reducing rain intensity.
e. Nitrogen gas from oil burning damages the ozone layer.

Fig. 4. Screenshot of the scientific competency task to explain scientific phenomena.
Note. Students select the correct responses based on their prior knowledge and understanding of the phenomena related to pollution and global temperature

6.2.5. Scoring and procedure

All tests have undergone content review by experts and were translated into Bahasa through back and forward translation by two translators from the university. All test items were scored dichotomously, with 1 for a correct answer and 0 for an incorrect answer. The online tests were administered using the Electronic Diagnostic Assessment (eDIA) system. This technology-based assessment platform administers online assessments and produces interpretable feedback and data (Csapó & Molnár, 2019). Under teachers' supervision, students completed the tests in the school's computer laboratory. Students completed the tests in the school's computer laboratory under the supervision of teachers. Before data collection, participants filled out the consent form, and the research received ethical approval from the Institutional Review Board (IRB) of the University ofSzeged, ensuring compliance with ethical standards.

6.2.6. Data analysis

There was no missing data in our dataset. Psychometric analysis was performed to examine the test's validity using confirmatory factor analysis (CFA). Since the data are dichotomous, scoring participants' responses as either correct or incorrect, we have decided to use the weighted least square mean and variance adjusted (WLSMV) estimator for the CFA, as it properly handles non-normally distributed data (Koziol, 2023; Li, 2016). The fit indices for CFA were examined with a comparative fit index (CFI) and Tucker-Lewis Index (TLI) higher than 0.90. The fit criteria also include the root mean square error of approximation (RMSEA) and standardised root mean square residual (SRMR) with an estimated value lower than 0.08 (Hu & Bentler, 1999; Marsh et al., 2004). In the problem-solving measure, a two-dimensional model of CPS, comprising knowledge acquisition and knowledge application phases, was tested. The CPS test demonstrated an acceptable model fit ($\chi^2(76) = 1.78, p < .001$, CFI = 0.99, TLI = 0.99, RMSEA = 0.02, $CI_{(90\ \%)}$ = [.02, 0.03], SRMR = 0.06), supporting its validity. The SPS was also tested using a two-dimensional model, consisting of identifying problems and generating solution phases, and the model fit the data well ($\chi^2(54) = 2.20, p < .001$, CFI = 0.98, TLI = 0.97, RMSEA = 0.03, $CI_{(90\ \%)}$ = [.02, 0.04], SRMR = 0.04). For IR, we tested a four-dimensional model comprising figure series, figure analogy, number series, and number analogy as correlated dimensions. This model fit the data well ($\chi^2(458) = 4.18, p < .001$, CFI = 0.96, TLI = 0.96, RMSEA = 0.04, $CI_{(90\ \%)}$ = [.04, 0.05], SRMR = 0.06). Furthermore, a two-dimensional model was also tested for the SC test, with explaining scientific phenomena and interpreting or evaluating scientific data as its correlated dimensions. The model displayed an acceptable fit ($\chi^2(88) = 3.02, p < .001$, CFI = 0.96, TLI = 0.95, RMSEA = 0.04, $CI_{(90\ \%)}$ = [.03, 0.05], SRMR = 0.05). The factor loadings of the models are presented in the Appendix.

Additionally, we conducted configural, metric, and scalar invariance analyses across genders for all measures (Table 1). The results for configural invariance showed that the model fit the data, indicating that the specified factors in the test models are consistent for both boys and girls across all tests. Similar results were observed for metric invariance, where the model fit the data, suggesting equal factor loadings for each item across gender groups (Vandenberg & Lance, 2000). In addition, scalar invariance was tested to verify the intercepts between groups (Bonaccio & Reeve, 2006). The model fit the data, indicating that intercepts in all tests were equivalent across genders. The fit indices showed no substantial changes across all types of invariances, suggesting an absence of gender bias in the tests. The internal consistency of the test was adequate, with α = 0.83 for MicroDYN, α = 0.73 for SPS, α = 0.86 for inductive reasoning, and α = 0.77 for scientific competency.

Prior to investigating the mediation effect of scientific competency on inductive reasoning and problem solving, we conducted structural equation modelling to assess the proposed models and subsequently ran each model with 10,000 bootstrapping to calculate the total, direct, and indirect effect. The 95 % confidence interval (CI) calculation was added to assess the statistical significance of the mediation effects. Data analysis was performed with SPSS 25 and Mplus 6 software.

