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Assessing self-regulated learning abilities of Indonesian students using cognitive diagnostic model

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ABSTRACT

This study has two objectives: to find out which cognitive diagnostic model (CDM) is suitable for extracting diagnostic information from non-diagnostic measurement data of Indonesian students' self-regulated learning abilities; and to find out the attributes of self-regulated learning (SRL) abilities that have not been mastered by Indonesian students. This study used a quantitative research method with a retrofitting approach (post-hoc analysis). There were 3,874 respondents, besides there were 22 items of Q-matrix that measure four attributes of SRL ability. The data were analyzed and empirically validated using the R program with the generalized deterministic input and gate (GDINA) package. The results showed that the GDINA model is the most appropriate model for extracting diagnostic information regarding the SRL abilities of Indonesian students. In addition, most Indonesian students have not been able to master the four SRL ability attributes where the planning attribute (A1) is the most difficult attribute for Indonesian students to master.

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1. INTRODUCTION

In early 2020, the Indonesian government announced the presence of the COVID-19 virus in the country. Consequently, all community activities, including education, had to transition to being conducted from home. This shift affected the entire educational spectrum, from elementary schools to universities [1], [2]. The teaching and learning process, traditionally carried out face-to-face in classrooms, was forced to transition to online learning, which relies heavily on a stable internet connection [3], [4]. These sudden changes posed significant challenges, particularly for teachers and students who were not accustomed to integrating technology into the education process [5], [6].

During the online learning period, students are expected to possess strong self-regulated learning (SRL) skills [7], as they are required to independently manage all aspects of their learning activities. SRL is a process through which students autonomously transform their mental capabilities into academic competencies [1]. This involves analyzing tasks effectively, setting clear goals, and regulating their thoughts, motivations, and behaviors to achieve those goals [8], [9]. Research has demonstrated that SRL significantly influences cognitive and metacognitive abilities, attitudes, and motivation [10], [11]. The OECD [12] has also recognized SRL as a critical skill that students must develop to meet the educational standards set for 2030. Therefore, cultivating strong SRL skills is essential for students navigating online learning, as it enables them to manage their learning activities independently and convert their mental potential into improved academic performance.

The shift in the learning process from classroom-based to online platforms can negatively impact students, particularly those with low SRL abilities. Low SRL levels can disrupt the learning process [13], lead to increased procrastination [14], [15], and hinder students from achieving their full potential [16]. Additionally, low SRL can contribute to heightened levels of mathematical anxiety [17]. To address these challenges, it is essential for teachers to assess their students' SRL levels. This information enables teachers and schools to implement targeted interventions for students with low SRL abilities, ensuring better support for their academic success.

Improving and developing students' SRL abilities requires strong support from various stakeholders, particularly teachers. As key figures in the educational process, teachers play a crucial role in guiding their students to enhance and refine their SRL skills [18], [19]. Research highlights that teachers can address low SRL abilities in students by providing scaffolding feedback, offering praise, or delivering constructive criticism [20]. To effectively guide their students, teachers must first understand the current levels of their students' SRL abilities, necessitating accurate and diagnostic measurement tools. However, existing methods for assessing SRL abilities primarily rely on the classical test theory (CTT) and item response theory (IRT) frameworks [21], [22]. While these frameworks provide an overall ranking of students' latent abilities on a single continuum scale, they fail to offer detailed diagnostic information regarding specific strengths and weaknesses related to SRL skills [23]–[25]. This limitation underscores the need for more advanced and nuanced assessment models to better support the development of SRL abilities.

One significant advantage of the cognitive diagnostic model (CDM) is its ability to offer detailed insights into students' strengths, weaknesses, and mastery profiles based on a predefined set of abilities or attributes. This level of granularity is not achievable with traditional methods like CTT and IRT [26]. CDM was developed to overcome these limitations, providing researchers and educators with detailed information about the skills or attributes necessary to solve specific items. This makes CDM applicable to various teaching practices and enables more targeted interventions [27]. Moreover, CDM delivers valuable insights into the psychological and cognitive characteristics of test takers, empowering educational stakeholders to design personalized learning strategies that effectively address students' needs [28]. By addressing the limitations of traditional measurement models, CDM supports a more nuanced approach to improving students' SRL abilities.

