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GOOGLE FORMS-BASED ADAPTIVE ASSESSMENT AS A DIGITAL ASSESSMENT STRATEGY TO EXAMINE SENIOR HIGH SCHOOL STUDENTS' ENGAGEMENT AND COGNITIVE LOAD

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Abstrak
Penelitian ini bertujuan untuk menganalisis penerapan adaptive assessment berbasis Google Forms serta keterkaitannya dengan cognitive load dan student engagement siswa SMA. Penelitian menggunakan pendekatan mixed methods dengan desain deskriptif. Subjek penelitian adalah tiga puluh lima siswa kelas XI di SMA yang dipilih menggunakan teknik purposive sampling. Instrumen penelitian berupa tes pilihan ganda yang dianalisis menggunakan *Classical Test Theory* (CTT) serta kuesioner skala Likert untuk mengukur ketiga variabel penelitian. Data kuantitatif dianalisis secara deskriptif, sedangkan data kualitatif diperoleh melalui observasi dan wawancara. Hasil penelitian menunjukkan bahwa adaptive assessment, cognitive load, dan student engagement berada pada kategori sedang. Mekanisme percabangan pada Google Forms mampu menyesuaikan tingkat kesulitan soal secara bertahap, sehingga siswa tidak mengalami beban kognitif yang berlebihan dan tetap terlibat dalam proses penilaian. Keterlibatan siswa dipengaruhi oleh rasa penasaran dan tantangan yang muncul dari variasi soal. Temuan ini menunjukkan bahwa adaptive assessment berbasis Google Forms dapat menjadi alternatif strategi penilaian digital yang cukup efektif, meskipun masih memerlukan pengembangan lebih lanjut untuk meningkatkan tingkat adaptivitas dan kualitas pengalaman belajar siswa.

Kata Kunci: adaptive assessment; Google Forms; cognitive load; student engagement; penilaian digital

Abstract
This study aims to analyze the implementation of adaptive assessment using Google Forms and its relationship with students' cognitive load and student engagement at the senior high school level. A mixed methods approach with a descriptive design was employed. The participants consisted off thirty-five eleventh-grade students at SMAN selected through purposive sampling. The research instruments included multiple-choice tests analyzed using Classical Test Theory (CTT) and Likert-scale questionnaires to measure the three variables. Quantitative data were analyzed descriptively, while qualitative data were obtained through observation and interviews. The results indicate that adaptive assessment, cognitive load, and student engagement are at a moderate level. The branching mechanism in Google Forms allows gradual adjustment of question difficulty, preventing excessive cognitive load while maintaining student engagement during the assessment process. Student engagement is influenced by curiosity and the challenge arising from varying levels of difficulty. These findings suggest that adaptive assessment using Google Forms can serve as a practical digital assessment strategy, although further development is needed to enhance its adaptivity and improve students' learning experiences.

Keyword*: adaptive assessment; Google Forms; cognitive load; student engagement; digital assessment*

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INTRODUCTION

The development of information and communication technology has brought significant changes to the field of education, particularly in learning and assessment processes. Assessment is no longer understood merely as a tool for measuring learning outcomes, but has shifted into becoming part of the learning process that shapes students' learning experiences through feedback and active engagement. This transformation aligns with the demands of the 21st century, which emphasize student-centered learning and the utilization of digital technology to support more effective learning processes (Sembiring & Rahayu, 2025). Data indicate that the use of digital technology in education continues to increase, with more than 70% of educational institutions having integrated digital platforms into learning and assessment processes (Entriza & Puspitasari, 2025). This condition requires assessment systems that are not only evaluative in nature, but also capable of adapting to the increasingly diverse needs and characteristics of learners. In digital learning environments, variations in students' abilities and learning needs must be accommodated through appropriate approaches (Falah & Ropitasari, 2025).

One approach that has recently gained attention is adaptive assessment. This approach enables the level of question difficulty to adjust according to students' abilities, speed, and responses during the assessment process. Through this mechanism, assessment is no longer uniform but develops dynamically according to each student's learning profile. Adaptive assessment is considered capable of creating a fairer and more inclusive evaluation system while simultaneously increasing student engagement because the questions provided correspond to their level of understanding. According to Vygotsky (1978), this approach aligns with the principle of the zone of proximal development, which emphasizes the importance of providing tasks that match students' levels of ability so that the learning process can be optimized (Aprianti et al., 2025). In addition, adaptive assessment supports the principle of differentiated instruction, which is increasingly relevant in classrooms with heterogeneous student abilities.

