Examining Cognitive Abilities and Academic Outcomes in Digital Learning Contexts of Higher Education

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Abstract. The rapid expansion of digital learning in higher education has reshaped the conditions under which students engage with academic content, raising questions about the role of cognitive ability in academic success. This study aimed to examine the relationship between cognitive ability and academic performance among undergraduate students in digital learning contexts. A total of 364 undergraduate students participated in the study (61 males and 303 females). Cognitive ability was measured using a self-report cognitive ability questionnaire, while academic performance was assessed using categorized grade point average (GPA) levels. Data were analyzed using descriptive statistics, one-way analysis of variance (ANOVA), Spearman correlation analysis, and independent samples *t*-tests. The results indicated that cognitive ability did not differ significantly across academic performance categories and was not significantly associated with academic performance. In addition, no significant gender differences in cognitive ability were observed. These findings suggest that cognitive ability alone is insufficient to explain academic outcomes in digitally mediated higher education. Academic performance appears to be influenced by a broader interaction of learning behaviors, engagement strategies, and instructional design. The study highlights the importance of adopting holistic approaches to understanding student learning and success in contemporary digital learning environments.

Keywords: cognitive ability, academic performance, digital learning, higher education; undergraduate student

1 Introduction

Recent developments in higher education have been marked by an accelerated implementation of digital learning, which has reshaped the dynamics of academic instruction [1][2]. These changes range from the delivery of course content to the ways students organize and process information within learning activities. Digital learning environments require students to engage with instructional materials across multiple digital platforms and interactive features [3][4], thereby increasing the cognitive demands and pressures they must manage throughout the learning process [5][6]. Emerging research shows that digital learning environments that are not optimally designed can generate extraneous cognitive load [7][8], which disrupts comprehension and reduces the overall effectiveness of students' learning [9][10]. This shift illustrates that academic success in the digital era depends not only on

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technological access but also on the capacity of students to process information efficiently within increasingly complex instructional conditions.

In this context, cognitive abilities such as working memory, attentional control, cognitive flexibility, and processing speed serve as central determinants of students' learning effectiveness in digital environments [11][12]. Digital learning requires students to manage rapid task switching and frequent multitasking, which place substantial demands on executive functioning and necessitate stable cognitive resources to distinguish relevant information from competing digital stimuli [13][14]. Recent open-access studies demonstrate that learners with higher working memory capacity exhibit greater resilience in maintaining sustained attention and stable academic performance even when confronted with digital distractions and intensive information processing demands [15]16][17]. These findings underscore that educational technologies operate not merely as learning tools but as cognitive ecosystems that continually challenge and reveal the limits of students' processing capacities.

Most previous studies on digital learning in higher education have concentrated on students' perceptions, levels of digital literacy, and technological readiness [18][19][20][21], without directly evaluating how cognitive abilities mediate digital learning processes. Prior research has documented associations between self-regulated learning and academic outcomes [22][23], yet these studies rarely connect those behavioral constructs with objectively measured cognitive functions obtained via performance-based cognitive assessments [24]. Moreover, literature on digital learning implementation in Indonesian higher education remains limited in offering empirical mappings of students' cognitive profiles within digitally mediated environments [25]. This gap indicates a clear need for studies that integrate cognitive assessment, digital learning behavior, and academic achievement into a single, comprehensive analytical framework.

The multimodal characteristics of digital learning environments can increase cognitive processing demands, particularly when instructional design is not aligned with students' cognitive capacities [8]. Research grounded in cognitive load theory has shown that digital interventions that fail to account for limitations in learners' processing capacity can induce cognitive fatigue and diminish learning motivation [26]. Studies from Indonesian contexts indicate that challenges related to blended and online learning include reduced interaction, increased cognitive strain, and difficulties maintaining focus due to technical and design constraints in instructional delivery [27]. These conditions are exacerbated when students lack effective metacognitive strategies for monitoring and regulating their study behaviors [28]. Collectively, these findings underscore that cognitive capacity plays a far more substantive role in digital learning outcomes than mere technical proficiency with digital tools.

Considering the research gaps that have been identified, this study aims to examine undergraduate students' cognitive ability profiles and their relationship with academic achievement within increasingly complex digital learning environments. The primary focus of this investigation is to understand how cognitive functions such as working memory, attentional control, and cognitive flexibility contribute to the optimization of digital learning processes, particularly as students navigate dynamic, information-rich learning contexts. The methodological approach integrates objective cognitive assessments with formal academic indicators, enabling a deeper empirical understanding of how cognitive abilities shape variations in academic performance in the digital era. This effort is intended to address the limitations of prior literature, which has seldom linked cognition and digital learning directly.

Through this conceptual framework, the study seeks to offer both theoretical and practical contributions to the development of digital learning design in higher education. Insights into students' cognitive capacities may serve as a crucial foundation for educators and institutions in crafting adaptive and inclusive instructional strategies that accommodate individual differences in cognitive functioning. The findings of this research are also expected to inform the development of evidence-based academic policies that mitigate academic disparities associated with rising cognitive demands in digital learning environments[29]. Accordingly, this study occupies a strategic position in deepening the understanding of how cognition interacts with learning effectiveness within the rapidly evolving landscape of digital education.

