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Role of inductive reasoning, gender, learning satisfaction, and educational and career preference in predicting scientific competency in high school

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ABSTRACT

Scientific competency has been known for its role as a core component of science education. Numerous studies in education have supported the development of scientific competency and demonstrated that analysing certain predictors and associated variables can provide better information for developing it. The current study explores the effect of certain predictors of scientific competency: inductive reasoning, gender, learning satisfaction, and educational and career preference. We recruited high school students (n = 613) in Indonesia, who completed online scientific competency and inductive reasoning tests, and questionnaires on learning satisfaction and educational and career preference. The scientific competency and inductive reasoning tests demonstrated acceptable construct validity and an acceptable Rasch fit index (with an infit mean square value ranging from 0.86 to 1.29). The results indicate that scientific competency is associated with inductive reasoning ($\beta = 0.63$, $p < 0.01$) and is slightly affected by gender. In addition, we found small effects of education preference and learning satisfaction on inductive reasoning, whereas career preference is strongly related to educational preference. These findings supported the claim that the development of scientific competency in high school should involve inductive reasoning and other predictors. Future research perspectives include exploring how other educational variables and strategies influence the development of scientific competencies.

1. Introduction

Developing scientific competency is one of the core components of science education. Scientific competency is defined as a cognitive disposition to address situations and demands in the science domain Dietrich et al. (2015) and as an ability to critically analyse and evaluate scientific research or phenomena (Ratte et al., 2018). Its importance is emphasised in global educational development, such as projects launched by the National Research Council (U.S.). They published a framework for K-12 science education consisting of scientific practices, crosscutting concepts, and disciplinary core ideas (Greenfield et al., 2017; National Research Council, 2015), presenting framework that is relevant for students in constructing their scientific knowledge and developing process skills (Lin et al., 2021). This framework influenced the development of teaching and learning practices such as inquiry-based learning,

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problem-based learning, computer-assisted instruction, and other learning methods that promote learners' scientific knowledge and competency (Chang, 2002; Demetriadis et al., 2011; Marzouki et al., 2017; Sung & Hwang, 2013).

Although, prominent educational practices have been provided to support scientific competency, further discovery of influential variable is necessary for scientific competency promotion. In the area of science education, inductive reasoning is considered a strong factor in students' learning performance and knowledge development. Inductive reasoning is known as the ability to detect rules, generalizations, and regularities (Klauer & Phye, 2008). It greatly contributes to students' readiness in the learning process and indirectly influences school achievement, such as grade point average and comprehension test scores (Díaz-Morales & Escribano, 2013; Molnár, 2011). It assists students in acquiring knowledge based on logic and rationality, drawing conclusions, and solving problems (Sternberg & Kalmar, 2004). Science learning is rich in problem analysis and knowledge application; thus, inductive reasoning can facilitate the development of scientific competency. Some research mentioned that scientific competency and inductive reasoning are essential abilities for those who conduct scientific research or are planning to become scientists (Ketokivi & Mantere, 2010; Ratte et al., 2018). Therefore, they need to be introduced in school level to equip students with the basic skills needed in modern society (Tsai, 2015). In addition, several studies demonstrate other variables that potentially influence scientific competency, such as: gender, learning satisfaction, and educational, and career choice (Bang & Baker, 2013; Gurpinar et al., 2010; LIbao et al., 2016). Considering such variable is important because the number of predictors is related to propensities and constrained opportunities that aid in competency development (Morgan et al., 2016). Consequently, identifying scientific competency and analysing its connection to inductive reasoning with the addition of several variables will be beneficial to provides further investigation in how instructional strategies can be designed to help students develop their abilities.

The present study focuses on the measurement of scientific competency and investigate the influence of inductive reasoning and other predictive factors in the Indonesian context. The results are then compared with studies conducted in other contexts such as Vietnam, Hungary, and Germany (Molnár et al., 2013; Van Vo & Csapó, 2020). We knoew relatively little about the performance of Indonesian students in scientific competency and inductive reasoning. The current investigation can therefore provide important information for further educational development in Indonesia.

1.1. *Inductive reasoning*

Inductive reasoning is defined as an ability to detect similarities and regularities (Klauer & Phye, 2008) and involves activities to make predictions based on existing knowledge (Hayes & Heit, 2018). It is also defined as drawing general inferences from empirical data to formulate theories (McAbee et al., 2017). Inductive reasoning is related to cognitive processes such as categorization, inference, probability judgement and decision making. Such cognitive processes involve the property of generalization which is driven by the relationship between premise and conclusion. A successful inductive process that relates premise to conclusion is affected by their similarity, that is, the feature overlap between the premise and conclusion categories and the average maximum similarity of the premise to a more general category (Hayes & Heit, 2018; Heit, 2000). A theory in inductive reasoning explains that the relationship between premise and conclusion is driven by prior knowledge. The effect of knowledge is explained by the Bayesian model (Kemp & Tenenbaum, 2009) when the generalization of categories involves access to prior knowledge about the distribution of familiar properties. Thus, the relationship between the categories of an object can be structured in many ways. For example, in biology, we know that an *eagle* has similar characteristics to a *sparrow* because they are taxonomically related. However, when relating an *eagle* to a *mouse*, the relationship remains correct in terms of food chain because an eagle will eat a mouse. These phenomena explain that different types of relationships exist between categories that support the induction process (Bright & Feeney, 2014; Shafto et al., 2008).

Another theory of the inductive reasoning process emphasises the transfer of knowledge (Csapó, 1997). The induction process enhances knowledge acquisition and its application in a new situation. As such, the knowledge transfer process is recognised as a general component of intelligence which focuses on discovering phenomena and logically finding regularities. This process requires certain strategies, such as engaging in activities and experience with particular cases, formulating logic, conjecturing, and evaluating and justifying cases (Christou & Papageorgiou, 2007). A further explanation that supports this claim is that detecting generalizations, rules or regularities represents the kinds of mental activities involved in inductive reasoning. In addition, inductive reasoning involves the detection of diversity and irregularities. Klauer and Phye (2008) propose that the inductive reasoning process features the same basic properties that regulate a set of elements, such as classification, analogy, incomplete series, and matrices, which are further used as a type of inductive reasoning task.

