

Predicting ICT Learning Outcomes through Intelligence and Learning Intensity among Vocational High School Students

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ABSTRACT

This study examined how intelligence and learning intensity relate to ICT learning outcomes among grade XI students at SMK Muhammadiyah Salawati. The issue was raised because a number of students had not yet reached the expected learning standard, while school psychological-test data and classroom observations indicated different levels of intelligence and study habits. The research used an ex post facto design involving the whole population of 20 students consisting of grade XI TKJ and XI DKV classes. Intelligence and ICT learning outcomes were obtained through documentation, whereas learning intensity was measured using a questionnaire that had been validated and tested for reliability. Data were analyzed using descriptive statistics, prerequisite tests, simple regression, and multiple regression at a significance level of 0.05. The findings showed that most students' intelligence was in the average category (60%), learning intensity was mostly high (45%), and ICT learning outcomes were mostly incomplete (60%). Intelligence had a positive and significant effect on ICT learning outcomes with a contribution of 9.1%. Learning intensity also showed a positive and significant effect with a contribution of 15%. Together, both variables explained 23% of the variance in ICT learning outcomes ($R = 0.480$, $R^2 = 0.230$, $F = 8.984$, $p < 0.001$). The study concludes that intelligence and learning intensity are meaningful predictors of ICT achievement, although other learning factors still require further attention and investigation. Theoretically, the findings extend cognitive-ability and learning-engagement research to ICT learning in a small vocational school setting and show that cognitive readiness and learning behavior work together rather than separately. Practically, the results suggest that ICT teachers should combine information on students' cognitive readiness with structured routines for regular practice and review.

Keywords: Intelligence; Learning Intensity; ICT Learning Outcomes

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INTRODUCTION

Formal education gives students a structured space to develop their potential, but the quality of that development depends on more than the presence of a school system. In classroom practice, learning outcomes are shaped by what students bring into the learning process, such as cognitive ability and motivation, and by how consistently they engage with learning activities (Kriegbaum et al., 2018; Wong et al., 2024). The Indonesian National Education System Law states that education should develop ability, character, and civilization in order to build learners who are knowledgeable, creative, independent, and responsible (UU Sisdiknas, 2003). This mandate makes the study of student learning outcomes important, particularly in vocational schools where academic achievement is closely linked to practical readiness. In vocational education, ICT competence is more than a subject target: digital literacy and ICT capabilities are treated as part of students' preparation for professional careers (Habibi et al., 2024), which makes weak ICT learning outcomes a concern for schools and for the students' future employers.

In the context of Information and Communication Technology (ICT), students are expected to master basic concepts and practical skills that support learning, work, and daily problem solving (Habibi et al., 2024). However, the thesis data indicate that ICT learning outcomes at SMK Muhammadiyah Salawati had not fully met expectations. About 41% of students were still below the required standard, and observations suggested that several students tended to study only before examinations. The concern is not limited to one school. Nationally, Statistics Indonesia (BPS, 2025) reported that vocational high school (SMK) graduates had the highest open unemployment rate of all education levels in February 2025, at 8.00%, which underlines the need to ensure that vocational students actually master the competencies, including ICT, that their programs are meant to build. This condition points to a familiar problem: students may attend the same classes, but their readiness, cognitive ability, and learning habits are not always the same.

One factor often associated with school achievement is intelligence. Intelligence is commonly understood as a general ability to reason, solve problems, adapt to new situations, and use thinking tools appropriately. Contemporary theories extend this view by describing adaptive intelligence, the ability to adapt to, shape, and select environments in order to achieve success (Sternberg, 2019), which is relevant to schooling because students must apply their reasoning to demanding and changing learning tasks. In school, students with stronger cognitive readiness may understand explanations faster, organize information more effectively, and respond better to assignments. Meta-analytic evidence supports this expectation: intelligence is one of the most influential predictors of school grades ($p = .54$) (Roth et al., 2015) and predicts school achievement more strongly than motivation does ($r = .44$ vs. $r = .27$) (Kriegbaum et al., 2018). In ICT-related learning, reasoning and problem-solving abilities have also been found to be significantly associated with computational thinking (Román-González et al., 2017). Still, intelligence alone does not guarantee achievement. A student with adequate ability may fail to reach good results when study habits are weak or inconsistent.

