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Examining Psychological Antecedents of Rapid Guessing Behavior in Low-Stakes Assessments: The Roles of Cognitive Load, Self-Efficacy, and Test-Taking Motivation

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Abstract

The validity of test scores may be threatened by guessing behavior in educational exams, especially quick guessing and solution activity. The psychological causes of this behavior are still poorly understood, despite the fact that a large portion of research has concentrated on detection techniques. The purpose of this study is to evaluate a causal model that incorporates cognitive load, self-efficacy, and test-taking motivation as predictors of quick guessing and solution behavior in Indonesian high school students. 297 students' data were gathered online using a quantitative method utilizing Structural Equation Modeling (SEM). The analysis revealed that cognitive load is a positive and significant predictor of rapid guessing behavior ($\beta = 1.051$, $p = 0.008$), accounting for 80.1% of the variance in the model. Conversely, motivation and self-efficacy did not show a significant influence on either rapid guessing or solution behavior. The low proportion of variance explained for solution behavior ($R^2 = 14.2\%$) suggests that other factors, such as prior knowledge and metacognitive skills, may play a more dominant role. Heavy thinking load has been shown to be a major trigger that drives students to guess, a reaction whose power can even override their internal motivation. In practice, designing assessments that take cognitive load into account is fundamental to anticipating students' desire to guess during exams.

Introduction

Tests are a fundamental instrument for measuring learning outcomes. However, their effectiveness is often hampered by low student engagement, which encourages guessing behavior (Nagy et al., 2022a), especially in multiple-choice tests (Jin, Siu, et al., 2022). This behavior subsequently impacts the validity of the measurement results. Furthermore, the habit of guessing also indicates that students are not fully engaged in the testing process itself. Students work on problems without consciously attempting to maximize their understanding of each question (Wise, 2017). In the literature, two terms are commonly used to describe this phenomenon: solution behavior and rapid-guessing behavior (Bulut et al., 2023; Deribo et al., 2021; Kong et al., 2007; Lu et al., 2020; Wise, 2019). Solution behavior is defined as an attempt to guess that still involves knowledge and problem-solving efforts. Conversely, rapid-guessing behavior is the act of guessing without any knowledge base and without any intention of attempting to solve the problem (DeMars, 2007).

Rapid guessing behavior is frequently indicative of low test-taking motivation among students (Guo et al., 2016; Jin et al., 2023; Wise, 2017). Conversely, highly motivated examinees tend to engage in genuine solution behavior, demonstrating sustained effort to identify correct responses (Nagy et al., 2022b). The level of student motivation itself is significantly influenced by the perceived stakes of the assessment. According to Ulitzsch et al. (2020), low-stakes conditions, characterized by an absence of meaningful consequences, often result in diminished student motivation. In such environments, students may adopt guessing strategies, operating under the assumption that random responses retain a non-trivial probability of success. However, the implementation of penalty scoring mechanisms, whereby incorrect answers incur negative point values (e.g., 1) while omitted items score zero, can effectively counteract this tendency. This scoring methodology encourages students to adopt a more cautious response

selection strategy, thereby minimizing guessing behavior by reducing or eliminating the expected utility gain from random chance responses (Slamet & Maarif, 2014).

Guessing behavior among students can be triggered by inadequate mastery of the material and limited testing time (Jin et al., 2023). Further research confirms that item complexity, or perceived difficulty, is a key factor driving test takers to guess (Jin, Hsu, et al., 2022; Jin, Siu, et al., 2022). For low-ability students, the difficulty of challenging items is especially noticeable (Deribo et al., 2021), which increases their cognitive load during the assessment process. Therefore, the emergence of guessing behavior, especially in its rapid form, is strongly associated with increased cognitive load (Mieth et al., 2016).

Findings from Soland & Kuhfeld (2019) also suggest that rapid-guessing behavior correlates significantly with student self-efficacy. Within this framework, associated anxiety can manifest either as apprehension regarding performance outcomes or as stress linked to time constraints during test completion (Wise, 2017). Typically, when examinees perceive that the allotted time is expiring while numerous items remain unanswered, they often resort to guessing. This strategy aims to capitalize on the probability of chance success for the remaining items under severe time pressure (Schnipke, 1995).

According to existing research, guessing behavior is not a single phenomenon, but rather the result of the interaction of multiple psychological antecedents. Although previous research has identified motivation, cognitive load, and self-efficacy as influential factors, there are significant gaps in our understanding of how these variables interact simultaneously within a comprehensive causal framework. As a result, this study aims to fill this gap by developing and testing a structural model. The primary goal is to look into the combined effect of test-taking motivation, self-efficacy, and cognitive load on students' proclivity to engage in solution versus rapid guessing behavior. These findings are expected to contribute to a more comprehensive understanding of the etiology of guessing, thereby providing an empirical foundation for increasing assessment validity.

In the existing literature on guessing behavior, especially rapid guessing, methodological development and detection have received more attention than the psychological underpinnings of the behavior. In order to accurately identify guessed responses, a substantial amount of research has focused on optimizing response time thresholds (Bulut et al., 2023; Kong et al., 2007; Wise, 2019). Simultaneously, other studies have developed complex statistical frameworks to identify and reduce data contamination from guessing, such as mixture models and hierarchical IRT models (Deribo et al., 2021; Lu et al., 2020; Ulitzsch et al., 2019). By addressing how guessing is detected, these methods significantly increase measurement validity; however, they offer little explanation for why students engage in this behavior. Therefore, there is still a significant research gap concerning the investigation of cognitive and psychological factors that lead to guessing during tests.