2 Method

This study employed a quantitative survey method to examine cognitive abilities among undergraduate students. Data were collected using a closed-ended questionnaire based on a Likert scale. The study population comprised undergraduate students enrolled at Universitas Negeri Padang. Participants were recruited using an accidental sampling technique, whereby respondents who met the study criteria and were willing to participate at the time of data collection were included.

A total of 364 undergraduate students participated in the study, consisting of 61 male and 303 female students. Data collection was conducted online by distributing the questionnaire via Google Forms, allowing respondents to complete the survey flexibly regardless of time and location. This approach was chosen to enhance accessibility and efficiency in data collection.

Cognitive ability was measured using the Self-Report Cognitive Abilities Questionnaire (SRCAQ), which consists of 12 items designed to assess individuals' perceptions of their cognitive functioning. Responses were recorded on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Higher total scores indicated higher perceived cognitive ability. The collected data were analyzed using both descriptive and inferential statistical techniques in accordance with the research objectives. Descriptive statistics were used to summarize participant characteristics and cognitive ability scores, while inferential statistics were applied to examine relationships among the study variables. All statistical analyses were conducted using JASP.

3 Results and Discussion

3.1 Results

Descriptive Statistics

A total of 364 undergraduate students participated in this study, consisting of 61 male students (16.8%) and 303 female students (83.2%). The overall mean score of cognitive ability was 43.08 (SD = 6.09), with observed scores ranging from 25 to 59, indicating moderate variability in students' cognitive profiles. Academic performance, measured using categorized GPA levels, yielded a mean score of 2.59 (SD = 0.54), suggesting that most participants were clustered in the higher academic performance categories. Visual inspection of the distribution plots indicated that cognitive ability scores were approximately normally distributed, whereas academic performance showed a categorical distribution consistent with institutional grading classifications.

Table 1. Descriptive Statistics of Study Variables (N = 364)

Variable	N	Mean	SD	Minimum	Maximum
Cognitive Ability	364	43.08	6.09	25	59
Academic Performance	364	2.59	0.54	1	3

Note. Academic performance was coded as 1 = Satisfactory, 2 = Very Satisfactory, and 3 = With Honors.

Cognitive Ability Across Academic Performance Categories

A one-way analysis of variance (ANOVA) was conducted to examine differences in cognitive ability across academic performance categories. The results indicated that cognitive ability did not differ significantly across the three academic performance groups, $F(2, 361) = 1.13$, $p = .323$. Descriptive statistics showed a gradual increase in mean cognitive ability from the Satisfactory group (M = 40.88, SD = 6.24) to the Very Satisfactory group (M = 42.67, SD = 6.02) and the With Honors group (M = 43.40, SD = 6.13); however, these differences were not statistically significant. Post hoc comparisons using Tukey's HSD further confirmed that no pairwise differences between academic performance categories reached significance.

Table 2. One-Way ANOVA of Cognitive Ability by Academic Performance Category

Variable	SS	df	MS	F	p
Academic Performance	84.05	2	42.02	1.13	.323
Residual	13393.80	361	37.10		
Total	13477.85	363			

Association Between Cognitive Ability and Academic Performance

To further examine the relationship between cognitive ability and academic performance, a Spearman rank-order correlation analysis was conducted due to the ordinal nature of the academic performance variable. The results indicated a weak and non-significant association between cognitive ability and academic performance, $\rho = .038$, $p = .473$. This finding suggests that higher cognitive ability scores were not systematically associated with higher academic performance categories in this sample.

Table 3. Spearman Correlation Between Cognitive Ability and Academic Performance

Variable	1	2
Cognitive Ability	—	
Academic Performance	.038	—

Note. Spearman's rho is reported. $p = .473$.

Gender Differences in Cognitive Ability

An independent samples *t*-test was conducted to examine differences in cognitive ability between male and female students. The results indicated no significant difference in cognitive ability between male students (M = 43.89, SD = 6.54) and female students (M = 42.91, SD = 6.00), $t(362) = 1.14$, $p = .257$. The effect size was small (Cohen's $d = 0.16$), indicating negligible practical significance. Assumption checks showed homogeneity of variances (Levene's test, $p = .880$), supporting the validity of the analysis.

Table 4. Independent Samples ***t***-Test of Cognitive Ability by Gender

Gender	N	Mean	SD	Statistic	Value
Male	61	43.89	6.54	*t*	1.14
Female	303	42.91	6.00	*df*	362
				p	.257
				Cohen's *d*	0.16

3.2 Discussion

The present findings indicate that cognitive ability did not significantly differentiate undergraduate students across categorized academic performance levels in digital learning contexts. This result challenges traditional assumptions that higher cognitive capacity directly translates into superior academic outcomes, particularly within contemporary higher education environments. Recent studies suggest that digital learning environments incorporate structural features such as asynchronous access, flexible pacing, and repeated exposure to learning materials, which may reduce the extent to which cognitive ability directly determines students' performance outcomes [30] Under such conditions, students with varying cognitive profiles may achieve comparable academic results through compensatory strategies. The non-significant association observed in this study aligns with emerging evidence that academic success in digitally mediated environments is increasingly shaped by contextual and behavioral factors. Consequently, cognitive ability may function as a background resource rather than a dominant predictor. This interpretation underscores the importance of situating cognitive constructs within their instructional ecology. The findings thus reflect broader transformations in how learning effectiveness is realized in higher education.