Learning intensity is another factor that deserves attention (Credé & Kuncel, 2008; Wong et al., 2024). It refers to how often and how seriously students engage in learning activities, including paying attention in class, studying independently, reading textbooks, joining group learning, and preparing for examinations. Empirical evidence shows that such behaviors matter. In a meta-analysis of 533 effect sizes, student engagement correlated positively with academic performance ($r = .33$), and behavioral engagement, which covers participation and effort in learning activities, showed the strongest association ($r = .39$; Wong et al., 2024). An earlier synthesis of 69 studies reached the same conclusion (behavioral engagement $r = .350$; Lei et al., 2018). Likewise, study habits, skills, and attitudes have been shown to predict academic performance with substantial incremental validity beyond standardized tests and prior grades (Credé & Kuncel, 2008). For ICT learning, intensity is especially relevant because students need repeated practice to understand concepts and operate digital tools. Learning that only occurs before a test may help students remember a small part of the material, but it is less likely to build stable understanding.

Previous studies have reported that intelligence and learning intensity are related to academic performance. Roth et al. (2015) synthesized 240 independent samples ($N = 105,185$) and reported a population correlation of .54 between intelligence and school grades. Kriegbaum et al. (2018), in a meta-analysis of 74 studies ($N = 80,145$), found that intelligence and motivation together explained about 24% of the variance in school achievement, with intelligence ($r = .44$) stronger than motivation ($r = .27$). On the behavioral side, Wong et al. (2024) and Lei et al. (2018) reported that student engagement, especially its behavioral dimension, was positively related to achievement ($r = .39$ and $r = .350$, respectively), and Credé and Kuncel (2008) showed that study habits and skills had incremental validity beyond standardized tests and prior grades in predicting GPA. In the ICT domain, Román-González et al. (2017) found that reasoning ($r = .44$) and problem-solving ability ($r = .67$) were associated with computational thinking among school students.

These studies differ from the present study in three ways. First, most of them examined general school or college achievement in large and heterogeneous samples, whereas evidence on ICT learning outcomes among vocational students is limited. Second, intelligence and learning behavior have mostly been examined separately, or intelligence has been paired with motivation, rather than together with the intensity of concrete learning activities such as following lessons, independent study, group learning, textbook reading, and examination preparation. Third, in the literature reviewed for this study, no report was found on the contribution of these two predictors in a vocational school in Southwest Papua. Even so, the specific contribution of both variables in the context of grade XI students at SMK Muhammadiyah Salawati had not been examined. Therefore, the novelty of this study lies in examining intelligence, measured with a school psychological test, and learning intensity together as predictors of ICT learning outcomes in this vocational school context. Specifically, this study aimed to describe students' intelligence, learning intensity, and ICT learning outcomes; to test the individual effects of intelligence and learning intensity on ICT learning outcomes; and to test their combined effect on ICT learning outcomes.

METHOD

This study used a quantitative ex post facto approach. The design was selected because the independent variables had already occurred before the research was conducted, and the researcher did not manipulate the treatment conditions. Ex post facto research is appropriate when the researcher examines possible relationships between naturally occurring conditions and an outcome after both have already occurred, and when assigning students to different levels of intelligence or study habits would be impossible or unethical (Cohen et al., 2018).

In this study, intelligence had been measured earlier by the school and learning intensity is a habitual behavior, so an experimental manipulation was neither feasible nor meaningful. The design therefore allows the contribution of each predictor to be estimated with regression analysis; however, because no variable was manipulated and no control group was used, the results are interpreted as predictive associations and not as proof of causal effects. The study focused on three variables: intelligence as the first independent variable, learning intensity as the second independent variable, and ICT learning outcomes as the dependent variable.

The research was conducted at SMK Muhammadiyah Salawati, Sorong Regency, Southwest Papua, from January to March 2026. The population consisted of all grade XI students who had taken a psychological test when they were in grade X. Because the population was relatively limited, all 20 students were included as the research subjects. The participants were grade XI students of two vocational programs, Computer and Network Engineering (TKJ) and Visual Communication Design (DKV), who were taking the ICT subject during the study period. The class distribution is presented in Table 1.