Cognitive diagnostic model has been extensively applied across various research areas, particularly in education and psychology. These applications include subjects, such as mathematics [29]–[31], English [32]–[34], and clinical psychology [35]. However, there is a notable gap in research regarding the use of CDM to provide diagnostic insights into students' SRL abilities, which has sparked researchers' interest in addressing this topic. The transition to online learning triggered by the COVID-19 pandemic has highlighted the critical need for strong SRL skills, as students must now independently manage their learning processes. Current SRL measurement methods, primarily based on CTT and IRT, fall short of providing the detailed diagnostic information needed to identify specific strengths and weaknesses in SRL. This limitation restricts teachers' ability to deliver targeted interventions for students with low SRL abilities, ultimately impacting learning outcomes. This study aims to investigate the potential of CDM as a more informative approach to assessing SRL skills, which could enhance teaching strategies and improve student performance. The research seeks to address two key questions: i) CDM model is best suited for classifying Indonesian students' SRL abilities?; and ii) What specific SRL attributes have students mastered?

2. LITERATURE REVIEW

2.1. Self-regulated learning (SRL) ability

Self-regulated learning is an important approach in improving student academic achievement. Research on student academic achievement is usually seen by linking students' abilities to academic achievement with teaching quality [36], school activities [37], [38] and their home environment [39]. In contrast, SRL theory focuses on how students are personally active, dynamic, changing or maintaining their way of learning in a more specific context. SRL theory assumes that the learning environment does not guarantee the success of student learning, because everything depends on how students' ability to independently absorb what is learned, in accordance with the goals and ways of learning [40]. SRL is an activity, a constructive process in which students make their own learning goals and in the process of achieving these goals, students monitor, regulate, control cognitive abilities, motivation and behavior and all of them are limited to predetermined learning goals and their learning environment [41], [42].

SRL is an activity that involves students in the construction of their own learning goals. In the process of achieving these goals, students engage in the regulation and control of their cognitive abilities, motivation, and behavior [43], [44]. All of these processes are constrained by the predetermined learning goals and the learning environment [45]. Bandura stated three principles underlying self-regulation, namely self-monitoring, judgement, and self-response [46]. Self-monitoring is the act of observing oneself, one's behavior, and taking care of it. Judgments are comparisons between what is seen and a standard. Self-response is the reaction to the results of the activity process in relation to the previously set goals. Consequently, educators must comprehend these three fundamental principles in order to comprehend the manner in which their pupils regulate their conduct and to assist them in attaining their objectives.

Pintrich defines SRL as an active, constructive process in which students set their learning goals. Then, they monitor, regulate, and control their cognition, motivation, and behavior based on the goals they have set themselves [47]. SRLs are generally characterized as active participants who efficiently control their own learning experiences in different ways. This encompasses the establishment of a conducive work environment and the effective utilization of resources, the organization and training of information to be learned, the maintenance of positive emotions during academic tasks, and the sustenance of positive motivational beliefs about one's abilities, learning value, and the factors that affect learning [48], [49].

2.2. Cognitive diagnostic model (CDM)

Cognitive diagnostic model is a family of psychometric models designed to analyze the detailed relationship between discrete latent attributes and item responses on a test [50]. Latent attributes refer to abstract constructs such as abilities, competencies, tasks, or cognitive processes [27], [51]. CDM aims to statistically determine respondents' mastery of these latent attributes and categorize them into latent classes based on their item responses. As a multidimensional model, CDM provides richer diagnostic information than traditional psychometric models [52], making it highly beneficial for supporting learning processes or psychological interventions [29], [53], [54].

CDM is a probabilistic model similar to IRT. It models the probability of respondents answering questions correctly based on their latent abilities [55]. In unidimensional IRT, the probability of a correct response is linked to a single latent trait, where higher ability increases the likelihood of a correct answer. In contrast, CDM assesses respondents' abilities by analyzing their likelihood of mastering specific measured attributes [56]. This means test takers with similar overall abilities can exhibit varying levels of mastery across different attributes.