Repositioning Guessing Behavior: From Statistical Noise to a Causal Dependent Variable

Previous studies predominantly conceptualize guessing behavior, particularly rapid guessing, as a statistical issue necessitating remediation to safeguard measurement validity. Within this framework, guessing is frequently treated as data noise that introduces potential bias into interpretations of student ability. Consequently, the primary research emphasis has centered on developing detection and correction strategies to either remove or accurately account for guessed responses during scoring procedures (Deribo et al., 2022). In essence, rapid guessing is more often positioned as methodological interference to be minimized rather than as a primary object of inquiry itself. Conversely, this study proposes a divergent perspective by operationalizing rapid-guessing behavior as a substantive dependent variable requiring explanation. This approach reframes guessing not merely as noise that degrades ability estimation, but as a critical signal reflecting underlying psychological and cognitive processes.

The behavior is thus treated as a phenomenon worthy of causal analysis rather than simple statistical correction. The application of Structural Equation Modeling (SEM) is highly pertinent in this context, enabling the modeling of causal pathways between antecedents, such as motivation, self-efficacy, and cognitive load, and guessing behavior. This methodology is anticipated to yield a deeper understanding of the factors driving guessing, providing theoretical contributions to test-taker behavior models that extend beyond mere methodological refinement.

Limitations of Descriptive Approaches in Prior Studies and the Need for Comprehensive Causal Modeling

Several studies have indeed attempted to link guessing behavior to student characteristics, yet these efforts often employed limited analytical approaches. For example, Soland & Kuhfeld (2019) conducted a longitudinal analysis correlating student disengagement, partially reflected in guessing, with student backgrounds and attitudes. Their work suggests that guessing is not a purely stochastic phenomenon but rather corresponds to specific psychological and demographic dimensions. Similarly, DeMars (2007) examined temporal variations in guessing behavior, highlighting dynamics of student engagement throughout the testing process.

The methods employed are primarily descriptive rather than formative, and they do not produce thorough causal models, despite the insightful information these findings offer. Instead of performing structural analyses to comprehend how multiple antecedents, such as motivation, self-efficacy, and cognitive load, predict guessing behavior simultaneously, previous research has mostly concentrated on observing simple associations. In order to fully understand the intricate interactions between these variables, this condition draws attention to a substantial research gap that calls for more advanced and comprehensive analytical techniques.

Test-Taking Motivation

The primary objective of this investigation is to examine factors that contribute to guessing behavior on multiple-choice examinations. This behavior occurs when participants select an answer under conditions of uncertainty or incomplete knowledge regarding the correct option (Alfian et al., 2023; Rupp et al., 2006). Student motivation during testing conditions is a critical factor that may affect the likelihood of engaging in guessing strategies, whether through rapid selection or more calculated, solution-based approaches. The concept of motivation finds its roots in the Latin term "movere," meaning "to move," highlighting its function as the underlying force driving human action (Urhahne & Wijnia, 2023). In educational psychology, several established theories offer frameworks for elucidating the role of motivation in student test-taking behavior.

Heckhausen & Heckhausen (2018) motivational framework provides a comprehensive basis for analyzing universal characteristics of human action and motives. A significant advancement of this framework is the Rubicon Model of Action Phases, developed by H. Heckhausen & Gollwitzer, (1987). This model delineates four stages: (1) pre-decisional deliberation, (2) post-decisional planning (pre-actional), (3) actional execution, and (4) post-actional evaluation. Contextualizing this within test performance, student motivation (i.e., the commitment to engage seriously versus superficially) is conceptualized not as a simple reflexive impulse, but as a structured process unfolding across these phases. The model's explanatory power also extends to behaviors such as rapid guessing. This study employs the Rubicon Model to investigate how students regulate and sustain motivation during assessment scenarios.

The initial pre-decisional phase involves deliberation on intentions prior to the assessment beginning. Here, students establish their intended level of engagement, influenced by prior test-taking experiences (Gollwitzer, 1944). Individual experiences vary and are subjectively appraised, creating different motivational foundations. Perceived test importance, intrinsic goals, and expected consequences are among the competing desires, outcome expectancies, and feasibility that must be considered during this deliberation stage. Following goal commitment in Phase 1, the post-decisional phase (Phase 2) shifts focus to implementation planning, where students devise strategies to achieve success during the test (Urhahne & Wijnia, 2023).

The actional phase (Phase 3) involves executing intentions formed during the planning stages. Behavior during implementation often diverges into a high-fidelity effort or disengagement marked by low enthusiasm. Students who retain motivation from the initial phase will demonstrate consistent effort, increased concentration, effective self-control, and more effective time management. The post-action phase then focuses on evaluating the process and outcomes. Students reflect on the effectiveness of their strategies, experience satisfaction or dissatisfaction, process emotional responses to the results, and develop strategies for future performance. This feedback loop directly influences behavior in future testing situations (J. Heckhausen & Heckhausen, 2018).