Table 1. Participant Distribution

No	Class	Number of Students
1	XI TKJ	13
2	XI DKV	7
Total		20

Data were collected using two techniques. First, documentation was used to obtain students' intelligence scores from the school psychological-test report and ICT learning outcomes from the odd-semester midterm examination. Second, a questionnaire was used to measure learning intensity. The questionnaire covered five indicators: following lessons, independent study, group learning, textbook reading, and examination preparation. The instrument validity was examined through expert judgment and Product Moment analysis. Expert judgment was used to check the relevance of each indicator and item wording to the construct of learning intensity. Item validity was then tested by correlating each item score with the total score using the Pearson Product Moment correlation; an item was considered valid when its calculated correlation coefficient (r -count) was greater than the critical value (r -table) at the 0.05 significance level. Reliability was tested using Cronbach's Alpha. The reliability coefficient for the learning-intensity instrument was 0.852, indicating a very high level of reliability, that is, strong internal consistency among the items (Cronbach's alpha is interpreted here as an index of internal consistency and not as evidence of unidimensionality (Zakariya, 2022).

The data analysis was carried out in several steps. Descriptive statistics were used to describe the profile of each variable. Before regression testing, normality, linearity, and multicollinearity tests were conducted to ensure that the data met the required assumptions. The effects of intelligence and learning intensity on ICT learning outcomes were examined using simple regression and multiple regression. Statistical analysis was performed with SPSS. All tests used a significance level of 0.05, so a result was regarded as statistically significant when the significance value (p) was smaller than 0.05. The coefficient of determination (R^2) was interpreted as the proportion of variance in ICT learning outcomes explained by the predictor(s), and Cohen's f^2 was calculated from R^2 ($f^2 = R^2 / (1 - R^2)$) to indicate practical magnitude, with 0.02, 0.15, and 0.35 regarded as small, medium, and large, respectively (Cohen, 1988).

RESULTS AND DISCUSSION

The descriptive analysis showed that the students' learning profile was uneven. Intelligence was mostly concentrated in the average category, learning intensity tended to be high, but ICT learning outcomes were still dominated by students who had not reached the mastery criterion. This means that frequent learning activities were present among many students, yet they did not automatically produce sufficient achievement for all students. The summary is shown in Table 2. This pattern needs careful interpretation. The learning-intensity questionnaire captures how often and how seriously students report engaging in five kinds of learning activity (following lessons, independent study, group learning, textbook reading, and examination preparation); it therefore reflects the frequency and self-reported seriousness of learning behavior rather than the quality or effectiveness of the learning strategies used. High reported intensity can thus coexist with low mastery when study time is spent on low-utility strategies such as rereading, or when studying is concentrated just before tests, as the school's observations also suggested. Research on learning techniques shows that effort alone is not enough: practice testing and distributed practice are among the most effective techniques, whereas rereading and highlighting are less effective (Dunlosky et al., 2013). Because the questionnaire did not measure

strategy quality, this study cannot separate effective learning from mere frequency, and this is acknowledged as a limitation.

Table 2. Descriptive Profile of the Research Variables

Variable	Dominant Category	Frequency	Percentage
Intelligence	Average	12	60%
Learning intensity	High	9	45%
ICT learning outcomes	Incomplete	12	60%

The first regression model indicated that intelligence had a positive and significant effect on ICT learning outcomes. The correlation coefficient was 0.302, with a coefficient of determination of 0.091. This indicates that intelligence explained 9.1% of the variation in ICT learning outcomes. Although the contribution was not large, the relationship was meaningful. Students with better cognitive readiness tended to obtain higher ICT scores because they could more easily process explanations, understand procedures, and connect new information with prior knowledge. The size of this association is smaller than those reported in international syntheses, in which intelligence correlated .54 with school grades after statistical correction (Roth et al., 2015) and .44 with school achievement (Kriegbaum et al., 2018). Two features of the present sample plausibly explain the difference. First, the study included only 20 students, and 60% of them fell in the same (average) intelligence category, so the restricted range of intelligence scores would attenuate the correlation, whereas the meta-analytic values come from large, heterogeneous samples and, in Roth et al., were corrected for range restriction and measurement error. Second, ICT learning outcomes were represented by a single midterm examination and not by aggregated grades. Even so, the direction of the association supports international evidence, and it agrees with the finding that reasoning and problem-solving abilities are related to computational thinking, a core ICT-related skill (Román-González et al., 2017).