7. Results

Descriptive statistics of students' performance in complex problem-solving (CPS), science problem solving (SPS), inductive reasoning, and scientific competency are presented in Table 2. For further analysis, all variables were standardised. As shown in Table 3, all measured variables are significantly correlated. A low correlation was observed between the CPS and SPS variables ($0.21 < r \leq 0.26; p < .001$). Inductive reasoning showed a low to moderate correlation with the CPS and SPS variables ($0.17 < r \leq 0.31; p < .001$). A moderate correlation was found between scientific competency and inductive reasoning ($0.31 < r \leq 0.46; p < .001$), and between CPS and SPS ($0.27 < r \leq 0.34; p < .001$).

The proposed model of the mediation effect of scientific competency on the relationship between inductive reasoning and problem solving is presented in Fig. 5. This model yielded $\chi^2(2328) = 1.61, p < .001$, CFI = 0.97, TLI = 0.97, RMSEA = 0.02, $CI_{(90\ \%)}$ = [.02, 0.03], and SRMR = 0.06, suggesting that the model fit with the data. The model showed inductive reasoning has a positive and

Table 1
Model fit indices for invariance analysis of complex problem solving (CPS), science problem solving (SPS), inductive reasoning (IR) and scientific competency (SC) across gender.

Instruments	χ^2	*df*	*p*	CFI	TLI	RMSEA	SRMR
CPS-MicroDYN							
configural	779.06	152	< 0.001	.87	.85	.08	.07
metric	839.97	164	< 0.001	.86	.85	.08	.08
scalar	849.92	176	< 0.001	.87	.86	.08	.08
Science problem solving (SPS)							
configural	151.07	86	< 0.001	.96	.95	.03	.03
metric	161.71	95	< 0.001	.96	.95	.03	.04
scalar	187.33	104	< 0.001	.95	.95	.03	.04
Inductive reasoning (IR)							
configural	3712.24	916	< 0.001	.77	.75	.07	.06
metric	3770.63	944	< 0.001	.76	.75	.07	.06
scalar	3838.01	972	< 0.001	.76	.75	.07	.06
Scientific competency (SC)							
configural	373.56	178	< 0.001	.94	.92	.04	.04
metric	386.98	191	< 0.001	.94	.93	.04	.04
scalar	397.44	204	< 0.001	.94	.94	.04	.04

Note. All instruments demonstrate an acceptable model fit, confirming that the construct fits the model and that no variance was found across genders.

Table 2
Descriptive statistics of complex problem-solving (CPS), science problem-solving (SPS), inductive reasoning (IR), and scientific competency (SC).

Instruments	Mean	SD	Min	Max
CPS-MicroDYN				
Knowledge acquisition	1.49	1.84	0.00	7.00
Knowledge application	0.68	1.20	0.00	7.00
Science problem solving (SPS)				
Identifying problem	1.95	1.56	0.00	6.00
Generating solution	1.88	1.48	0.00	5.00
Inductive reasoning (IR)				
Figure series	4.48	2.36	0.00	8.00
Figure analogy	4.94	2.20	0.00	8.00
Number analogy	4.02	2.25	0.00	8.00
Number series	6.37	2.26	0.00	8.00
Scientific competency (SC)				
Explaining phenomena	2.51	1.54	0.00	6.00
Interpreting and analysing data	3.94	2.13	0.00	7.00

Table 3
Pearson correlation between latent variables in complex problem-solving (CPS), science problem solving (SPS), inductive reasoning (IR), and scientific competency (SC).

	CPS (MicroDYN)		Science problem solving (SPS)		Inductive reasoning (IR)				Scientific competency (SC)
	1	2	3	4	5	6	7	8	9
CPS-MicroDYN									
Knowledge acquisition (1)	–								
Knowledge application (2)	.58**								
Science problem solving (SPS)									
Identifying problem (3)	.26**	.23**							
Generating solution (4)	.25**	.21**	.54**						
Inductive reasoning (IR)									
Figure series (5)	.31**	.27**	.17**	.21**					
Figure analogy (6)	.30**	.28**	.23**	.25**	.54**				
Number analogy (7)	.28**	.29**	.22**	.22**	.42**	.50**			
Number series (8)	.21**	.19**	.21**	.25**	.39**	.46**	.48**		
Scientific competency (SC)									
Explaining phenomena (9)	.30**	.28**	.29**	.27**	.39**	.46**	.43**	.41**	
Interpreting and analysing data (10)	.34**	.32**	.31**	.29**	.31**	.38**	.34**	.34**	.53**

Note. ** significant at $p < .001$.

significant connection to scientific competency in high magnitude ($\beta = 0.78$, $SE = 0.03$, $p < .001$, $CI_{(95\%)} = [.74, 0.82]$), proposing that students with high inductive reasoning demonstrate better scientific competency. Scientific competency showed positive connections to both CPS ($\beta = 0.45$, $SE = 0.09$, $p < .001$, $CI_{(95\%)} = [.31, 0.60]$) and SPS ($\beta = 0.46$, $SE = 0.08$, $p < .001$, $CI_{(95\%)} = [.33, 0.59]$). Meanwhile, a positive correlation was found between residuals of CPS and SPS ($r = 0.18$, $SE = 0.07$, $p = .008$, $CI_{(95\%)} = [.06, 0.29]$) in the model, indicating that the existing predictors did not fully explain the relationship between these two types of problem-solving.