CDM models are classified into three groups: compensatory, non-compensatory, and general models [32]. Non-compensatory models require all necessary attributes for a correct response to a question. The examples include deterministic input, noisy "and" gate (DINA), noisy input, deterministic "and" gate (NIDA), non-compensatory reparameterized unified model (NC-RUM), and reduced reparameterized unified model (RRUM) [57]. In contrast, compensatory models allow the absence of one attribute to be compensated by the presence of others. Examples include deterministic input, noisy "or" gate (DINO), noisy input, deterministic "or" gate (NIDO), compensatory reparameterized unified model (C-RUM), and additive CDM (ACDM) [58]. Meanwhile the general model category is more flexible than the compensatory and non-compensatory models. It accommodates various attribute relationships, both compensatory and non-compensatory [59]. Examples of general models include the general diagnostic model (GDM), log-linear cognitive diagnostic model (LCDM), and generalized deterministic-input "and" gate model (GDINA). These models offer a comprehensive framework for exploring and diagnosing latent attributes, enhancing their utility in diverse educational and psychological contexts.

3. RESEARCH METHOD

3.1. Method and data

This study used a quantitative method by adopting a retrofitting approach (post hoc analysis) [60]. The retrofitting approach is a data analysis process in adapting the CDM model by testing data from assessments that were originally designed based on different measurement approaches such as IRT or CTT to extract richer information [34], [61]. To answer the research questions posed, researchers used survey data on students' SRL abilities that had been conducted by Sulisworo *et al*. [62]. There are 3,874 respondent data used in this study, where the data has passed the person fit test based on the Rasch model approach. The respondent's data came from 61 schools in Indonesia (37 elementary schools, 12 junior high schools, and 12 high schools) where the education levels of the respondents' data ranged from grade 1 to grade 12.

3.2. Instrument

The research questionnaire to measure students' SRL abilities was adapted from Noonan and Erickson [63]. The questionnaire consists of 22 items that measure the four SRL phases, namely plan (5 items), monitor (6 items), control (6 items), and reflect (5 items), where the questionnaire has been validated using the Rasch model approach. Each item statement uses a Likert scale of five answer choices with answer choices starting from 1 (Strongly disagree) to 5 (Strongly agree). Before being analyzed using the CDM approach, the participant's initial response data was changed from polytomous to dichotomous answers. Data from the "Strongly disagree" to "Agree" categories were combined into category 0, while the "Strongly agree" became category 1 because the majority of the CDM analysis was based on dichotomous data [64]. Although the GDINA sequential model has been developed and can be used to analyze polytomous data, when the category responses are assumed to have the same q-vector, the results of the G-DINA sequential model analysis with GDINA using nominal responses are not much different [35], [65].

3.3. Initial Q-matrix

The Q-matrix is an integral part when analyzing using the CDM approach. The Q-matrix is a matrix that connects the items or statements and the attributes or abilities being measured, where 1 represents the attribute needed to answer a question or statement correctly, and 0 is the opposite [30], [66]. For the preparation of the Q-matrix, five domain experts consisting of two practitioners who have expertise in SRL and three doctoral students were involved in this process. First, domain experts were asked to code the 22 item questionnaire statements used to measure students' SRL abilities. There are four attributes identified, coded, and approved by the domain expert. The four attributes are as: i) The ability to plan what you want to achieve (A1); ii) Ability to monitor developments and disruptions related to the goals to be achieved (A2); iii) The ability to control oneself to achieve the goals to be achieved (A3); and iv) The ability to reflect on what has been done is related to goals (A4). After the domain expert agrees, the researcher and the domain expert work together to create an initial Q-matrix by matching certain items with attributes. In full, the initial Q-matrix can be seen in Table 1.

Table 1. Initial Q-matrix

	Statement	A1	A2	A3	A4
1.	I plan out projects that I want to complete	1	0	0	0
2.	If an important test is coming up, I created a study plan.	1	0	1	0
3.	Before I do something fun, I consider all the things that I need to get done.	1	1	0	0
4.	I can usually estimate how much time my homework will take to complete.	1	0	0	0
5.	I have trouble making plans to help me reach my goals. (N)	1	0	0	0
6.	I keep track of how my projects are going.	0	1	0	0
7.	I know when I'm behind on a project.	0	1	1	0
8.	I track my progress in reaching my goals.	0	1	0	0
9.	I know what my grades are at any given time.	0	1	0	0
10.	Daily, I identify things I need to get done and track what gets done.	1	1	0	0
11.	I have trouble remembering all the things I need to accomplish. (N)	0	1	0	1
12.	I do what it takes to get my homework done on time.	0	0	1	0
13.	I make choices to help me succeed, even when they aren't the most fun right now.	0	0	1	0
14.	As soon as I see things aren't going right, I want to do something about it.	0	0	1	0
15.	I keep trying as many different possibilities as necessary to succeed.	0	0	1	0
16.	I have difficulty maintaining my focus on projects that take a long time to complete. (N)	0	1	1	0
17.	When I get behind on my work, I often give up. (N)	0	0	1	1
18.	I think about how well I'm doing on my assignments.	0	0	0	1
19.	I feel a sense of accomplishment when I get everything done on time.	0	0	0	1
20.	I think about how well I've done in the past when I set new goals.	0	0	0	1
21.	When I fail at something, I try to learn from my mistake.	0	0	0	1
22.	I keep making the same mistake over and over again. (N)	0	0	0	1