Self-Efficacy

Guessing behavior during assessments, which ranges from informed estimations based on partial knowledge to random, rapid responses, is shaped by both internal and external factors. Internally, alongside motivation, self-efficacy functions as a pivotal psychological determinant. As a central construct in Bandura (1991) cognitive theory, self-efficacy concerns an individual's belief in their capacity to organize and execute actions required to achieve specific goals (Bandura, 1982). Crucially, this belief system represents a subjective perception of capability, which may not align with objective ability levels (Waddington, 2023).

Strong self-efficacy encourages persistence and perseverance in problem-solving. However, a higher tendency to guess quickly, possibly without fully engaging with the problem content, is associated with low self-efficacy (Bandura, 1982). Indirect experience, verbal persuasion, physiological and affective states, and mastery experiences are the four categories of efficacy beliefs distinguished by Bandura (1981).

Past successes build confidence to face future challenges. According to Cervone (2000) this is a "mastery experience", which empowers students to complete difficult tasks. Confidence can also grow by observing the success of others, especially those they know well. This is known as vicarious experience (Waddington, 2023; Wilde & Hsu, 2019). So, how do students react to challenging exams? Their responses can vary greatly depending on their level of confidence. Confident students tend to view challenges as opportunities to overcome. They are confident that they can find the right answer, so they work on the exam methodically, eliminating the wrong choices. However, students who lack confidence may view the same challenge as an insurmountable obstacle. They perceive it as a threat and are more likely to give up and rely on random guessing instead of trying to find a solution (Linnenbrink & Pintrich, 2003). They neglect consistent effort.

Verbal persuasion includes feedback and support from significant others such as teachers and parents (Waddington, 2023). Social acceptance influences a person's exam-taking strategy and increases self-confidence. For example, general encouragement from parents can increase overall confidence in an exam, and specific instructions given by a teacher (e.g., "make sure you read carefully before answering") can influence how you approach the task. Finally, physiological and affective states influence the influence of physical experience on ability beliefs (Bandura, 1982). Physical fatigue and negative affective states, especially anxiety, can significantly reduce self-efficacy beliefs. Regarding guessing, excessive anxiety during difficult exam sections can interfere with rational thought processes. This often leads to cognitive disengagement, meaning students start guessing too early, instead of taking time to review.

Cognitive Load

According to Cognitive Load Theory (CLT), which was developed by John Sweller (1988), human working memory has a restricted amount of processing power. If the task's cognitive demands exceed this capacity, cognitive overload occurs, causing learning to be slowed down and complex reasoning to

occur. Mental stress is often caused by the complexity of an item in an assessment setting, which can lead to students being more inclined to avoid laborious processing.

Interpreting the CLT framework as capable, probability-assisted guessing behavior can help people cope with cognitive overload. When test items have a particularly high intrinsic load, their inherent complexity can cause working memory resources to become saturated. Due to the saturation of reasoning, people frequently resort to avoidance strategies such as random guessing. This is a common procedure. This trait is especially common in objective test formats, which allow for guessing by providing explicit answer options (Sweller et al., 2011).

The Intrinsic, Extraneous, and Germane Cognitive Load are the three components that make up the cognitive load construct (Sweller et al., 2011). The interdependence of information components determines the level of complexity in the learning material, which is independent of presentation techniques. ECL is a result of inadequate instructional design, which results in non-essential cognitive demands. To ensure enduring comprehension, the Germane Cognitive Load (GCL) highlights the effective cognitive activity that is dedicated to processing the intrinsic load and creating mental schemas.

Guessing Behavior

By introducing error variance into assessment data and misrepresenting the latent trait of an examinee, it undermines the accuracy of score interpretations because answers no longer reflect the actuality of the answer. There are multiple instances of this behavior, ranging from stochastic selection on several multiple-choice items to rapid guessing, where test-takers respond without time for comprehension of the item. By comprehending the causes of this behavior, we can develop more dependable and just evaluation methods. The Demands-Capacity Model (DCM) is an effective tool for explaining this phenomenon, as it offers a straightforward explanation of how test-taking dynamics can lead to high levels of guesswork (Wise, 2017).

According to the DCM, when there is a perceived discrepancy between Resource Demands and the examinee's available Effort Capacity, they are more likely to engage in guessing behavior (Wise & Kong, 2010). Resource demands include any features of an item that make it difficult or mentally taxing. At any given moment, the amount of resources an examinee can devote to a problem is known as effort capacity. The capacity is highly variable and may change during the testing period, as noted by Wise & Kong (2005). Time constraints, tiredness from previous tasks, and the presence of motivating factors such as intrinsic interest and test stakes are among the many effort capacity determinants.

Insert Fig. 1 Individual Capacity and Response Behavior

When a person's available capacity meets or surpasses item demands, solution behavior emerges, making it easier to apply effective problem-solving techniques. Based on how demands and capacity interact, the dynamics of test-taking behavior can be divided into four main quadrants: 1) Solution

behavior is produced by the combination of high demands and high capacity. High student motivation and ability are matched with challenging tasks, which lead to sustained engagement where examinees use the right cognitive techniques. Examinees exhibit both cognitive ability and emotional commitment to the task. 2) Low Capacity/High Demands: This mismatch usually leads to quick guessing. Cognitive overload occurs when the perceived item difficulty greatly outweighs the examinee's available resources. In order to reduce the cognitive load, people thus engage in an avoidance strategy by quickly guessing and disengaging.