The use of technology in assessment still presents several issues, particularly those related to cognitive load. This term refers to the mental burden that must be processed by working memory during learning activities (Putra et al., 2025). Within the framework of Cognitive Load Theory, cognitive load is divided into intrinsic load, extraneous load, and germane load, each of which affects how information is understood and processed by students. When assessments are designed with a high level of complexity, supported by various digital media, but are not aligned with students' abilities, such conditions tend to excessively increase extraneous load (Liwei et al., 2025; Utomo et al., 2025). The impact is reflected not only in difficulties understanding the material, but also in reduced focus and learning motivation. Several studies even show that high cognitive load is associated with decreased learning performance and weak information retention (Zaman, 2026). This situation indicates that assessments that fail to consider cognitive capacity may actually disrupt the learning process they are intended to support.

This condition is also directly related to the level of student engagement. Student engagement describes the extent to which students are cognitively, emotionally, and behaviorally involved in learning, as reflected in their participation, attention, and mental effort (Farazwati et al., 2025). When cognitive load is maintained at an appropriate level, students tend to be more focused and engaged in learning activities. Conversely, excessively high cognitive load rapidly exhausts students' mental capacity, thereby reducing their engagement. This demonstrates that assessment design should not only be adaptive to students' abilities, but must also consider the balance between cognitive demands and learning engagement so that the learning process can continue optimally.

Several previous studies have examined these aspects in different contexts. Zhu (2024) emphasized the effectiveness of adaptive microlearning but did not simultaneously relate it to cognitive load and student engagement. Faber et al. (2024) demonstrated that adaptive scaffolding is capable of optimizing cognitive load and engagement, although the study was conducted within a game-based simulation environment, making its context different from classroom learning. On the other hand, Diniyah et al. (2025) focused on measuring student engagement without linking it to adaptive assessment design or the cognitive factors influencing it. Research related to the use of Google Forms as a digital assessment medium has also mainly emphasized its practicality, without connecting it to adaptive assessment approaches or analyses of cognitive load and student engagement.

Previous studies have not integrated adaptive assessment, cognitive load, and student engagement into a single interconnected framework, particularly within the context of digital assessment at the senior high school level. Furthermore, the use of Google Forms in assessment has not been developed using an adaptive assessment approach combined with item selection based on Classical Test Theory (CTT). In fact, such a combination is important to ensure that assessments not only adapt to students' abilities, but also utilize validated instruments while considering students' cognitive load and learning engagement.

An approach that integrates Google Forms-based adaptive assessment with item selection using CTT, while examining its relationship with cognitive load and student engagement, is therefore important to investigate further. This integration is expected to contribute to the development of digital assessment strategies that are more effective, personalized, and aligned with students' cognitive capacities. Based on this rationale, the present study focuses on analyzing the relationship between the implementation of Google Forms-based adaptive assessment and the levels of student engagement and cognitive load among senior high school students in technology-based assessment processes, as formulated in the research title "Google Forms-Based Adaptive Assessment as a Digital Assessment Strategy to Examine Senior High School Students' Engagement and Cognitive Load."

METHOD

This study employed a mixed methods approach with a descriptive design aimed at describing the implementation of adaptive assessment, cognitive load, and student engagement. The quantitative approach was used to describe the level of each variable without examining relationships among variables, while the qualitative approach was utilized as supporting data through observations and interviews to strengthen the interpretation of the quantitative findings (Hmoud et al., 2025). The study was conducted at SMAN 1 Purwadadi with eleventh-grade students who had participated in adaptive learning and assessment as the research subjects. The sampling technique used was non-probability sampling with a purposive sampling method, namely the selection of one class that was aligned with the objectives of the study, consisting of 35 students.