1.2. *Scientific competency: knowledge and process*

In science education, scientific competency plays an important part in helping students engage in scientific phenomena and solve science-related problems. Many educators suggest the inclusion of scientific knowledge, competency, and literacy as one of the main objectives of the learning process to increase the proficiency level and preparation for students' future careers (Rittle-Johnson, 2017). Numerous studies recognise the importance of scientific concepts and knowledge (Chang et al., 2010; Lederman et al., 2013; Wang & Degol, 2017). The development of scientific competency influences a great deal of teaching practice for the adaptation of content knowledge and its integration into learning progression (Yeh et al., 2015). In addition, curricula and syllabi based on content knowledge have been progressively developed with the objective of enhancing students' proficiency in science (Bankel et al., 2003).

The type of knowledge used in educational practice is categorized into four major dimensions: factual, conceptual, procedural, and metacognitive. Factual knowledge captures the terminologies, details, and elements of concepts. Conceptual knowledge includes the classification and categorization of information, theories, models, structures, principles, and the generalization of concepts. Procedural knowledge is related to methods and techniques. It also denotes knowledge in identifying processes or tasks to solve problems (Star, 2005). Metacognitive knowledge comprises knowledge of cognitive tasks and self-ability. These dimensions of knowledge require cognitive processes attained through learning activities. Based on the current taxonomy, the level of the cognitive process is broken down into six domains: *remember* (recognising and recalling information), *understand* (interpreting, classifying, and summarizing information), *apply* (executing and implementing a concept), evaluate (verifying and critiquing), and create (generating, planning, and producing materials) (Anderson & Krathwohl, 2001). The use of the types and dimensions of knowledge in science topics forms the basic core of scientific competency.

In the assessment process, the measurement of scientific competency is based on the understanding of scientific literacy used in the Programme for International Student Assessment (PISA) science assessment. The term scientific literacy on the PISA test represents competency to engage in discussion about issues that involve scientific knowledge (OECD, 2004). Three major competencies in scientific literacy, which are denoted as scientific competency, are as follows: *explaining phenomena scientifically*: recognising, offering, and evaluating explanations for a range of natural and technological phenomena, which requires in depth understanding to recall and use theories, ideas, information, and facts; *evaluating and designing scientific enquiry*: describing and appraising investigations and proposing solutions to address problems in scientific manner, which associated with the scientific method, procedures, research, and measurements that emphasize knowledge of common procedures used in science; *interpreting data and evidence scientifically*: analysing and evaluating data, providing claims and arguments, and drawing conclusions (OECD, 2017). This framework encompasses four dimensions of knowledge and applies several cognitive dimensions. When categorizing the scientific competency framework on the basis of a cognitive taxonomy, the first competency is involved in the low domain of the cognitive process, while the second and third competencies are classified as high cognitive processes (Anderson & Krathwohl, 2001; Zywno, 2003). The PISA framework has been employed to measure scientific competency in several countries, and the results have been used for further data for specific objectives (Chiang & Tzou, 2018).

1.3. Influence of inductive reasoning and predictors of scientific competency

The inductive process involves a series of cognitive processes such as categorization, analogy, decision making, and drawing conclusions, which can be categorized as components involved in scientific competency (Bybee & McCrae, 2011; Hayes & Heit, 2018). Inductive reasoning supports information recognition and interpretation through the justification process by detecting components of information (Klauer & Phye, 2008). It promotes the argumentation process and aids in drawing evidence-based conclusion that can be applied to scientific competency (Tsai, 2018). Furthermore, research has demonstrated that inductive reasoning is strongly related to specific knowledge, such as scientific knowledge (Crisp-Bright & Feeney, 2010). Thus, it promotes the possibility that inductive reasoning can facilitate the development of scientific competency.

In addition, gender has also become an interesting topic to explain scientific competency because it has been widely used as one of the predictive variables of science education (Baker, 2016; Stoet & Geary, 2018). The PISA science survey revealed that boys tend to show greater variation in performance than girls, but their overall proficiency level is almost equal (OECD, 2016). Tsai et al. (2017) reported low levels of correlation between gender and scientific competency ($r = 0.19$). Many studies have also investigated the effect of gender on inductive reasoning (Kambeyo, 2018; Soeharto & Csapó, 2022; Van Vo & Csapó, 2021) and have shown varied results. A few studies have reported no difference between males and females in inductive reasoning (Molnár, 2011; Van Vo & Csapó, 2020). In contrast, other studies have found that female students obtained higher scores on inductive reasoning tests than their male peers (Díaz-Morales & Escribano, 2013). A meta-analysis by Waschl and Burns (2020) discovered a small effect of gender difference in inductive reasoning scores in general with substantial magnitude variability and effect size.

Alternatively, affective factors, such as satisfaction and engagement in learning, can be used to predict scientific competency (Lin et al., 2012). Satisfaction is a feeling of pleasure or disappointment which reflects one's perspective on patterns underlying an entire programme (Li et al., 2016). It relates to students' performance and academic progress in the learning process. Awuor et al. (2022) investigated the flipped classroom and found that students' satisfaction with learning is tied to individual and teamwork competency. Furthermore, students who expressed high levels of satisfaction and dominant learning abilities in the case of web-based learning generally excel in inductive reasoning (Hong, 2002). Moreover, studies find that inductive reasoning strategies can strengthen students' satisfaction with the learning process (Abdullah et al., 2020). Wang (2013) revealed that learning satisfaction is positively correlated to the assimilator learning mode, which is associated with inductive reasoning.

Students' preference of an education and career in science acts as a future orientation that potentially influences their performance and competency in that field (Kjærnsli & Lie, 2011). Many studies have consistently linked academic performance to educational choice, career development, and occupational expectations (Castellano et al., 2003; Perry et al., 2010). For example, Hazari et al. (2010) report that career orientation is related to students' performance in specific subjects. Other studies propose that students interested in particular disciplines and careers may exhibit sufficient skills to promote their academic success and competency (Masnick et al., 2010). This notion open up the possibility that education and career preference potentially influence academic performance, particularly in such areas as scientific competency and inductive reasoning.