3) Solution behavior and high-capacity conditions are also mentioned. Due to the student's high capacity, the task is perceived as simple and requires little effort, resulting in accurate and timely completion. 4) The Low Capacity condition produces a variety of outcomes, including general disengagement and quick guessing. People with low capacity (due to low motivation or exhaustion, for example) may react carelessly or superficially because they are uninterested in the task, even if the item is not particularly difficult.

Thus, the Demands-Capacity Model (DCM) emphasizes that guessing behavior is determined not only by static ability but also by the dynamic interaction of task load and an individual's motivation and energy in real time. In assessment contexts, the DCM provides an important framework for identifying and analyzing ineffective responses. Numerous factors influence the aforementioned behaviors of Rapid Guessing and Solution Behavior.

Significance of the Study

The existing body of research on guessing behavior has predominantly emphasized psychometric aspects, focusing heavily on detection methodologies and response time thresholds (Guo et al., 2016; Rios & Deng, 2021; Soland et al., 2021; Wise & DeMars, 2006; Wise & Kong, 2010), or on the development of sophisticated mixture models (Gorney et al., 2023; Lu et al., 2023; Ulitzsch et al., 2019). To close this gap, we empirically investigate the effects of motivation, self-efficacy, and cognitive load on guessing behavior. This study goes beyond simply identifying the problem and investigates its psychological causes. It contributes to test-taking behavior theories by clarifying the processes that influence a student's decision to exert effort versus disengage and guess. While there are many powerful statistical methods available, few studies have used Structural Equation Modeling (SEM) to fully model these psychological antecedents. As a result, this study also makes a methodological contribution by emphasizing the importance of SEM as a powerful tool for understanding the complex interactions between variables that lead to guessing.

Insert Fig. 2 Conceptual Framework of Guessing Behavior

This study provides solid evidence-based recommendations for creating effective interventions and improving assessment design, with important practical implications. The findings will have an effect on educators and those who create assessments. For example, interventions to improve test relevance or incentives to encourage participation can be developed if low motivation is identified as the primary

cause of test guessing. If high cognitive load is determined to be a major issue, test design procedures must be rethought in order to improve instructional clarity, eliminate unnecessary item complexity, and improve layout comprehensibility. Furthermore, strategies should focus on increasing students' confidence through practice, constructive criticism, and the reinforcement of mastery experiences if low self-efficacy is determined to be a significant contributing factor. By offering comprehensive, workable strategies for improving measurement validity and students' overall assessment experiences, this study makes a theoretical and practical contribution.

Theoretical Framework and Hypothesis

This study, which synthesizes findings from previous research, suggests that test-taking motivation, self-efficacy, and cognitive load all have a significant impact on test-taking behaviors. Thus, the following theories are put forth:

The hypothesis states that Solution Behavior (Y1) is positively predicted by Test-Taking Motivation (X1). Justification: Students who are more motivated are anticipated to be more conscientious and persistent in their search for the right response.

H2: Solution Behavior (Y1) is positively predicted by self-efficacy (X2). Justification: When solving complex problems, persistence is increased when one has more faith in their abilities.

H3: Solution behavior (Y1) is negatively predicted by cognitive load (X3). Justification: It's thought that excessive cognitive demands weaken mental capacity, which prevents information processing and lowers the use of solution-focused techniques.

Test-Taking Motivation (X1) is a negative predictor of Rapid Guessing Behavior (Y2). Justification: Students who are more motivated place a higher value on successful outcomes and are therefore less prone to guessing and other avoidance behaviors.

H5: Rapid Guessing Behavior (Y2) is badly predicted by Self-Efficacy (X2). Justification: When faced with challenging items, people who have high self-efficacy are more resilient and are less likely to lose interest or turn to hunches.

H6: Both Rapid Guessing Behavior (Y2) and Cognitive Load (X3) are positively predicted. Reason: Cognitive overload can cause a person's processing capacity to be overloaded, which makes low-effort shortcuts like quick guessing more likely to be used.

Methods

This study examined the connection between test-taking motivation, self-efficacy, cognitive load, and subsequent test-taking behaviors using a quantitative cross-sectional design. Students from Indonesian high schools in grades X, XI, and XII were the study's target participants. Due to logistical issues caused

by the population's size and geographic dispersion, a nonprobability sampling approach was required. Participants were gathered through online platforms using a snowball referral technique and convenience sampling in order to reach a wider audience.

The research protocol has been reviewed and approved by the Institutional Research Ethics Committee (Approval No: 015/EC-IAIN.SAS/2024). In addition, this research has also received permission from the schools in Indonesia that are the target samples, and written consent has also been obtained from parents and students.

Using the G*Power 3.1 software, an a priori power analysis was carried out to guarantee statistical robustness and evaluate sample size adequacy (Faul et al., 2007). The computation parameters of a model with three major predictors were adjusted to yield a small to medium effect magnitude ($f2 = 0.05$). The target statistical power was 88% ($1-\beta = 0.88$), and the significance level was set at $\alpha = 0.05$. A minimum of 295 participants is required for the sample, according to this analysis. N = 297, the final sample, met this minimal requirement. The size of the sample is consistent with accepted Structural Equation Modeling (SEM) guidelines, which typically recommend sample sizes ranging from 100 to 500, contingent on the complexity of the model (Jackson, 2001; Sharif et al., 2024). This adds even more evidence that it is suitable for the analyses that follow.

The study's theoretical framework was evaluated using Structural Equation Modeling (SEM), with statistical computations performed via JASP version 0.9.5.1.0.