The research instruments consisted of tests and questionnaires. The test instrument comprised 100 multiple-choice questions in the Informatics subject, developed to support the implementation of adaptive assessment. These questions were piloted with students from another school and analyzed using the Classical Test Theory (CTT) approach to determine validity, difficulty level, and item quality. The results of the analysis were used to select and classify the questions into easy, moderate, and difficult categories, which were then arranged into a Google Forms-based adaptive assessment scheme (Ipinnaiye & Risquez, 2024).

The questionnaire instrument was used to measure adaptive assessment, cognitive load, and student engagement. The questionnaire was designed using a 1–5 Likert scale with a total of 30

statements. The research procedure began with the development and pilot testing of the test instrument, followed by item analysis using CTT. Subsequently, the adaptive assessment was implemented in the research class using Google Forms. After the assessment implementation, students were asked to complete the questionnaire, followed by observations during the assessment process and interviews with several students to obtain supporting data.

Quantitative data were analyzed descriptively through the calculation of mean scores, percentages, and categorization levels for each variable. Qualitative data obtained from observations and interviews were analyzed descriptively through an interpretative process to provide a deeper understanding of students' experiences in the implementation of adaptive assessment.

RESULT

The initial stage of the study was conducted through item analysis using the Classical Test Theory (CTT) approach. Item validity was analyzed through item–total correlation with an r-table criterion of 0.361 ($\alpha = 0.05$; $N = 30$). The analysis results showed that most items had correlation coefficients above the r-table value and were therefore declared valid and used in the preparation of the adaptive assessment instrument. Meanwhile, items that did not meet the validity criteria were not included in the implementation stage. The distribution of difficulty levels from the 100 analyzed items is presented in Table 1.

Table 1. Distribution of Level of Difficulty of Question Items

Category	Number of Questions
Easy ($p > 0{,}70$)	27
Medium ($0{,}30 \leq p \leq 0{,}70$)	71
Hard ($p < 0{,}30$)	2
Total	**100**

Most of the items were categorized as moderate, with a smaller proportion categorized as easy and only a very limited number categorized as difficult. Descriptive analysis of students' scores showed a minimum score of 4 and a maximum score of 10, with a mean of 7.31 and a standard deviation of 2.272. Based on the score classification, the mean score was categorized as moderate. The instrument that had undergone the selection stage was then used in the implementation of adaptive assessment for 35 eleventh-grade students through Google Forms by utilizing the branching feature. This mechanism enabled students to receive different question pathways according to the responses they provided during the assessment process. The results of the descriptive analysis of the research variables are presented in Table 2.

Table 2. Descriptive Statistics of Research Variables (N = 35)

Variable	Min	Max	Mean	Std. Dev	Category
Adaptive Assessment	19	50	34,94	6,553	Medium
Cognitive Load	25	50	37,17	6,909	Medium
Student Engagement	23	50	36,66	7,384	Medium

All three variables showed mean scores within the moderate category range. The adaptive assessment variable recorded a score of 34.94, followed by cognitive load at 37.17 and student engagement at 36.66. These quantitative findings were supported by observational data collected during the implementation of the adaptive assessment. In terms of student engagement, most students demonstrated attention to the explanations provided (score 3), although several students were still distracted (score 2). Students' participation in responding to questions was categorized as moderately active (score 3), while the enthusiasm aspect showed the highest score (score 4). Students' emotional engagement during the learning process was also recorded at a score of 3.

Regarding cognitive load, most students demonstrated an understanding of the instructions provided before answering the questions (score 3). Indications of confusion only appeared among a small number of students (score 2), and the mental pressure experienced during the assessment was relatively low (score 2). In addition, students' ability to manage time and maintain concentration during the assessment each received a score of 3. Observations of the adaptive assessment implementation indicated that the branching mechanism functioned according to the design. Changes in question difficulty levels occurred gradually, and students continued to complete the questions until the end despite receiving different question pathways. From a technical perspective, the assessment process was carried out without significant obstacles, and the completion time remained within the established limit.

The researcher also conducted interviews with five students. The students stated that the question model, which changed according to their answers, provided a different experience compared to conventional tests. Variations in difficulty levels made the assessment process feel more dynamic. Most students stated that the questions provided matched their abilities. When they received easier questions after answering incorrectly, students tended to feel calmer. Conversely, when they received more difficult questions, students responded with a sense of challenge.