The second model showed that learning intensity also had a positive and significant effect on ICT learning outcomes. The correlation coefficient was 0.388, and the coefficient of determination was 0.150. Thus, learning intensity contributed 15% to ICT learning outcomes. This finding is reasonable because ICT learning requires repetition, attention, and practice. Students who study more regularly have more opportunities to correct misunderstanding, recall procedures, and become familiar with the tasks given by the teacher. This result is in line with self-regulated learning theory, which describes learning as a cyclical process in which students plan, monitor, and reflect on their own learning (Panadero, 2017); training that strengthens self-regulation has been shown to improve academic performance among university students ($g = 0.37$; Theobald, 2021). It also agrees with engagement research, in which behavioral engagement, meaning participation, effort, and persistence, shows the strongest association with achievement (Wong et al., 2024; Lei et al., 2018). In the present study, indicators such as following lessons, independent study, and examination preparation correspond to the behavioral and self-regulatory components of these frameworks. The correlation found here ($r = 0.388$) is of similar magnitude to that reported for behavioral engagement in the meta-analysis of Wong et al. ($r = .39$), which supports the view that consistent learning behavior is a robust correlate of achievement across contexts.

When both predictors were tested together, intelligence and learning intensity had a positive and significant effect on ICT learning outcomes. The multiple correlation coefficient was 0.480, and the coefficient of determination was 0.230. In practical terms, the two variables explained 23% of ICT learning outcomes, while 77% was still influenced by other variables not examined in this study, such as motivation, teaching method, learning facilities, home support, classroom climate, and student interest. The regression findings are summarized in Table 3.

Table 3. Regression Summary

Model	R	R Square	F	Sig.	Interpretation
Intelligence -> ICT outcomes	0.302	0.091	6.108	0.016	Positive and significant
Learning intensity -> ICT outcomes	0.388	0.150	10.802	0.002	Positive and significant
Intelligence + learning intensity -> ICT outcomes	0.480	0.230	8.984	0.000	Positive and significant

In terms of magnitude, the combined model corresponds to Cohen's $f^2 = 0.30$, which lies between the conventional thresholds for a medium (0.15) and a large (0.35) effect (Cohen, 1988); the separate models correspond to $f^2 = 0.10$ for intelligence and $f^2 = 0.18$ for learning intensity. For educational practice, this means

that the two predictors together account for a substantial share of the differences in ICT outcomes, enough to help teachers identify students who may need support early, but not enough to serve as the sole basis for decisions about individual students, because about three quarters of the variance remains unexplained. Decisions should therefore combine information on cognitive readiness and learning routines with other evidence such as classroom performance and teacher judgment.

These findings support the idea that learning achievement cannot be viewed only from one side. Intelligence helps students understand learning material, but it works more effectively when students also maintain regular learning routines. The data show that learning intensity made a larger individual contribution than intelligence. This suggests that, in this sample of 20 students, study behavior was a factor that could be improved more directly through school intervention. Teachers can guide students to build consistent study schedules, prepare before lessons, work through exercises, and review ICT material after class. A useful way to integrate the two predictors is to see cognitive ability as the capacity that sets how quickly and deeply students can process ICT material, and learning behavior as the process through which this capacity is turned into achievement. In this view, intelligence supports comprehension and problem solving, whereas regular practice, review, and self-monitoring give students the opportunity to apply that capacity, detect errors, and consolidate procedures. This synthesis is consistent with evidence that intelligence and motivation each contribute unique as well as shared variance to school achievement (Kriegbaum et al., 2018) and with the view of intelligence as adaptation to environments through learning experiences (Sternberg, 2019). Because the present study tested only additive effects, a possible interaction between the two predictors, for example whether regular study compensates more for lower cognitive readiness, was not examined and remains a question for studies with larger samples.