Results

The participants in this research consisted of senior high school students in Indonesia. The gender distribution of the sample was 40% male and 59.9% female. Further details concerning the number of items and the sources of the questions for each variable are presented in Table 1.

Table 1
Measurement levels of the variable

Source	Code	Sample	Ques	Dimensions	Variable
H. Heckhausen & Gollwitzer, (1987)	X1.1. PRE	I realise that every test I take has a purpose for the advancement of my learning.	1–2	Predecisional Phase	Test-Taking Motivation
	X1.2. POS	I realise that tests/exams are important, so I am used to planning my strategy by revising the material, reading and understanding the questions carefully, and praying.	3–4	Postdecisional Phase	
	X1.3. ACP	Even though I knew that the test time was about to end, I remained focused on completing the test.	5–6	Actional Phase	
	X1.4. EVP	I realise that the test/exam results I obtain are commensurate with my efforts and abilities.	7–8	Evaluative Phase	
Bandura, (1982)	X2.1. MEP	I feel confident because I often get good results when doing practice questions.	9–10	Mastery Experiences	Self-Efficacy
	X2.2. VCS	I learned a lot from the way my friends solved problems, and that helped boost my confidence in answering test/exam questions.	11–13	Vicarious Experiences	
	X2.3. VRP	I am certain that the support of my parents and family motivates me to complete test questions and examinations.	14–15	Verbal Persuasion	
	X2.4. PHA	When facing exams/tests, I feel healthy and fit, which makes me more confident.	16–17	Physiological and Affective States	
Sweller, (1988)	X3.1. ICL	When taking tests/exams, I do not focus on which questions are difficult and which are easy. Instead, I focus more on problem-solving.	18	Intrinsic Cognitive Load	Cognitive Load
	X3.2. ECG	I will ask the teacher directly if I find the language/sentences in the questions confusing.	19	Extraneous Cognitive Load	

Source	Code	Sample	Ques	Dimensions	Variable
	X3.3. GCG	I am accustomed to reviewing all the answers I have given previously to see if there are any errors.	20	Germane Cognitive Load	
Wise, (2019) (2007); Lu et al., (2020); Bulut et al., (2023); Kong et al., (2023); Deribo	Y1.1. RSD	Because I am unsure of the correct answer, I usually just guess without thinking about it first.	21–23	Resource Demands	Rapid Guessing Behavior
	Y1.2. EFC	When I felt tired doing the questions, without thinking twice I just guessed the answers to the questions.	23–26	Effort Capacity	
	Y2.1. RSD	For questions that I find difficult, if I ultimately have to guess, I still try to analyse the question before choosing an answer.	27–29	Resource Demands	Solution Behavior
	Y2.2. EFC	With the knowledge I have, I am confident that I can solve difficult problems.	30–32	Effort Capacity	

Insert Table 1 Measurement levels of the variable

A Structural Equation Modeling (SEM) analysis was conducted using JASP (v. 0.17.0.0) on a sample of 297 senior high school students in Indonesia to investigate the proposed model. The measurement model's initial assessment showed an insufficient goodness-of-fit. With a Tucker-Lewis Index (TLI) of 0.851 and a Comparative Fit Index (CFI) of 0.887, the fit indices fell below acceptable bounds. Additionally, the Root Mean Square Error of Approximation (RMSEA) of 0.094 was higher than the ≤ 0.06 threshold that is advised for a close fit (Hu & Bentler, 1999). In order to improve the fit with the empirical data, model respecification was necessary.

The model was adjusted in accordance with Modification Indices (MI), which indicated noteworthy residual covariances and possible cross-loadings. When supported by theoretical justification and not just to boost fit statistics, such changes are deemed appropriate (Sathyanarayana & Mohanasundaram, 2024). Correlating the error terms of indicators X1.1. PRE and X1.2. POS, which displayed the highest MI value (MI = 60.682), was the first respecification. Another change added a cross-loading from item X2.4. PHA to the Cognitive Load factor (MI = 16.069), which was thought to be a conceptually reasonable route.

Insert Table 2 Comparison of the Initial and Modified Models

Table 2
Comparison of the Initial and Modified Models

Fit Index	Initial Model	Model After Modification	Threshold	Initial Model Description	Modified Model Description
CFI	887	967	≥ 0.90 (Acceptable) ≥ 0.95 (Good)	Not Fit	Very Good
TLI	851	955	≥ 0.90 (Acceptable) ≥ 0.95 (Good)	Not Fit	Very Good
RMSEA	94	51	≤ 0.08 (Acceptable) ≤ 0.06 (Good)	Not Fit	Very Good
SRMR	60	35	≤ 0.08 (Good)	Good	Very Good

The decision to correlate the residuals of the Pre-test experience (PRE) and Post-test attitude (POS) indicators stemmed from a re-examination of their conceptual overlap within the Motivation construct. Because of their similar temporal context (before and after an intervention), their high MI value indicated that a portion of their covariance could not be explained by the common factor. Likewise, the Cognitive Load construct was allowed to cross-load onto the Physiological and Affective States (PHA) indicator (X2.4). This was supported by the fact that it measures perceived mental effort (e.g., perceived close attention), which is essential to the definition of cognitive load, as well as its conceptual relevance and strong MI (16.069).