Inductive reasoning has a positive and significant connection to CPS ($\beta = 0.25$, $SE = 0.09$, $p = .009$, $CI_{(95\%)} = [.09, 0.40]$), but not to SPS ($\beta = 0.09$, $SE = 0.08$, $p = .224$, $CI_{(95\%)} = [-0.04, 0.22]$), indicating that inductive reasoning does not influence SPS directly. Furthermore, the effect of inductive reasoning on both problem-solving was further investigated through the mediation of scientific competency (see Table 4). Inductive reasoning has a significant and positive indirect effect on CPS through scientific competency as a mediator ($\beta = 0.35$, $SE = 0.07$, $p < .001$, $CI_{(95\%)} = [.24, 0.47]$) with the total effect of $\beta = 0.60$ ($SE = 0.04$, $p < .001$, $CI_{(95\%)} = [.54, 0.67]$). Furthermore, there was a positive and significant indirect effect of inductive reasoning on SPS mediated by scientific competency ($\beta = 0.36$, $SE = 0.07$, $p < .01$, $CI_{(95\%)} = [.26, 0.47]$) with the total effect of $\beta = 0.45$ ($SE = 0.03$, $p < .001$, $CI_{(95\%)} = [.40, 0.50]$). This also indicates that the connection between inductive reasoning and SPS is fully mediated by scientific competency.

8. Discussion and future recommendations

The present study investigated the interplay between inductive reasoning, scientific competency, and domain-general and domain-specific problem solving. We assessed students' ability in each construct using standardized measurements that showed valid and reliable results within the Indonesian sample (Table 1). All constructs were substantially correlated but represented a discrepant relationship model. An investigation of relationships between inductive reasoning, domain-general, and domain-specific problem solving showed that all the constructs were significantly correlated, explaining that inductive reasoning served as a basic skill for processing information during problem solving (Klauer et al., 2002; Molnár et al., 2013). In another study, prior knowledge was connected to problem solving (Weise et al., 2020). Yang et al. (2022) stated that knowledge-rich content is prominent in problem