3.4. Data analysis

After creating the initial Q-matrix, model selection was carried out to find out which model was suitable for modeling the data in this study. Furthermore, the Q-matrix validation process is carried out in two stages. In the first stage, the Q-matrix was analyzed with the GDINA model to obtain modified elements of the Q-matrix based on the proportion of variance accounted for (PVAF) approach [51], [67]. After getting the modified elements, in the second stage, these modified Q-matrix elements are discussed again with the domain expert to make a decision about whether to accept or reject these modified elements to obtain the final Q-matrix. Next, diagnostic information analysis was analyzed using the selected model and the final Q-matrix.

The analysis was carried out with the help of R software with the "G-DINA" package version 2.9.2 [68]. Before being analyzed, the research data was divided into two equal parts where the initial half data was used for validating the Q-matrix and selecting the right model. While the final half data is used to generate diagnostic information. This is recommended when the data is large enough [69]. Selection of the right model is based on two model fit indices, namely the relative model fit index and the absolute model fit index. For relative model fit, four model fit indices are used, namely loglikelihood, deviance, Akaike information criterion (AIC), and Bayesian information criterion (BIC). The general criterion for this index is that the smaller the value, the better the model [31].

For absolute model fit, three model fit indices are used. These indices are M_2, root mean square error of approximation (RMSEA), dan standardized root mean square residual (SRMSR). In particular, statistic M_2 is used to see the suitability of the model for a dichotomous response where the model is said to be fit if the M_2 score is not significant [70], [71]. The RMSEA index value <0.05 indicates sufficient model fit [35], [72]. The model that has the smallest SRMSR value is the most suitable model [73].

4. RESULTS AND DISCUSSION

4.1. Results

4.1.1. Q-matrix validation

The initial Q-matrix that was built before was based on the decisions of domain experts so it was prone to misspecification. Misspecification of the Q-matrix will impact the accuracy of the analysis results [74], [75]. Q-matrix validation was carried out to reduce misspecification and was carried out in two stages. In the first stage, the Q-matrix was analyzed with the GDINA model to obtain modified elements of the Q-matrix based on the PVAF approach [51], [76]. Based on the results of the first stage of validation, there are six statements where the Q-matrix needs to be modified. These items are item 2, item 3, item 5, item 11, item 17, item 21 and item 22. Then the recommendations from the validation results are discussed again with the domain expert whether the recommendations are fully approved. After consulting the domain expert, they accepted the three suggested modifications for item 3, item 21, and item 22 as shown in Table 2. That is, they agreed that item 3 measures the three attributes A1, A2, and A3. Meanwhile, point 21 and point 22, they agree that these two items measure two attributes, namely attributes A3 and A4.

Table 2. Q-matrix final (modified elements only)

Statements	A1	A2	A3	A4
3. Before I do something fun, I consider all the things that I need to get done.	1	1	1[a]	0
21. When I fail at something, I try to learn from my mistake.	0	0	1[a]	1
22. I keep making the same mistake over and over again. (N)	0	0	1[a]	1

Note: [a] indicate the changes from 0 to 1; N is negative statement

4.1.2. Model selection

To answer the first research question, this research investigates which CDM model fits the empirical data. Parameters in the CDM can only be interpreted when a specific model fits the data. For relative model fit statistics, there are five models being compared, namely GDINA, DINA, DINO, ACDM, and RRUM. Loglikehood, deviance, AIC, BIC values are calculated and used for the relative model fit index. Models with lower values are better suited to the data. Simply put, a lower value indicates that the model has a better fit, and a higher value indicates a mismatch for that model. All model fit index values are presented in Table 3. Model fit index in Table 3 provides information about the fit of the data for five different models, namely GDINA, DINA, DINO, ACDM, to find out which model fits the data better. The results of the analysis revealed that the values of the three relative model fit indices (loglikelihood, deviance, AIC) were higher for the DINA, DINO, ACDM, and RRUM models compared to the GDINA model. This shows that GDINA has a better model fit.