After making these adjustments, the model's fit to the data became very good (see Table 2). The traditional standards for a good fit were exceeded by the key fit statistics, such as CFI, TLI, RMSEA, and SRMR. This demonstrates that a model with better correspondence to the sample data was produced as a result of the theoretically supported and empirically motivated modifications (Shi et al., 2018) (Shi et al., 2018).

Measurement Model Evaluation

A look at the factor loadings confirms the strong convergent validity of our measurement model. We found that almost all items had high, statistically significant ($p < .001$) loadings on their assigned factors, which tells us that each group of items is reliably measuring a single, unified concept (Cheung et al., 2023). For instance, the indicators for both Cognitive Load (ICL, ECG, GCG) and Self-Efficacy (MEP, VCS, VRP, PHA) all hung together exceptionally well. This rigorous validation is more than just a procedural step; it's a critical prerequisite for causal hypothesis testing and a cornerstone of best practices in modern educational psychology (Seufert et al., 2024). With the validity of our measures firmly established, we were confident in moving forward to analyze the structural model.

Insert Table 3 Factor Loading

The path coefficients in the structural model were examined in order to test the study's hypotheses. Only one of the six advanced hypotheses was supported by the data, as the Regression Coefficients table showed. Cognitive load was found to have a significant positive impact on rapid guessing (β = 1.051, SE = 0.396, z = 2.653, p = 0.008). This result implies that a higher inclination to engage in rapid guessing behavior is correlated with an increase in perceived cognitive load.

Table 4 Regression coefficients

Discussion

This study examined how important psychological antecedents (self-efficacy, test-taking motivation, and cognitive load) affected students' test-taking behaviors (rapid guessing and solution behavior). After making theoretically supported adjustments, the final model fit the data well. The main conclusion was that cognitive load had a strong and significant predictive effect on the tendency to guess quickly. On the other hand, no meaningful predictive relationships between any of the other variables and either solution behavior or rapid guessing were discovered, underscoring the importance of cognitive load in this situation.

Cognitive Load as a Primary Driver of Rapid Guessing

The main finding of this study was that cognitive load was the only significant predictor of rapid guessing behavior (beta = 1.051, p = 0.008). This discovery provides compelling empirical evidence in support of a fundamental principle of Cognitive Load Theory, which states that cognitive overload forces people to use low-effort, avoidance-based coping mechanisms (Sweller et al., 2011), with quick guessing serving as a prime example (Los et al., 2022).

Rapid guessing is caused by exceeding information processing capacity rather than a lack of knowledge, as evidenced by the model's high explanatory power (R2 = 80.1%). Students in Indonesian secondary schools are prone to abandoning deep problem-solving in favor of guesswork when they believe a task is impossible to complete. This supports Jost (2021) claim that attempting to solve problems in situations of extreme complexity yields results no better than chance.

The whole problem of student guessing, in my opinion, comes down to one pivotal moment: the moment at which a student's mental capacity is totally depleted. The relationship between a student's motivation and the mental effort required to complete a task, known as cognitive load, is crucial. Although we are aware that effort is the foundation of a legitimate test response (Rios & Deng, 2021; Soland et al., 2021), I have discovered that an excessive amount of cognitive load not only makes a task difficult, but also actively undermines a student's motivation to attempt it.

This is more than just a theory; it relates to more general concepts of human motivation. As Evans et al., (2024) noted, for instance, when unclear instructions deprive a student of control, it supports the long-

held idea put forth by Self-Determination Theory that people must feel competent in order to remain engaged. They check out when they don't. Therefore, I do not perceive a student's guessing as being lazy. I observe a coping strategy, a purposeful, albeit ineffective, withdrawal from an emotionally distressing circumstance. Sweller's research on working memory (2023) effectively encapsulates a tipping point. Guessing turns into a sensible way to get out of a severe mental stressor at that precise moment of overload.

Motivation and Self-Efficacy Are Not Significant Predictors of Rapid Guessing and Solution Behavior

One of our study's most unexpected findings was the apparent lack of influence of motivation and self-efficacy on guessing behavior. This directly contradicts the field's underlying theories (Bandura, 1982; Ryan & Deci, 2020), leaving us wondering: what could be strong enough to counteract these significant factors? Our main hypothesis is that cognitive load exerts an overwhelming force. According to the reasoning, a cognitive bottleneck occurs when a task is simply too mentally demanding. Positive characteristics such as confidence or high motivation simply do not translate. Given this level of mental exhaustion, even the most committed students may begin to speculate (Kirschner et al., 2006). The fundamental tenet of Cognitive Load Theory, that our working memory is limited, supports the notion that cognitive load can take precedence over other variables. Higher-order processes such as self-regulation and metacognition may fail when a task exceeds the available space (Sweller, 1988). Motivation and self-efficacy are essentially rendered ineffective when cognitive overload takes up all available bandwidth because they depend on mental resources to be converted into action. Recent research supports this interpretation by demonstrating a direct link between a decline in self-regulatory processes and high cognitive demands (Kleka et al., 2024; Wang et al., 2023).