The use of categorized GPA as an indicator of academic performance may also contribute to the absence of significant differentiation based on cognitive ability. While GPA categories serve important administrative and evaluative purposes, they may compress individual differences and mask subtle cognitive variability. Research has demonstrated that categorical academic indicators often lack granularity, particularly in environments where assessment criteria emphasize completion and participation over fine-grained cognitive performance [31]. In digital learning contexts, assessment practices frequently integrate collaborative tasks, open-resource examinations, and formative evaluations, which may reduce reliance on individual cognitive efficiency. Such assessment designs allow students to offset cognitive limitations through strategic engagement and resource use. As a result, cognitive ability may exert only an indirect influence on categorized academic outcomes. This highlights the need for more sensitive academic indicators in cognitive research. Future studies may benefit from incorporating continuous performance metrics alongside institutional classifications.

The absence of a significant monotonic relationship between cognitive ability and academic performance further reinforces the notion that cognitive capacity alone is insufficient to explain academic success in digital learning environments. Digital contexts are characterized by frequent task switching, information abundance, and sustained attentional demands, which may privilege self-management over raw cognitive resources. Recent empirical work has emphasized the role of attentional control strategies and learning regulation in navigating such environments effectively [32][33][34]. Students with moderate cognitive ability but strong self-regulatory skills may outperform peers with higher cognitive capacity but weaker regulation. The present findings are consistent with this perspective, as no systematic trend linking cognitive ability and GPA categories was detected. This suggests that cognitive ability operates within a network of interacting factors rather than as an isolated determinant. Accordingly, research frameworks that prioritize single-variable explanations may be increasingly inadequate. A systems-oriented approach to learning outcomes is therefore warranted.

Gender-based analyses in the present study revealed no meaningful differences in cognitive ability between male and female students. This finding is consistent with contemporary research indicating that gender differences in general cognitive ability are minimal and highly context-dependent. In digitally supported learning environments, both male and female students encounter comparable instructional demands and technological affordances. Recent studies have shown that digital learning may further reduce gender-based disparities by offering flexible engagement modes and self-paced learning opportunities ([4][35][36]. The negligible effect size observed in this study suggests that gender is unlikely to serve as a meaningful stratifying variable for cognitive ability in higher education. This supports the adoption of gender-neutral assumptions in instructional design and academic support initiatives. Moreover, it reinforces the view that observed performance differences, when present, are more likely attributable to contextual or motivational factors. Such findings contribute to evidence-based discussions on equity in digital education.

The present results also point toward the growing importance of non-cognitive factors in shaping academic outcomes within digital learning environments. Constructs such as learning engagement, academic persistence, and metacognitive awareness have been shown to exert substantial influence on student performance in online and hybrid settings [37][38]. These factors may mediate or even supersede the role of cognitive ability, particularly in learning contexts that require sustained self-direction. Digital learning environments often place greater responsibility on students to organize their learning activities, monitor progress, and manage distractions. Consequently, students' success may depend more on how they deploy their cognitive resources than on the absolute level of those resources. The present findings indirectly support this shift in emphasis. Integrating cognitive and non-cognitive dimensions therefore represents a promising direction for future research.

From an applied perspective, the findings of this study carry important implications for instructional design and academic policy in higher education. The lack of strong cognitive differentiation across academic performance categories suggests that educational interventions should avoid rigid ability-based assumptions. Instead, instructional strategies that promote effective learning behaviors, reduce unnecessary cognitive demands, and support adaptive engagement may benefit a broader range of students. Recent work has highlighted the effectiveness of scaffolding, feedback-rich environments, and learning analytics in supporting student success regardless of cognitive baseline [39][40][41]. These approaches align with inclusive pedagogical principles and are well-suited to digital learning contexts. Moreover, institutional policies that emphasize learning process indicators rather than solely outcome classifications may provide a more accurate reflection of student development. In this regard, the present study contributes to ongoing efforts to reconceptualize academic success in digitally mediated higher education.

4 Conclusion

This study examined the relationship between cognitive ability and academic performance among undergraduate students in digital learning contexts and found no significant differences in cognitive ability across academic performance categories, no meaningful association between cognitive ability and academic performance, and no gender-based differences in cognitive ability. These findings suggest that cognitive ability alone does not serve as a primary determinant of academic outcomes in digitally mediated higher education. Instead, academic performance appears to reflect a broader interaction of learning behaviors, engagement strategies, and instructional design features that may compensate for individual differences in cognitive capacity. The results underscore the importance of adopting holistic approaches to learning design and evaluation that move beyond ability-based assumptions. Future research should integrate cognitive, behavioral, and contextual factors to better understand student success in evolving digital learning environments.

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