In addition to the relative model fit index, the absolute model fit index is also used to determine whether the model fits the data without reference to other models. Three absolute model fit indices, namely M_2, root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMSR) are used to see the fit of the model with the data. The absolute model fit index shows that GDINA has a better model fit than the other models. This can be seen from the RMSEA value <0.05 which is the cut-off value [35], [72] where this indicates GDINA matches the data. In addition, GDINA has a smaller SRMSR value than the DINA and DINO models together with ACDM and RRUM. Meanwhile, the M_2 index indicates that the GDINA model does not meet model fit. Based on the overall model fit index, it can be concluded that the GDINA model fits the data.

The CDM model is only useful when the classification results are reliable. Therefore, it is necessary to determine how reliable the CDM is. In the CDM measurement framework, reliability is a measure of internal consistency that represents the ratio of the actual score to the variance of the scores observed in the items that measure each attribute [77], [78]. The reliability estimation for the CDM framework refers to the measurement of test-level accuracy and attribute-level accuracy [79], [80]. Table 4 summarizes information regarding the accuracy of classification at the attribute level. All attributes have attribute-level accuracy greater than 0.90. Meanwhile, the estimated result of the test-level accuracy is 0.847. A good classification reliability index on CDM measurements if the coefficient test-level accuracy is at least 0.80 [81], [82] and the attribute-level accuracy coefficient is above 0.80 [83]. Thus, the classification results have good reliability so that they can provide an accurate and reliable classification of attribute skills so that they can distinguish proficient and non-proficient students.

Table 3. Relative and absolute model fit indices for the five CDM models

	GDINA	DINA	DINO	ACDM	RRUM
Relatives fit					
Loglikelihood	-22349.2*	-22444.8	-22461.8	-22362.5	-22361.8
Deviance	44698.41*	44889.68	44923.63	44724.94	44723.69
AIC	44856.41*	44889.68	45041.63	44860.94	44859.69
BIC	45296.35	45336.25	45370.19	45239.62	45238.37*
Absolute fit					
M_2	982.277	1427.239	1421.31	1428.203	1414.188
	(df=174)	(df=194)	(df=194)	(df=185)	(df=185)
	p=0.000	p=0.000	p=0.000	p=0.000	p=0.000
RMSEA	0.049	0.057	0.057	0.059	0.059
SRMSR	0.072	0.073	0.074	0.072	0.072

*The smallest value

Table 4. Distribution of student attribute mastery probability and test accuracy at attribute level

Attribute SRL	Attribute mastery probability		Attribute-level accuracy
	Not mastery	Mastery	
A1. The ability to plan what you want to achieve	0.650	0.350	0.943
A2. Ability to monitor developments and disruptions related to the goals to be achieved	0.630	0.370	0.950
A3. The ability to control oneself in order to achieve the goals to be achieved	0.539	0.461	0.954
A4. The ability to reflect on what has been done is related to goals	0.611	0.389	0.942

4.1.3. Overall diagnostic information about student's SRL

Mastery of SRL ability of Indonesian students was analyzed by looking at the probability of mastery of the population for each attribute of SRL ability. Table 4 shows the probability of mastery of the four SRL ability attributes obtained by students as a whole by analyzing data using the GDINA package [68] in R software. As shown in Table 4, there are 35% (n=679) of students demonstrated mastery the ability to plan, 37% (n=717) of students demonstrated mastery of monitoring abilities, 46.1% (n=893) of students demonstrated mastery of self-control abilities, and 38.9% (n=753) of students demonstrated mastery of reflection abilities. The probability of mastering the attribute ranges from 0.350 (plan) to 0.461 (control). That is, 35% (n=679) of Indonesian students mastered the attribute of planning, which made it the most difficult attribute of the SRL ability. However, 46.1% (n=893) of Indonesian students mastered the self-control attribute, which makes it the easiest SRL ability attribute.