Explaining the Limited Prediction of Solution Behavior

A notable finding requiring discussion is the model's negligible explanatory power for solution behavior (R^2 = 14.2%) and the absence of any significant predictors. This suggests that test-taking motivation, self-efficacy, and cognitive load were not the primary drivers of correct problem-solving within this study's context. A primary contention is that solution behavior hinges more on students' prior knowledge and domain-specific skills rather than their transient psychological states during the assessment (Chen et al., 2023). A highly motivated student lacking the necessary knowledge schemas will likely fail, whereas a student with strong content mastery may succeed even with low motivation. This perspective is strongly supported by Cognitive Load Theory (CLT), which posits that engaging with instructional materials is fundamentally dependent on pre-existing schemas in long-term memory (Sweller et al., 2019). Students with extensive prior knowledge have automated many procedures, reducing their intrinsic cognitive load and freeing working memory resources for complex problem-solving. Consequently, the influence of affective factors like motivation and self-efficacy is diminished.

While non-cognitive factors are crucial for learning engagement, the literature consistently demonstrates that cognitive factors, such as prior knowledge, are far more reliable indicators of achievement on

structured assessments (Malanchini et al., 2024). Motivation may be the driving force behind learning, as demonstrated by Molnár & Kocsis (2024) and Liu & Nesbit (2023). However, assessments measure internalized knowledge, the result of learning, rather than the motivation itself. In addition to content knowledge, strategic and metacognitive competencies, like organizing, tracking, and assessing one's own problem-solving process, are necessary for coming up with the right answer (Zepeda & Nokes-Malach, 2023). Experts who use deep strategies are distinguished from novices who might rely on trial-and-error by these abilities, which are developed with expertise (Fiorella, 2023; Olop et al., 2024). Therefore, it is more likely that the study's inability to reach a solid conclusion was due to a lack of knowledge or strategic competence than to a lack of motivation.

The low stakes of the assessment environment may be another significant factor. Intrinsic motivation might not change enough in these situations to have a major effect on performance. In contrast to high-stakes tests, where extrinsic motivation is more important (Fidjeland, 2023; Pools & Monseur, 2021). Cognitive ability might then become the determining factor. Future studies must thus broaden to incorporate direct assessments of prior knowledge and metacognitive abilities, which are probably the main unknown variables in the current model, to gain a deeper understanding of solution behavior.

Conclusion

The results show that rapid guessing behavior is primarily determined by cognitive load, whereas students' test-taking performance seems to be unaffected by motivation or self-efficacy. Given this, lowering excessive cognitive demands through task difficulty proportionality and improving students' cognitive readiness should be a priority of both assessment design and pedagogical approaches. Furthermore, the model's limited capacity to explain solution behavior implies that stable cognitive elements, particularly past knowledge and domain-specific problem-solving skills, are more important and ought to be incorporated into lesson plans and instructional strategies. The lack of direct measurement of important cognitive constructs like prior knowledge and metacognitive competence, which future research should take into account, is the study's main limitation despite these contributions.

Declarations

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Acknowledgements have been removed for anonymous peer review.

Author contributions

All authors contributed to the study's conception and design. DP performed material preparation, data collection, and conducted the psychometric analysis using Structural Equation Modeling. The first draft of the manuscript was written by DP. AR supervised the research and provided critical revisions on the theoretical framework. All authors read and approved the final manuscript.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Ethical Approval

This study was approved by the Research Ethics Committee (Approval No: 015/EC-IAIN.SAS/2024)

Consent to Participate

This study was conducted in accordance with the ethical principles outlined in the applicable guidelines and regulations. Written consent was obtained from all participants before their involvement in the study. Informed written consent was obtained from all individual participants involved in the study. Participants were fully informed about the purpose, procedures, risks, and benefits of the study, and they voluntarily agreed to participate. All data is collected and processed in strict compliance with confidentiality and privacy standards. Participants are assured that their responses will remain anonymous and will only be used for research purposes.

Consent to Publish

Consent for publication was obtained from all participants and their parents and/or legal guardians. Participants were informed that their data and any identifying information may be included in publications resulting from this research. Efforts were made to anonymize the data wherever possible to protect participant privacy.

Competing Interests

The authors declare that they have no competing interests.

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Table 3 and 4

Table 3 and 4 are available in the Supplementary Files section.