2. Objectives and research questions

The current study presents two objectives. First, we aim to examine the students' inductive reasoning and scientific competency. Second, we aim to identify the effect of several predictors: gender, learning satisfaction, and science education and career preference on inductive reasoning and scientific competency. To obtain thorough and reliable results, we verified the validity and reliability of the tests for inductive reasoning ability and scientific competency. The tests were applied to an Indonesian sample without previous information on test validity in a particular context. Thus, we intend to answer the following research questions:

1 Based on confirmatory factor analysis (CFA) and the Rasch parameter, what is the validity of the tests for inductive reasoning ability and scientific competency in the Indonesian context?
2 How can students' inductive reasoning ability and scientific competency be evaluated?
3 What are the effects of gender, learning satisfaction, and further education and career preference on inductive reasoning ability and scientific competency?

3. Methods

3.1. Participants

The participants were 613 students from ten public high schools located in an urban area in Central and East Java District, Indonesia. Tenth-grade students were randomly selected to complete the tests and a questionnaire. The students were provided with the same learning content because all schools in Indonesia implement the country's national curriculum (K-13), which uses general frameworks for science (biology, chemistry, and physics), mathematics, social studies, language (Indonesian and English), arts, physical education, and religious study (BSNP, 2013). Male and female students consist of 208 (33.9%) and 405 (66.1%) of the students, respectively, with an average age of 16.38 years ($SD = 0.66$).

3.2. Instruments

This study focused on the measurement of inductive reasoning ability and scientific competency of students at the high school level. The inductive reasoning tasks included examples of attributes that enable students to examine objects and discover their similarity, dissimilarity, or both, which are represented by domain-general, non-verbal materials (de Koning et al., 2003). On these tasks, students are given certain attributes and asked to determine the relationship between them by detecting similarities and dissimilarities. Afterward, they predict the next attributes that reveal correct relationship patterns. The inductive reasoning test consists of four subtests: figure series (FS), figure analogy (FA), number analogy (NA), and number series (NS) (Csapó, 1997; Pásztor et al., 2017). The study used a total of 32 items for the inductive reasoning test with eight items per subtest.

Competency tasks are used to assess the cognitive skills required by individual students to solve a given problem (Weinert, 2001). On the scientific competency assessment, we delivered science tasks that focused on cognitive dispositions such as understanding (low), and analysing and evaluating (high). The framework for the scientific competency tasks was developed based on the PISA scientific competency adaptation (OECD, 2017). The adaptation was conducted using the scope of the cognitive process from low to high levels, resulting in two categories of scientific competency sub-tasks. The first level was defined as the ability to explain scientific phenomena (SCA), and the second level is the ability to interpret and evaluate scientific data or evidence (SCB). Scientific competency was assessed using multiple-choice items on the natural sciences. Five topics lie at the core of the scientific competency test: plants and agriculture, animal physiology, animal behaviour, environment and energy, and pollution and global warming. A total of 15 items were generated to measure scientific competency skills with SCA expressed by eight items and SCB by seven. A correct answer on the test is assigned a value of 1, while an incorrect answer results in a value of 0.

In addition to the tests, the study used a background questionnaire with three questions to investigate the students' learning satisfaction and their preference of science education and career. One question each asked whether or not the students wanted to pursue science-related study and to choose a career in science (score: 1 or 0). The study also presented a question on their level of satisfaction with science learning at school, which was rated on a five-point scale (5 = *very satisfied*, 4 = *satisfied*, 3 = *neutral*, 2 = *dissatisfied*, and 1 = *very dissatisfied*). The tests and questionnaire were originally in English, which were back and forward translated into Bahasa by two translators and reviewers.

3.3. Data collection and analysis

Data collection was administered online with the Electronic Diagnostic Assessment (eDia) system, which is an integrated assessment platform for online test administration that produces interpretable data (Csapó & Molnár, 2019). The students participated on a voluntary basis, and the tests were sent to the participants from the University of Szeged server. The students completed the tests in their school computer laboratory with the teachers' assistance, while the data were processed and analysed for internal consistency with Cronbach's alpha and McDonald's omega reliability. The test's validity was confirmed with CFA and the Rasch model. The study performed CFA to check the assumption that the observed indicator of the instruments (items) is linked to specific categories based on the theoretical structure (Xiao et al., 2019). It measures the difference between the observed and estimated covariance matrices derived from the data and the hypothesized model (Mishra, 2016). Moreover, CFA was tested using weighted least squares means and variance (WLSMV) estimation via MPLUS. The criteria for CFA followed a series of rules that involves several fit indexes such as the comparative fit index (CFI), Tucker Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). The cut-off values in assessing the fit index are CFI > 0.90, TLI > 0.90, RMSEA < 0.06, and SRMR < 0.08 (Hu & Bentler, 1999).

Item validity was assessed using the Rasch model in addition to CFA to estimate the fit and difficulty level of the individual item on the test. The study used Rasch analysis with Winsteps to assess the unidimensional model and to confirm the quality of the items and the students' ability level. Rasch analysis with Winsteps can support CFA through the unidimensional estimation of the latent variables for each test based on a fundamental assumption of multidimensional model (Aryadoust & Michelle, 2019). The Rasch model manifests the items as a logistic function of the relative distance between their location parameters (Boone, 2016). Furthermore, it measures the individual fit and position of the items based on logit parameters to determine their level of difficulty. The acceptance range for productive measurement is determined using infit mean square (MNSQ) values from 0.5 to 1.5 (Boone et al., 2014).