The G-DINA model classifies students into several latent classes or commonly referred to as attribute mastery patterns. The number of latent classes that are formed depends on the number of attributes that are measured where if K refers to the number of attributes, then there are 2^K latent classes that are formed because each K attribute can be grouped into two (i.e. mastering and not mastering) [33]. Regarding the number of attributes in this study (i.e. K=4), then there are 2^4 (i.e. 16) latent classes formed as shown in Table 5. As can be seen in Table 5, 74.1% of students are grouped into two the dominant latent class group is latent class [0000] and latent class [1111]. Specifically, the latent class [0000] is the latent class which has the largest proportion (46.4%) which indicates that most Indonesian students have not mastered all the SRL ability attributes. The latent class [1111] is the latent class that has the second largest proportion value (27.7%) where students who enter this latent class are students who have mastered all the attributes of SRL abilities. These results emphasize that the majority of Indonesian students still have not mastered SRL skills well.

Table 5. Latent class probabilities

No.	Latent class	Proportion	N	No.	Latent class	Proportion	N
1	0000	0.464	900	9	0110	0.019	37
2	1000	0.015	29	10	0101	0.007	14
3	0100	0.006	12	11	0011	0.048	93
4	0010	0.067	129	12	1110	0.015	30
5	0001	0.015	29	13	1101	0.004	7
6	1100	0.018	35	14	1011	0.005	9
7	1010	0.007	14	15	0111	0.023	45
8	1001	0.009	18	16	1111	0.277	537

Note: N is the number of students per latent class

4.1.4. Students' SRL individually

The main result in measuring skills using the CDM model framework is the mastery profile of students' attributes, which can provide information about students' mastery of SRL ability attributes. The six SRL ability attributes were determined when the Q-matrix was constructed to diagnose students' skills to master SRL abilities: planning ability (A1), development monitoring ability (A2), self-control ability (A3), and reflection ability (A4). Case analysis was carried out to show the student's mastery profile and the three individual student diagnostic reports (Students A, B, and C) are presented in Table 6 and Figure 1.

In this example, three students get the same overall score (i.e., they get a score of 10) with different mastery of the attribute and different probability of mastery of the attribute for each ability. Statistically, students with an attribute mastery probability greater than or equal to 0.6 in an ability are classified as proficient in that ability and less than 0.4 as not proficient [84]. Furthermore, students between 0.4 and 0.6 can be classified as "indecisive" because the assessment does not provide sufficient information.

Figure 1 and Table 6 show that students with the same score do not necessarily have the same ability profile. For example, even though all students get 12 points, student A is proficient in the ability to monitor progress (A2) and the ability to control oneself (A3) but is not proficient in the ability to plan (A1) and the ability to reflect (A4). Students B and C have different ability proficiency even though they have the same total score. When only a single score is used on students, information about their specific SRL-related strengths and weaknesses will be obscured.

Table 6. Attribute mastery pattern for individual student

Student	Total score	Attribute mastery A1	A2	A3	A4	Attribute mastery pattern
A	10	0.325	0.847	0.995	0.089	0110
B	10	0.788	0.799	0.169	0.176	1100
C	10	0.908	0.295	0.192	0.385	1000