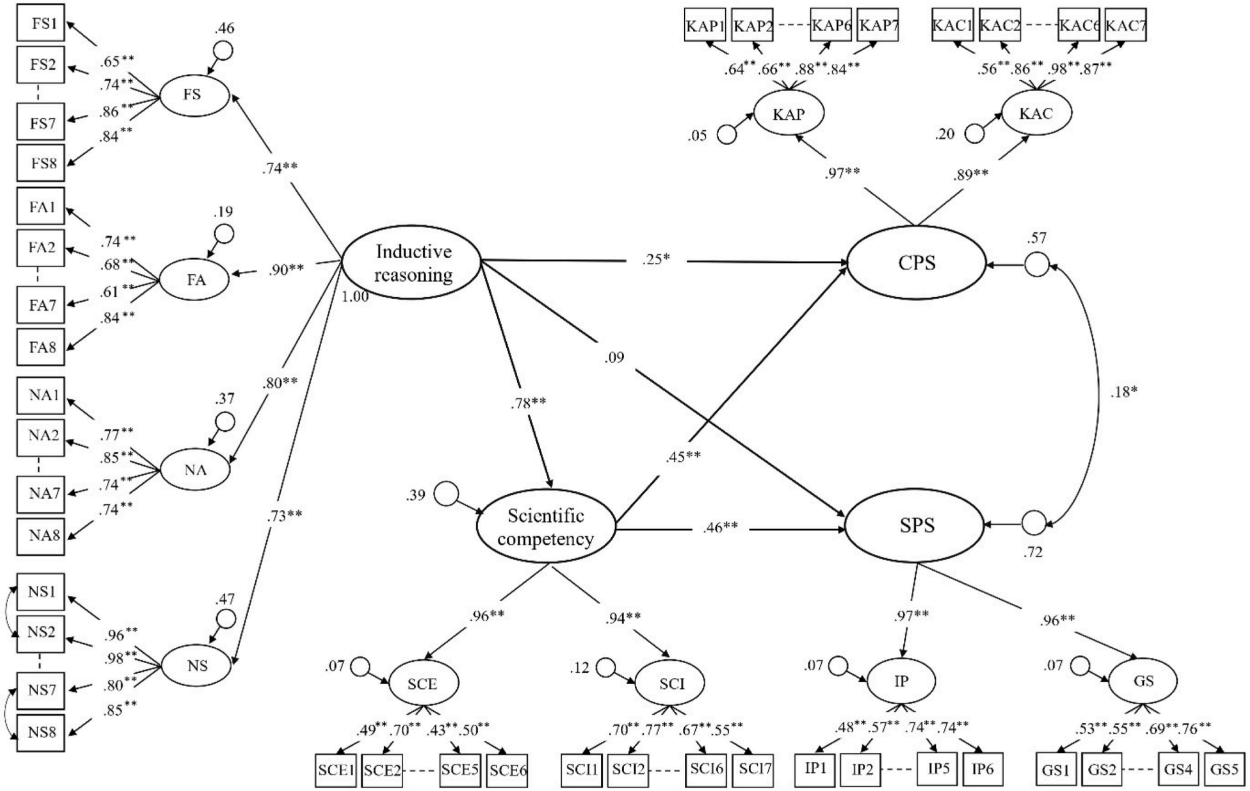

Fig. 5. The model of the connection between inductive reasoning, scientific competency, and problem solving.
Note. CPS = complex problem solving, SPS = science problem solving, KAP = knowledge acquisition, KAC = knowledge application, IP = identifying problem, GS = generating solution, SCE = explaining phenomena, SCI = interpreting and evaluating, FS = figure series, FA = figure analogy, NA = number analogy, NS = number series. * $p < .05$, ** $p < .01$.

Table 4
The direct, indirect, and total effects of the variables.

Model pathway	Effect	β	SE	$CI_{(95\ \%)}$	*p*
IR → CPS	direct	.25	.09	.09, 0.40	.009
IR → SC → CPS	indirect	.35	.07	.24, 0.47	< 0.001
	total	.60	.03	.54, 0.66	< 0.001
IR → SPS	direct	.09	.08	−0.04, 0.21	.224
IR → SC → SPS	indirect	.36	.07	.25, 0.47	< 0.001
	total	.45	.03	.40, 0.50	< 0.001

Note. IR = inductive reasoning, SC = scientific competency, CPS = complex problem solving, SPS = science problem solving, β = standardized estimates, CI = confidence interval, SE = standard error.

solving. Alternatively, this research considered scientific competence as a mediator between inductive reasoning and problem solving.

Our results suggest that scientific competency significantly mediates the relationship between inductive reasoning and problem solving. This result was supported by the Elshout-Raaheim studies (Leutner, 2002), in which the relation between problem-solving and intelligence (i.e. inductive reasoning) was moderated by prior knowledge and later changed into mediation (Karazsia & Berlin, 2018). Bright and Feeney (2014) also supported the mediation role of scientific competency and explained how causal knowledge is related to inductive reasoning and problem-solving. They used inductive reasoning tests that involved biological domains, such as food chain and genetics. Their results revealed that the increase in knowledge complexity complemented students' reasoning process, suggesting that the development of inductive reasoning is closely linked to how students acquire knowledge and understand the context. Wicaksono and Korom (2023a) also investigated the connection between inductive reasoning and scientific competency, confirming that inductive reasoning supports information processing and scientific conclusions. Additionally, problem solving requires the cognitive process to regulate information and apply it in new situations (Greiff & Neubert, 2014). When students attain higher inductive reasoning ability, their capacity to regulate knowledge and competency increases, improving their problem-solving ability.

Further investigation the connection between inductive reasoning and problem-solving was extended by examining domain-general and domain-specific problem-solving using CPS and SPS measures, respectively. First, inductive reasoning significantly enhances CPS, indicating that students with higher inductive reasoning are better at solving general and complex problems. Even when considering scientific competency, the effect of inductive reasoning on CPS remains significant with a strong total effect. This result suggests that scientific competency supports the relationship between inductive reasoning and CPS. The contribution of scientific competency has been explained by many studies, which suggest that successful activities in solving domain-general problems require logical arguments and reasoning or application of previous experience (Jonassen, 2000; Shin et al., 2003). Problem solvers must justify their interpretation and judgement to make decisions for solutions. This process also involves knowledge in its cognitive operations (Funke, 2010) and necessitates scientific competency. Indeed, the mechanism of domain-general problem-solving with CPS approaches requires information or prior knowledge, but not all of them are required (Wüstenberg et al., 2012). In this situation, domain knowledge is necessary to develop problem-solving strategies but has limitations due to the generality of the problem context. Additionally, new knowledge is generated in accordance with problem situations.