Comparative analysis was conducted with the *t*-test and ANOVA to examine the students' ability level across several predictors (gender, learning satisfaction, and educational and career preference). Beforehand, the data distribution was identified with coefficient kurtosis (0.26 – 0.55) and skewness (−0.64 – −0.35) within the range of ± 1.96 for normal distribution (Field, 2013). The logit value generated from the Rasch model was used as a standardized estimator to measure students' proficiency levels on each test (Boone & Noltemeyer, 2017). Furthermore, we used structural equation modelling (SEM) analysis with MPLUS to investigate the relation between inductive reasoning and other predictors of scientific competency.

4. Results

4.1. Validity of the instruments

The study calculated Cronbach's alpha and McDonald's omega as a prerequisite analysis to check the reliability and consistency of the instruments (Gliner et al., 2016). The inductive reasoning test achieved high reliability ($\alpha = 0.868$; $\omega = 0.869$) as well as acceptable reliability for the scientific competency test ($\alpha = 0.708$; $\omega = 0.716$). These values indicated that the inductive reasoning and scientific competency tests are reliable and consistent according to the participants responses. Table 1 presents the CFA results for the inductive reasoning and scientific competency tests. Specifically, the result for inductive reasoning with four factors (FS, FA, NA, and NS) and scientific competency with two factors (SCA and SCB) reached indices within the range for the cut-off values, indicating that both tests fit the theoretical constructs.

Each item on the inductive reasoning test loaded well on the general factor (loadings ranged from 0.48 to 0.84) out of which only two items (FA6 and NA8) exhibited loadings below 0.40. The correlation between the latent variables ranged from 0.48 (FS and NA) to 0.73 (FS and FA) with residual correlations ranging from −0.35 (NA1 and NA6) to 0.34 (NS2 and NS4). For the scientific competency test, the factor loading for the majority of the items ranged from 0.35 to 0.67, with two items producing loadings less than 0.30 (SCA4 and SCB4). The residual correlation between items ranged from −0.12 (SCA5 and SCB4) to 0.18 (SCA4 and SCA7). Moreover, the correlation between the residuals from both tests had a low threshold (≤ 0.30), which indicates that all the items satisfied the acceptable local independency assumption (Chen & Thissen, 1997), except for two correlations (NA1-NA6 and NS2-NS4), which are slighlty higher than the threshold. This result implies that each item on the inductive reasoning and scientific competency tests was independent. However, the imperfect result in factor loading for a few items also raises the possibility of correcting those items based on the construct. The study considered retaining the items in the construct due to the theoretical structure and the goodness of fit index (Ximénez, 2009).

The study conducted further analysis with the Rasch model to provide additional information about the quality of the items on both tests. The Rasch model displayed infit MNSQ values ranging from 0.86 to 1.29 and from 0.88 to 1.20 for the inductive reasoning and scientific competency tests, respectively. In addition, unidimensionality analysis was performed for each inductive reasoning and scientific competency variable to support the theoretical construct of the test based on their model assumption (Aryadoust & Michelle, 2019). The dimensionality of the inductive reasoning variables (FS, FA, NA, and NS) displayed acceptable threshold values with more than 30% raw variance (eigenvalue < 2), which confirm the acceptability of the four dimensions. For scientific reasoning, the variables produced values below the threshold (22–27%) with eigenvalues less than 2 confirming that the test was close to two dimensions. Additionally, the study involved differential item functioning (DIF) analysis to confirm bias on the tests towards specific groups. The assessment of the DIF magnitude followed statistical probabilities ($p < 0.05$) with an estimated size of DIF contrast (≥ 0.64) (Boone et al., 2014). Items with significant and high contrast are categorized as showing DIF, whereas a low size contrast can be classified as negligible. We evaluated DIF based on gender and found that the majority of the items on the tests lack DIF. Only four items on the inductive reasoning test exhibited significant probabilities (FS2, FS8, NA1, and NA7), but generated low size (< 0.64), thus being considered as negligible DIF. In scientific reasoning, three items also produced significant results (SCA1, SCA3, and SCA7) but low size (< 0.45), thus rendering the items negligible in terms of DIF.

The Wrightmap in Fig. 1 represents the difficulty level of the items (represented by item codes on the right) and the students' level ability (represented by "*X*" on the left). On the inductive reasoning test, the most difficult and easiest items are NA8 (1.95 logits) and NS4 (−1.89 logits), respectively. All the items on the inductive reasoning test are distributed well from the easiest to the most difficult ones. The students' ability is distributed throughout the test items and reached a peak at logit 0. In other words, the majority of the students' ability in inductive reasoning is well distributed from low to high. In the scientific competency test, items SCB4 and SCA3 are

Table 1
Confirmatory factor analysis (CFA) results for the inductive reasoning and scientific competency test.

Measure	CFI	TLI	SRMR	RMSEA [90% CI]
Inductive reasoning	0.92	0.91	0.08	0.04 [0.04, 0.05]
Scientific competency	0.96	0.96	0.06	0.03 [0.02, 0.04]