Figures

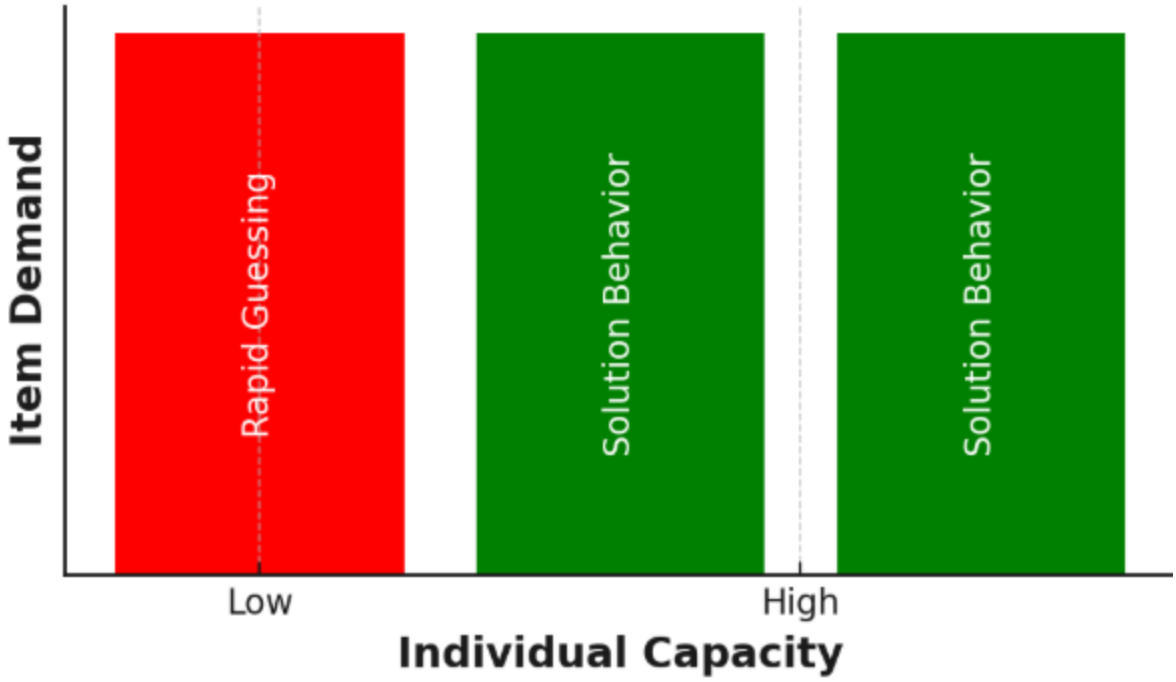


Figure 1

Individual Capacity and Response Behavior

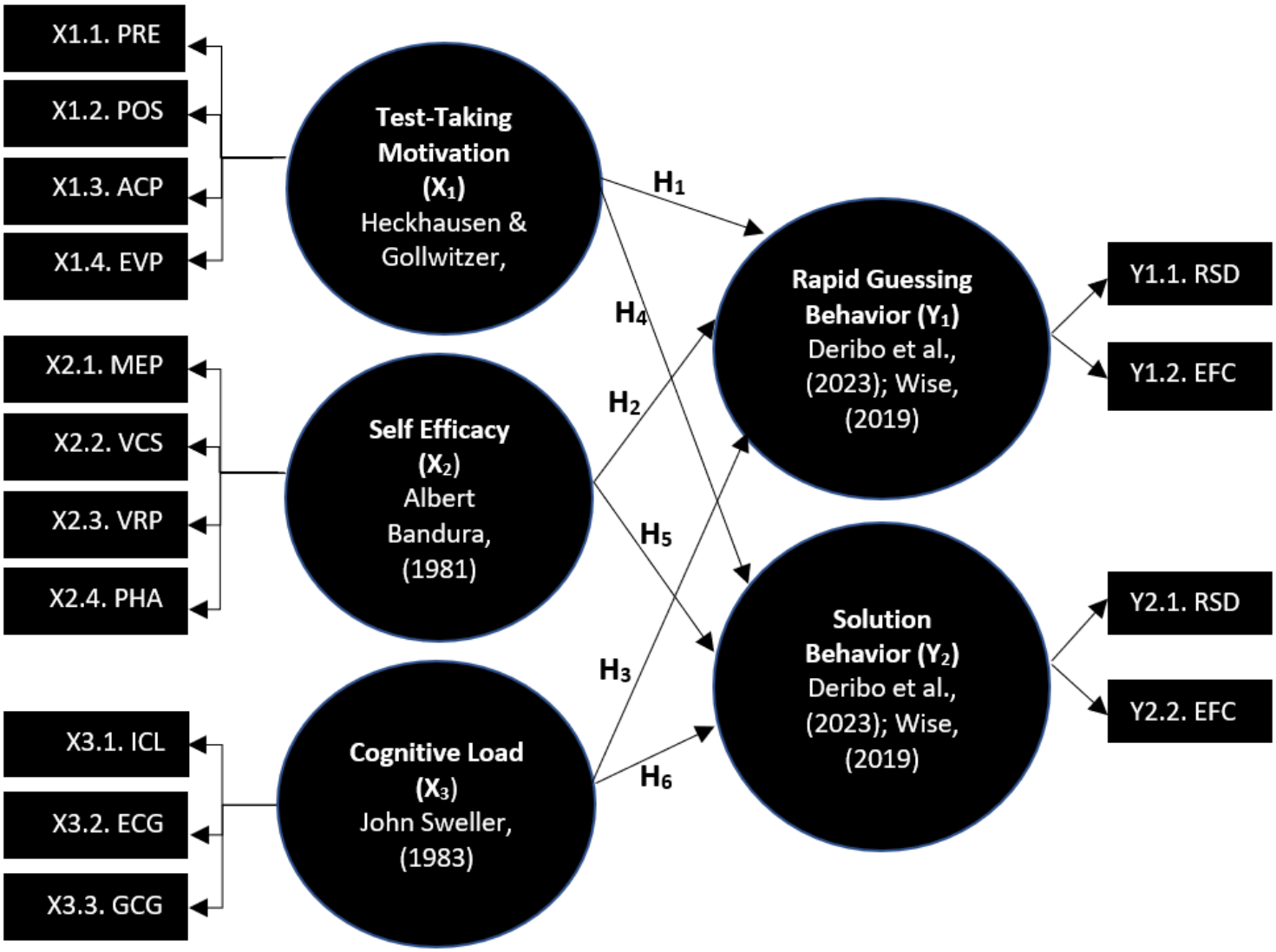


Figure 2

Conceptual Framework of Guessing Behavior

Supplementary Files

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- Table34.docx