Second, inductive reasoning did not affect SPS directly; however, its influence became significant with the mediation of scientific competency. This result implies that students with high inductive reasoning improve their scientific competency, supporting their domain-specific problem-solving performance. In connection with domain-specific problem solving, inductive reasoning is necessary to build a mental model and apply reasoning schema from experience to the new situation (Haverty et al., 2000), helping problem solvers apply their prior knowledge and acquire new knowledge. As a result, the acquired knowledge enhances the ability to comprehend the problem, facilitating more effective solutions generation. Solving domain-specific problems also requires forming analogies based on previous experience and using similar methods to deal with new problems (Jonassen, 2000). This condition requires the support of inductive reasoning for information processing, allowing problem solvers to choose essential knowledge that can be applied to manage the problems. Additionally, the solution for specific problems involves an original approach or novel combination of knowledge and information associated in memory (Wiley, 1998). For this reason, the ability to recall information is essential for domain-specific problems, as prior knowledge and information will constrain the category during problem identification, increasing the efficiency of the process. This study demonstrated that inductive reasoning supports problem-solving performance either in general or specific domains with the support of scientific competency and knowledge.

Notably, this study has limitations. First, the domain-specific measurement focused on science concepts to align with the application of the Indonesian K-13 curriculum. Thus, constructing a problem-solving test in different contexts could involve mechanisms and the strength of the connection between constructs. Second, the measurement of inductive reasoning is limited for series and analogy tasks (figural and numerical form). However, there are also tests for other categories (i.e., matrices and schemes) (Klauer & Phye, 2008). Third, regarding the test's scoring, we applied a dichotomous scoring procedure for all measures. Although this procedure has been supported by good reliability results (Lotz et al., 2022; Van Vo & Csapó, 2020), other scoring procedures are also available for problem-solving assessments. Another concern is using the MicroDYN test for measuring CPS, as most participants failed to achieve high scores. This may be due to students being unfamiliar with or disinterested in the tasks, which could potentially influence their performance. Furthermore, the mediation effects cannot be interpreted as causal in the current study since it was purely correlational. Establishing causality between variables requires longitudinal or experimental studies, suggesting that future research should employ these methodologies to better understand the causal relationships between inductive reasoning, scientific competency, and problem-solving.

Future studies are recommended to assess students' interest and the difficulty of the tasks, as well as consider the use of alternative measurement methods. Additionally, comparisons with other samples through cross-cultural studies may be necessary to fully confirm the CPS assessment's usability and understand the socio-cultural impact on the sample.

The results of this study demonstrated the importance of competency and inductive process in explaining the mechanism of domain-general and domain-specific problem-solving. We found that the ability to make analogies and analyze the connections between variables through an inductive process helps students enhance their problem-solving strategies. Acquiring knowledge and competencies allows students to apply problem-solving strategies more effectively. Therefore, instructional programs should incorporate tasks that focus on analogies, checking similarities, understanding information, and making careful observations to support students in succeeding at solving problems. Additionally, applying inductive strategies and introducing general and specific problem-solving tasks in classroom practice may help students become familiar with the problem-solving process. This study focused on problem-solving, inductive reasoning, and scientific competency, but it may also be important to examine the impact of other variables. Therefore, future research should consider including other cognitive and affective variables to further investigate the mechanisms of problem-solving (see Fung et al., 2014; Guven & Cabakcor, 2013; Spoon et al., 2021), and further exploration of problem solving in association with inductive reasoning, scientific competency, and other prominent cognitive or affective variables.

9. Conclusions

The results of this study align with those in the literature on the connection between inductive reasoning, scientific competency, and problem-solving. Furthermore, we extended the role of scientific competency as a mediator variable in explaining the connection between inductive reasoning and problem solving. Our results indicate that the mediation effect of scientific competency is greater in supporting the connection between inductive reasoning and domain-specific problem-solving. Otherwise, the effect is lower for the inductive reasoning and domain-general problem-solving model. Notably, the limitations regarding the domain specificity and scoring must be considered when explaining the results of this study. In conclusion, research on the relationships among inductive reasoning, knowledge-based competency, and problem-solving should be continued in assessment and learning instructions. We also recommend involving other cognitive and affective variables to explain the dynamics and complexity of problem-solving abilities.

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CRediT authorship contribution statement

Azizul Ghofar Candra Wicaksono: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Erzsébet Korom:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that there are no financial or personal competing interests that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.tsc.2025.101830.

Data availability

Data will be made available on request.

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