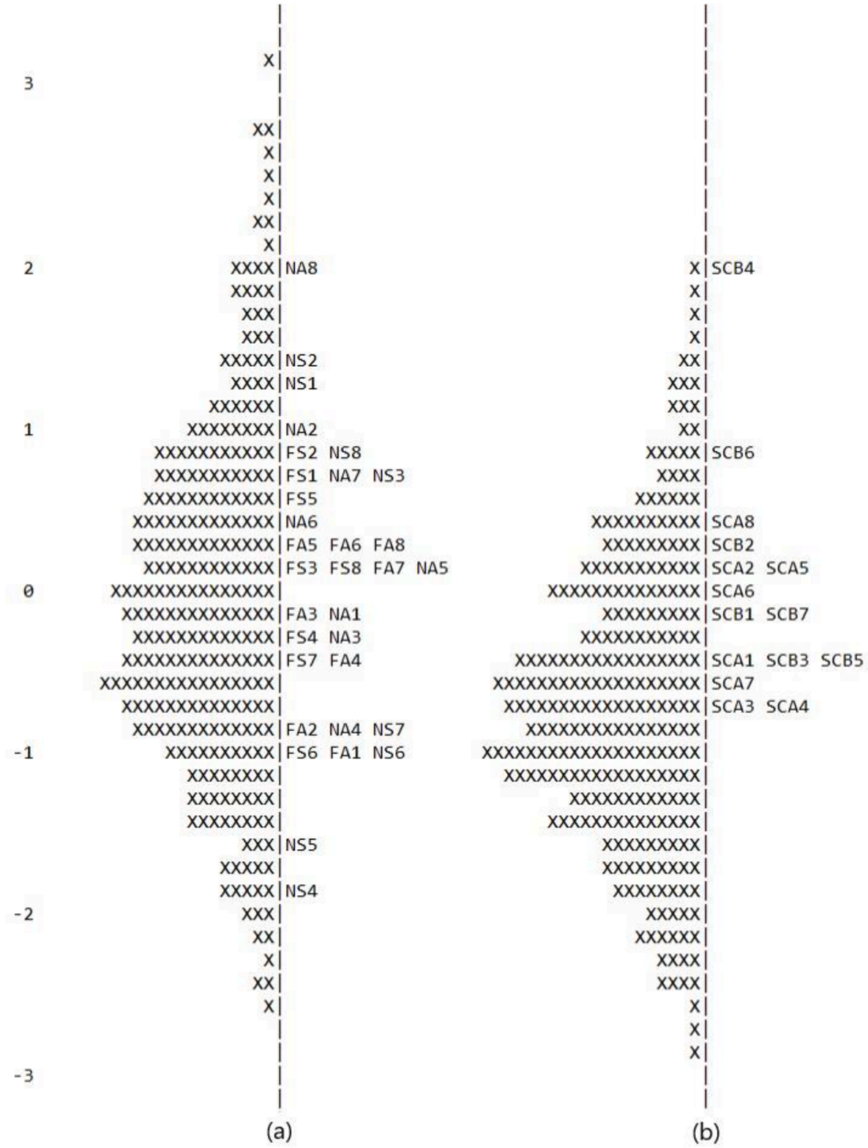

Fig. 1. Wrightmap of the (a) inductive reasoning and (b) scientific competency tests, where 'X' represents 2.2 cases.

categorized as the most difficult (2.14 logits) and easiest (−0.77 logits), respectively. The majority of the students' ability is less than logit 0, in which the peak of the distribution at logit −1 implies that students experience difficulty with the most difficult items. A large gap exists between the easy and difficult items, rendering the test predominantly moderate or difficult for the students.

A number of studies have demonstrated good validity for the inductive reasoning test in a range of contexts: Vietnam, Palestine, Hungary, Zambia, Turkey, and the Netherlands (Molnár et al., 2013; Mousa & Molnár, 2020; van de Vijver, 2002; Van Vo & Csapó, 2020). In the current sample, the results exhibited good reliability and validity. Thus, the study argues that the tests that intend to assess inductive reasoning ability, in fact, measure the same constructs. In the case of the scientific competency test, all the test items displayed a good individual item fit, which confirms that all items consistently measure students' ability. The two factors on the scientific competency test have been proven to be acceptable in construct validity analysis, indicating that the two factors test theoretically measures the students' scientific competency.

4.2. Profile of the students' inductive reasoning ability and scientific competency

The violin plot in Fig. 2 illustrates the students' inductive reasoning and scientific competency. A violin plot is a box plot used for comparing a range of data. It expresses a central measurement characterised by several features, such as the symmetry of distribution, the location of the central value, and the spread of data observations. It enables one to obtain additional information about the

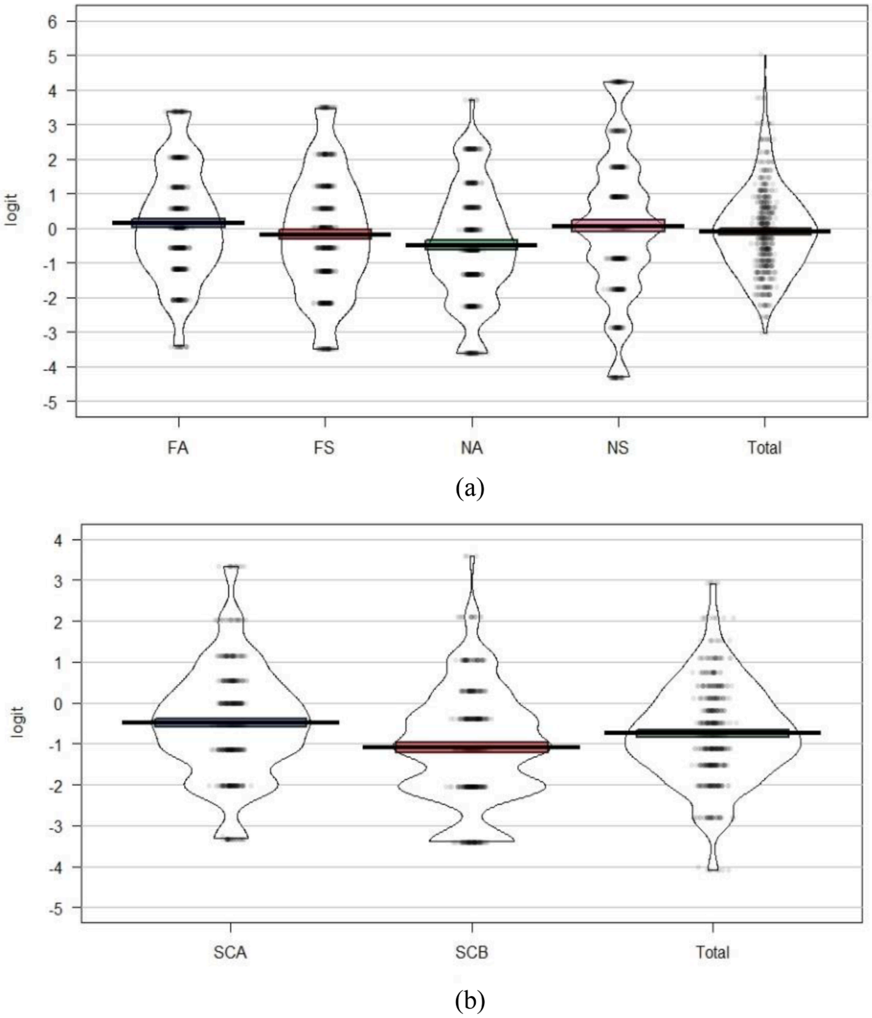

Fig. 2. Violin plot of the students' performance on the (a) inductive reasoning and (b) scientific competency tests (FA = figure analogy; FS = figure series; NA = number analogy; NS = number series; SCA = explaining scientific phenomena; SCB = interpreting and evaluating scientific data).