The result concerning intelligence is consistent with Arini (2012), who reported that intelligence had a positive effect on academic achievement. It also fits the view that intelligence supports students in adapting to learning tasks and solving problems (Dalyono, 2009; Purwanto, 2004). More recent evidence points in the same direction. Intelligence is among the strongest single predictors of school grades, yet it explains only part of the variance and operates together with motivation and learning behavior (Roth et al., 2015; Kriegbaum et al., 2018). Contemporary theories also treat intelligence as adaptive rather than fixed: it is expressed in how students adapt to, shape, and select their learning environments, which helps explain why students with average intelligence can achieve well when they organize their learning effectively (Sternberg, 2019). However, the relatively small contribution found in this study confirms that intelligence is not the only determinant of learning success. Students with average intelligence may still achieve good outcomes when they study consistently, while students with higher intelligence may underperform if they rarely review material.

The result concerning learning intensity is in line with Andriyani (2011), who found that learning intensity was related to ICT learning outcomes. In the present study, learning intensity contributed 15%, making it the stronger individual predictor. This finding carries an important implication for teachers and schools: improving study habits may be one of the most realistic ways to support ICT achievement. Concretely, ICT teachers can (a) begin lessons with short, low-stakes practice quizzes so that students retrieve procedures from memory instead of only rereading notes; (b) space practical tasks across weeks, for example by revisiting network-configuration or design-software skills in later lessons, rather than concentrating them before the midterm; (c) provide weekly lab-practice logs or checklists in which students plan, record, and reflect on their independent practice, which supports self-regulation (Panadero, 2017); and (d) organize structured peer-learning sessions with clear roles, in line with the "own it, learn it, and share it" framework for engagement in student-centered learning (Lee & Hannafin, 2016). Practice testing and distributed practice are among the learning techniques with the strongest evidence of effectiveness (Dunlosky et al., 2013).

The combined effect of intelligence and learning intensity was significant but still moderate. The remaining unexplained variance shows that the school should not rely only on cognitive data and study-frequency indicators. ICT learning outcomes may also depend on the availability of computers, internet access, teacher explanation, practical assignments, assessment design, student confidence, and family support. Therefore, future studies should include additional variables to obtain a more complete picture of ICT learning success in vocational schools.

This study has four limitations that should be considered when interpreting the results. First, the sample consisted of 20 students from one school, which limits statistical power and generalizability; future studies should involve more schools and larger samples. Second, the ex post facto design does not permit causal claims, so "effect" in this article should be read as predictive contribution; longitudinal or experimental studies

are needed to test whether strengthening learning routines actually raises ICT outcomes. Third, learning intensity was measured by self-report and captures frequency and seriousness rather than the quality of learning strategies, and ICT learning outcomes were taken from a single midterm examination; future work could add measures of strategy use, time-on-task records, teacher observations, and aggregated assessments. Fourth, other determinants, namely motivation, teaching methods, learning facilities, family support, classroom climate, and student interest, were not measured, although they probably account for part of the 77% unexplained variance. Future studies are therefore recommended to include these variables in multi-factor models, for instance by testing motivation and self-regulated learning as mediators or moderators of the relationship between intelligence and ICT learning outcomes.

CONCLUSION

This study concluded that intelligence and learning intensity are positive and significant predictors of ICT learning outcomes among grade XI students at SMK Muhammadiyah Salawati. Most students had average intelligence, high learning intensity, and ICT scores that were still categorized as incomplete. Intelligence contributed 9.1% to ICT learning outcomes, learning intensity contributed 15%, and both variables together contributed 23%. These results indicate that cognitive ability and learning habits both matter, but learning outcomes are still influenced by other factors outside the scope of this study. Schools and teachers should therefore use intelligence information wisely while also strengthening students' regular learning routines, practice opportunities, and preparation habits in ICT learning. Because 77% of the variance remains unexplained, future research should test multi-factor models that add motivation, self-regulated learning, teaching methods, learning facilities, and family support, use larger multi-school samples, and apply longitudinal or experimental designs to examine whether strengthening learning routines improves ICT learning outcomes.

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