In terms of cognitive load, students stated that completing the questions did not create excessive mental burden. However, several students identified that questions with longer explanations and certain topics, such as network topology, required greater attention and more intensive processing. All students stated that the allocated completion time was adequate. Regarding student engagement, students revealed that the adaptive assessment model encouraged them to remain focused while answering the questions. Their curiosity about the next questions and the variation in difficulty levels were factors that influenced their engagement throughout the assessment process.

DISCUSSION

After the implementation of Google Forms-based adaptive assessment, the results of the study showed that the three variables, adaptive assessment, cognitive load, and student engagement, were all categorized at a moderate level. These findings indicate that the adaptive assessment system used was able to function in practice, although its effectiveness has not yet been fully optimal in supporting students' learning experiences to the maximum extent.

The mean score of adaptive assessment, which reached 34.94, indicates that the use of the branching logic feature in Google Forms was capable of accommodating the fundamental principles of adaptive assessment, namely adjusting the level of question difficulty based on students' responses. This mechanism caused the sequence of questions to no longer be uniform, but instead to develop according to the answers provided by students. Although Google Forms is not a computerized adaptive testing (CAT) platform, the available branching feature is sufficiently adequate to simulate adaptive mechanisms within the context of classroom assessment (Prasetya & Widiyatmoko, 2025). These findings are consistent with the study conducted by Panchbudhe et al. (2024), which demonstrated that MCQ-based Google Forms is effective as a formative assessment tool capable of improving student understanding and providing more targeted feedback. In addition, ease of access became one of the main advantages of this platform, as confirmed by Ibhar and Ibhar (2023), who found that students gave positive responses toward its use.

Nevertheless, the achievement that remained within the moderate category indicates the existence of limitations in the mechanism employed. The branching system in Google Forms is linear in nature, meaning that it only directs students to certain question paths based on a single response without real-time ability calculations. This condition differs from CAT systems based on Item Response Theory (IRT), which are capable of dynamically adjusting question difficulty levels.

This limitation is in line with Xie and Zhang (2024), who stated that truly fair adaptive assessment still requires support from more complex algorithms. Even so, observational results indicated that the implementation still proceeded effectively, as reflected by the gradual increase in question difficulty and the minimal occurrence of technical problems. This demonstrates that simple approaches can still be effectively utilized when supported by appropriate item selection.

The findings related to adaptive assessment were subsequently associated with students' cognitive load conditions. The mean score of 37.17 indicates that cognitive load was maintained at a manageable level. Students did not experience excessive pressure while answering the questions, yet they still encountered sufficient challenges to stimulate their thinking processes. This condition is consistent with the Cognitive Load Theory developed by Sweller (2024), which emphasizes that effective instructional design must maintain cognitive load balance in order not to hinder comprehension. The adjustment of question difficulty levels in adaptive assessment appeared to play a role in reducing extraneous load without decreasing the intrinsic load required to understand the material (Auliah et al., 2025).

The observational results reinforced these findings. Most students completed the questions calmly (score 3), only a small number experienced confusion (score 2), and mental pressure was categorized as low (score 2). Interviews also indicated that students did not feel excessively burdened. This condition is in accordance with the perspective of Van Merriënboer and Sweller in Nordin (2026), who stated that increasing task complexity would increase intrinsic load, but that it can be controlled through gradual adjustments to difficulty levels. This adaptive mechanism adjusted question difficulty according to students' abilities, allowing students to remain challenged without experiencing excessive cognitive load.

Another finding that emerged from the interviews indicated that certain types of questions generated higher cognitive load, particularly questions with lengthy explanations and materials related to network topology. This condition is associated with the concept of element interactivity in Cognitive Load Theory, in which the greater the amount of information that must be processed simultaneously, the higher the cognitive load experienced by students (Chen et al., 2023; Sweller, 2024). Questions on network topology require the integration of visual and procedural understanding, thereby increasing the complexity of information processing. This finding indicates that the level of question difficulty is not determined solely by the difficulty index, but also by the complexity of the elements involved within the question itself (Latief et al., 2026).