Table 2
Summary of the students' inductive reasoning and scientific competency of students across several categories.

Category	*N*	Inductive reasoning			Scientific competency		
		M_{score}	M_{logit}	*SD*	M_{score}	M_{logit}	*SD*
Gender							
Male	208 (33.9%)	0.45	−0.26	1.14	0.31	−1.02	1.20
Female	405 (66.1%)	0.49	−0.01	1.21	0.39	−0.61	1.16
Learning satisfaction							
Very dissatisfied	17 (2.8%)	0.44	−0.46	1.35	0.27	−0.52	1.18
Dissatisfied	34 (5.5%)	0.48	−0.16	1.12	0.31	−1.16	1.14
Neutral	250 (40.7%)	0.45	−0.23	1.23	0.34	−0.90	1.11
Satisfied	254 (41.5%)	0.49	0.01	1.16	0.39	−0.60	1.20
Very satisfied	58 (9.4%)	0.53	0.16	1.16	0.40	−0.58	1.40
Education preference							
Science	377 (61.5%)	0.50	0.00	1.18	0.38	−0.63	1.21
Non-science	236 (38.5%)	0.44	−0.24	1.21	0.33	−0.93	1.13
Career preference							
Science	382 (62.3%)	0.49	−0.02	1.17	0.38	−0.64	1.20
Non-science	231 (37.7%)	0.45	−0.22	1.23	0.34	−0.93	1.15

distribution of data values (Potter et al., 2006). The students' average score for inductive reasoning ability was −0.09 logits (*SD* = 1.20), which represents the majority of the students with a 50% probability to complete tasks. When viewed at the subtest level, the difference is significant ($F_{(608)} = 12.95$, $p < 0.01$) with a relatively small effect size ($\eta^2 = 0.02$). The students' highest score was achieved in figure analogy followed, by number series, figure series, and number analogy. On the scientific competency test, the average score was −0.75 logits (*SD* = 1.19). The study found a significant difference between the two subtests when the students performed better on the explanation subtest than on the interpretation and evaluation subtests ($t_{(612)} = 11.02$, $p < 0.01$, $d = 0.45$).

We profiled inductive reasoning and scientific competency on the basis of several categories: gender, learning satisfaction, and educational and career preference (Table 2). In terms of gender, the study found a significant difference in inductive reasoning ability ($t_{(611)} = -2.45$, $p < 0.05$, $d = 0.21$), in which the female students scored higher than the male students. A similar result was found for scientific competency ($t_{(611)} = -4.11$, $p < 0.01$, $d = 0.35$).

Within the learning satisfaction category, inductive reasoning ability tends to grow along with an increase in the level of satisfaction with learning performance. The comparative analysis via ANOVA revealed a significant difference in inductive reasoning ability based on the students' satisfaction with learning ($F_{(608)} = 2.40$, $p < 0.05$, $\eta^2 = 0.02$). LSD post-hoc analysis demonstrated that the students who were extremely satisfied with the learning process obtained higher average scores compared with those in the other groups. On the scientific competency test, the study noted an increasing level of scientific competency among the students with growth in their level of satisfaction with learning. According to ANOVA, a significant difference existed in the students' scientific competency based on learning satisfaction ($F_{(608)} = 3.55$, $p < 0.01$, $\eta^2 = 0.02$). Specifically, the students who were very satisfied with their learning performance produced better scores in scientific competency compared with those who were very dissatisfied.

In terms of educational preference, the results point to a significant difference in inductive reasoning ability ($t_{(611)} = -2.45$, $p < 0.05$, $d = 0.20$). The students who plan to pursue further science education obtained higher scores than those who did not. This result was similar to that for scientific competency in that a significant difference existed between the two groups ($t_{(611)} = -3.06$, $p < 0.01$, $d = 0.27$) when students who opted for science education displayed high levels of performance. For career preference, we found a significant difference in inductive reasoning between students who plan to choose a science-related career and those who do not ($t_{(611)} = -2.02$, $p < 0.05$, $d = 0.17$). For scientific competency, a similar result was found with a significant difference for both groups ($t_{(611)} = -2.97$, $p < 0.01$, $d = 0.25$).

4.3. Influence of inductive reasoning and other predictive factors on scientific competency

We used SEM to measure the relation between inductive reasoning and several predictors of scientific competency (gender, learning satisfaction, and educational and career preference). Fig. 3 presents the direct predictive effect of each variable. The diagram for the model complied with the recommended values of the statistical fit indices (CMIN/df = 2.09, $p < 0.01$; RMSEA = 0.04, CFI = 0.98, TLI = 0.97, SRMR = 0.03), which indicates an acceptable result. Based on the model, we found that inductive reasoning strongly influences the development of scientific competency ($\beta_0 = 0.63$, $p < 0.01$; see Table 3). The effect of gender on scientific competency was significant, but relatively small ($\beta_0 = 0.11$, $p < 0.05$). Gender was slightly related to educational preference ($\beta_0 = 0.07$, $p < 0.05$), and learning satisfaction ($\beta_0 = 0.10$, $p < 0.05$), whereas learning satisfaction was associated with inductive reasoning ($\beta_0 = 0.10$, $p <$