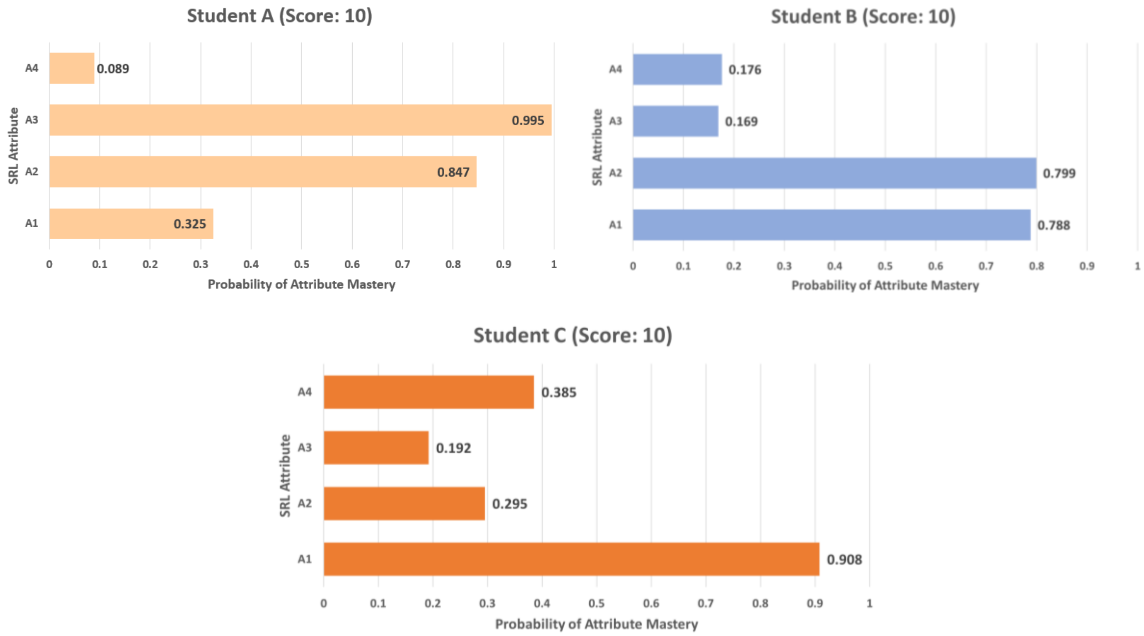

Figure 1. Individual attribute mastery related to SRL

4.2. Discussion

By applying the CDM model framework to Indonesian SRL ability data, this study attempts to provide diagnostic information from measurements of non-diagnostic SRL abilities of Indonesian students. The results presented in the research results section are based on the outputs of the "G-DINA" package [68]. To this study, statistics for model fit, attribute mastery/prevalence, latent classes and their proportions, and individual attribute mastery for three individuals with the same score are reported. The results of the model fit test in this study revealed that the GDINA model is a promising model in providing accurate diagnostic information for SRL skills. The results, however, are specific to the current data and Q-matrix.

Self-regulated learning ability is an ability that needs to be mastered by students. By mastering SRL skills, students can understand and control their learning environment, both the learning environment at school and the learning environment at home. Also, SRL has an influence on cognitive, metacognitive abilities, attitudes, and motivation [10], [11]. SRL abilities include the ability to plan goals (planning), the ability to self-monitor (monitoring), the ability to control oneself (controlling), and the ability to reflect on what has been done (reflecting) related to learning objectives [85]. Based on the results of this study, Indonesian students still need teacher assistance to improve their SRL skills where there are no attributes that are mastered by more than 50% of Indonesian students. This result is in line with several studies that have been conducted previously that the SRL abilities of Indonesian students are still far from proficient, so they need guidance from teachers to improve their SRL abilities [86], [87]. However, the results of this study are in contrast to the results of a study conducted by Eva *et al.* [88] which aims to compare the SRL ability levels of Indonesian and Malaysian students where the majority of Indonesian students whose education level is high school and below are in the high category.

The ability to plan is an important component of students' SRL abilities. The achievement of a student learning goal can be predicted from the high or low ability of students in planning their learning activities [89]. When students learn without clear intention and direction from the beginning, they can easily fail, lose motivation, and give up in the learning process, especially in online learning [90], [91]. Based on the results of the analysis using the GDINA model in this study, it is known that the ability to plan is the SRL ability that is the most difficult for the majority of Indonesian students to master. The difficulty in mastering planning skills makes it difficult for Indonesian students to master the three attributes (monitoring ability, controlling ability, and reflection ability) of other SRL abilities. Good planning by students will help students to monitor and reflect on their learning process [92] and vice versa.

5. CONCLUSION

This research was conducted to find out the appropriate CDM model to use to extract diagnostic information from measuring SRL abilities of students in Indonesia as well as to find out the attributes of SRL abilities that have not been mastered by Indonesian students. Based on the results of this study, it was concluded that the GDINA model is the right model to extract information on the SRL abilities of Indonesian students. In general, there is no SRL ability attribute that can be mastered by the majority of Indonesian students where the planning attribute is the most difficult attribute for Indonesian students to master. Further study need to be done in the context of giving the intervention based on student SRL profile. Next, instrument development which measure students' SRL based on CDM approach must be carried out.

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