These findings are related to the study conducted by Faber et al. (2024), which demonstrated that adaptive scaffolding can reduce cognitive load and improve learning performance. Although that study was conducted within the context of game-based learning, the underlying principle remains relevant, namely adjusting challenge levels according to students' abilities. The primary difference lies in the adaptation mechanism employed, where the present study still utilized static branching in Google Forms, while Faber et al. employed a more dynamic system based on real-time interaction data.

The cognitive load condition was subsequently associated with the level of student engagement, which was also categorized as moderate, with a mean score of 36.66. Student involvement appeared relatively stable throughout the assessment process. The emotional dimension, particularly student enthusiasm, obtained the highest score (4), while behavioral dimensions such as participation and focus obtained a score of 3. This pattern indicates that adaptive mechanisms more quickly generated positive emotional responses compared to consistent behavioral engagement.

Interview data indicated that student engagement was influenced by curiosity regarding subsequent questions and by the challenges arising from changes in question difficulty levels. These two factors are related to the concepts of curiosity-driven engagement and challenge-based motivation, which serve as major drivers of learning engagement (Reschly & Christenson, 2022). The variation in questions generated by the branching system also reduced the boredom that commonly occurs in conventional tests, allowing students to remain engaged throughout the process.

These findings are also consistent with the perspective that student engagement is dynamic and can be influenced by variations in instructional and assessment practices (Fredricks, 2023). Adaptive assessment provides a different experience because students not only receive questions, but also indirectly influence the sequence of subsequent questions. This condition makes students more cognitively and emotionally engaged throughout the assessment process. The relationship between cognitive load and student engagement was clearly visible in this study. When cognitive load was maintained at a balanced level, student engagement could also be sustained. This condition is consistent with Zhao et al. (2024), who demonstrated that there is an optimal point of cognitive load capable of maximizing learning engagement. Cognitive load that is too low causes students to feel insufficiently challenged, while excessively high cognitive load disrupts focus and decreases motivation.

These findings are reinforced by the study conducted by Togatorop et al. (2025), which showed that adaptive systems are capable of balancing cognitive load and increasing learning engagement. The branching mechanism in this study functioned as a simple regulator that maintained this balance, enabling students to continue completing the questions even though the difficulty levels changed. This demonstrates that adaptivity, although still limited, nevertheless has a positive impact on students' learning experiences. The study conducted by Saekoko et al. (2025) also demonstrated that digital assessment platforms with adaptive feedback can improve student motivation and engagement. These findings are relevant to the condition of students in this study, who were already accustomed to using digital technology and therefore adapted more easily to digital-based assessment systems.

Feedback from students indicated that the learning experience could still be improved, particularly through the use of visual elements in questions. This is related to multimedia principles in Cognitive Load Theory (Sweller, 2024) as well as the findings of Ouwehand et al. (2025) regarding the split-attention effect, in which integrated information presentation can help students understand material more effectively. The appropriate use of images can reduce cognitive load while simultaneously increasing student engagement. The findings of this study indicate that Google Forms-based adaptive assessment can serve as a sufficiently effective alternative for digital assessment at the senior high school level. The integration of adaptive mechanisms and CTT-based item selection was capable of creating a more personalized assessment experience compared to conventional methods. Although limitations still exist, this approach provides a strong foundation for the development of assessment systems that are more adaptive and responsive to students' needs in the future.

CONCLUSION

The implementation of Google Forms-based adaptive assessment demonstrates that adaptive assessment systems can be applied within the context of learning at the senior high school level, although they have not yet reached a fully optimal stage. The results of the study revealed that adaptive assessment, cognitive load, and student engagement were all categorized at a moderate level, indicating a balance between cognitive demands and student involvement during the assessment process. The branching mechanism employed was able to gradually adjust the difficulty

level of the questions, allowing students to avoid excessive cognitive load while still feeling challenged in completing the tasks. Student engagement was also fostered through curiosity and variations in question difficulty levels, which made the assessment process more dynamic compared to conventional tests. Nevertheless, the limitations of the adaptation system, which remained linear in nature, as well as the limited variation in question presentation, indicate that further development is still necessary. The integration of adaptive mechanisms, the quality of CTT-based test items, and more varied instrument designs constitutes an important aspect in improving the effectiveness of digital assessments that are more personalized and responsive to students' abilities.

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