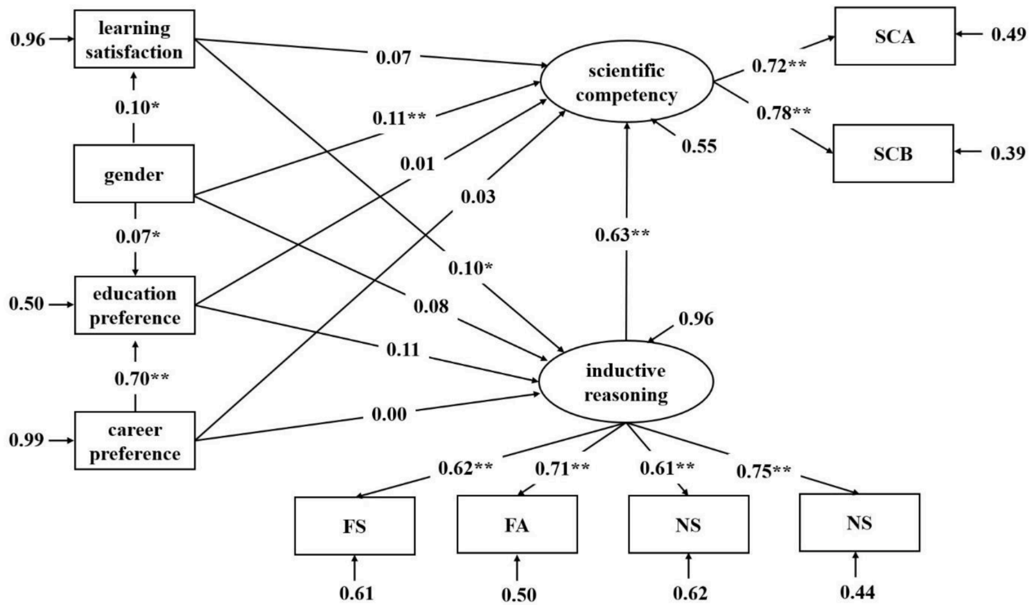

Fig. 3. Standardized SEM results for scientific competency, inductive reasoning, learning satisfaction, gender, and science education and career preference (* $p < 0.05$; ** $p < 0.01$).

Table 3
Result of model analysis.

Measurement model	β_0	β_1	S.E	p
Inductive reasoning → figure series (FS)	0.62	1.00	0.03	< 0.01
Inductive reasoning → figure analogy (FA)	0.71	1.09	0.03	< 0.01
Inductive reasoning → number analogy (NA)	0.61	0.91	0.03	< 0.01
Inductive reasoning → number series (NS)	0.75	1.10	0.03	< 0.01
Scientific competency → explaining phenomena (SCA)	0.72	1.00	0.03	< 0.01
Scientific competency → interpreting and evaluating data (SCB)	0.78	1.02	0.03	< 0.01
Inductive reasoning → scientific competency	0.63	0.61	0.04	< 0.01
Gender → inductive reasoning	0.08	0.03	0.04	> 0.05
Gender → scientific competency	0.11	0.04	0.04	< 0.05
Gender → learning satisfaction	0.10	0.17	0.04	< 0.05
Gender → educational preference	0.07	0.07	0.03	< 0.05
Learning satisfaction → inductive reasoning	0.10	0.02	0.05	< 0.05
Learning satisfaction → scientific competency	0.07	0.01	0.04	> 0.05
Career preference → educational preference	0.70	0.70	0.02	< 0.01
Career preference → inductive reasoning	0.00	0.00	0.06	> 0.05
Career preference → scientific competency	0.03	0.01	0.06	> 0.05
Educational preference → inductive reasoning	0.11	0.04	0.06	> 0.05
Educational preference → scientific competency	0.01	0.00	0.06	> 0.05

Note: β_0 = standardized coefficient; β_1 = unstandardized coefficient; S.E = standard error.

0.05). Educational preference in science was strongly tied to the choice of science career ($\beta_0 = 0.70$, $p < 0.01$); however, the study found no direct effect of either variable on inductive reasoning nor scientific competency. Therefore, the study suggests that inductive reasoning greatly influences scientific competency, a finding which is supported by the moderate latent correlation between the two variables ($\beta_0 = 0.63$, $R^2 = 0.44$). Conversely, gender, learning satisfaction, and educational and career preference variable exerted low or no direct effect on scientific competency.

5. Discussion

In profiling inductive reasoning ability, we found that the majority of the students can complete moderate to easy tasks, showing a logit measure below 0 (Fig. 2a). The students tended to perform better on the figural tasks than the numerical ones, which is confirmed by other studies (Van Vo & Csapó, 2020). The figural tasks comprise an arranged figure as the object of inductive reasoning analysis, while the numerical tasks use numbers. When completing a figural task, students need to analyse the layout of the figure, and then recognise the pattern of relationships. Doing numerical tasks is relatively different because students must find a correspondence between adjacent numbers and identify the relationship between task patterns (Liang et al., 2014). It require students to perform mathematical computations to reveal the relationship between numbers and identify a pattern. The numerical task is more cognitively demanding and, therefore, more complex for certain learners. In scientific competency, the average students score is below logit 0, indicating that they have difficulty to complete the test correctly. The scientific competency task mainly measured the ability to acquire and apply scientific knowledge. It represents a personal cognitive level and the processing of information in working memory. Based on the cognitive domain Anderson and Krathwohl (2001), the ability to explain is categorized as being at a low cognitive level, while the ability to interpret and evaluate are classified as being at high cognitive levels and requiring a high-order cognitive process. Among the two components of scientific competency, the students performed better on the explanation subtest rather than the interpretation and evaluation. Indeed, the students performed better in low level tasks and have difficulties in solving higher cognitive tasks, which represent low scientific competency performance overall.

This students' assessment result presents several possibilities in related to the influence of the learning environment. Cukurova et al. (2018) revealed that the learning process and instruction influence knowledge acquisition and application in science. Students' engagement and participation in learning determine the extent of their thinking ability and knowledge acquired in science. Moreover, the complex situation, which involves the motivation to conduct independent study and gather secondary and tertiary information from many sources, presents a factor that potentially influences their competency (Younis, 2022). This result also implies that educational practices in Indonesia should focus on the development of scientific competency as well as inductive reasoning ability. Regarding students' learning satisfaction variable, the results indicate that it has connection to inductive reasoning ability and scientific competency. The students with higher satisfaction level also show higher scores in inductive reasoning and scientific competency compared to those who are not. Satisfaction in learning can be interpreted as reflective thinking about and perspective on their learning progress (Saddawi-Konefka et al., 2021). It is related to goal orientation and learning performance (Sánchez-Cardona et al., 2021). The students who are satisfied with their learning will perform better during their studies, be actively involved in the learning process, and have a strong chance of achieving better academic outcomes. In addition, when the students experienced good satisfaction and performed better actions, they showed improvement in some psychosocial constructs, such as engagement, motivation, emotions, belonging, and self-efficacy, which support academic outcomes (Picton et al., 2018). In addition, education and career plans can be categorized as extrinsic factors related to academic performance (Glynn et al., 2011; Shin et al., 2017). The students who choose science as their future education choice and career shows higher inductive reasoning and scientific competency score compare to those who are not. This result makes education and career preference prominent factors associated with scientific competency and inductive reasoning ability.

In terms of gender, the female students performed better in inductive reasoning than their male classmates. This result is consistent with those of previous studies conducted in the Vietnamese (Van Vo & Csapó, 2020) and Namibian contexts (Kambeyo, 2018). Other gender studies on inductive reasoning also revealed that female students intend to achieve higher scores than their male peers (Díaz-Morales & Escribano, 2013). Under the sub-category of inductive reasoning tasks, male students produced higher scores on the figural tasks, whereas the female students performed better on the numerical tasks. This finding is supported by Miller and Halpern (2014), who explained that male students enjoy an advantage on the range of tasks that require recalling an abstract spatial diagram and picture. Alternatively, female students are good at listing words and numbers (Herlitz & Lovén, 2013). With regard to scientific competency, the study noted a significant difference in performance between the male and female students. The girls obtained higher average results on the explanation and interpreting and evaluating tasks. Several previous studies also showed that female students perform better in science compared to their male peers (Sungur & Tekkaya, 2003; Yenilmez et al., 2006). The advantages of female students lie in memory tasks such as remembering and identifying objects (Voyer et al., 2007). The performance gap between male and female students is also considered to be tied to behaviour in the completion of the science tasks. Vincent-Ruz and Schunn (2017) found that female students in eighth grade exhibit a higher level of cognitive behavioural engagement than their male classmates. In turn, behavioural engagement is related to the preference for learning involvement, which enables students to learn more science content.

SEM results revealed that inductive reasoning ability greatly influenced scientific competency. Inductive reasoning works with the mental process related to the ability to perceive knowledge of an event or pattern and apply it to a similar situation (Christie & Gentner, 2014). The students needed to understand the relationship between objects and apply it to complete the pattern. This ability is required when one intends to solve science problems and develop one's competency. Moreover, Fisher (2018) explained that the analogy task in the inductive reasoning is indispensable for scientific discovery, which is a notable predictor of scientific competency. Inductive reasoning makes it possible to apply the probability method and to justify scientific conclusions. The use of analogy was implemented during the quantitative research process (Hallyn, 2000). In the context of science, this process can be considered a scientific experiment. For example, chemists typically discuss the difference between accuracy, experimental error and precision, and the influence of the order of operation can affect the result (Buchwald, 2006). When forming a hypothesis, scientists use analogy to make certain predictions on the basis of prior findings or related information. A similar case occurs when they want to draw comparisons from several experiments. They use analogy to compare the patterns in similar experiments, identify the similarity and differences in the effect of variables, and draw conclusion through this process. The study thus concludes that inductive reasoning ability is one of the strong factors that influence scientific competency. As such, an increased inductive reasoning ability will trigger the development of scientific competency.

Furthermore, the other predictive variables, such as learning satisfaction and educational preference, were associated with inductive reasoning. Gender also exerted positive effects on scientific competency, learning satisfaction, and educational preference. These results lead to the possibility that female students who want to choose science for their future education exhibit a slightly higher level of learning satisfaction and scientific competency than their male peers. The connection between the predictive variable and inductive reasoning and scientific competency produced a small effect (< 0.3), thus signalling an opportunity for the further identification of this variable in relation to inductive reasoning and scientific competency. Notably, inductive reasoning is a strong predictor of scientific competency, suggesting that inductive reasoning is a potential learning strategy for the promotion of scientific competency.

This study provides the assessment results about students performance in inductive reasoning and scientific competency in Indonesia. The low result of students' performance indicate that there is a need to improve teaching and learning methods by intergrating inductive reasoning and scientific competency into the Indonesian educational system. Furthermore, using standardized assessment and considering several factors that potentially influence students' ability are important in programmes that support the development of inductive reasoning and scientific competency.

6. Conclusions

Scientific competency and inductive reasoning are two of key achievement goals in science learning. The fact that inductive reasoning exerts a strong effect on scientific competency makes it an important factor that cannot be ignored in teaching and learning. As such, the development of scientific competency and inductive reasoning should be encouraged, especially in the Indonesian context due to the difficulty experienced by the students during task completion. Many predictors have the potential to influence scientific competency and inductive reasoning ability, such as gender, satisfaction during the learning process, and even future education and career preference. Thus, including these predictive factors in the educational process could provide opportunities for developing inductive reasoning and scientific competency among students. Despite these results, this study has its limitation. The first is the sample size and context, whereas the level of influence of each predictors on inductive reasoning ability and scientific competency may differ when examined in various contexts and with various sample sizes. A possibility also exists for the addition of other predictors for the model to obtain insightful information about the extent of the impact of socio-cultural and psychological aspects in predicting inductive reasoning ability and scientific competency.

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CRediT authorship contribution statement

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

Declaration of Competing Interest

The authors declare that there is no conflict of interest.

Data Availability

The dataset generated during the current study are available in the "Dataset" repository doi: 10.17632/x7xwhvd6gx.1

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.tsc.2023.101376.

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