The Impact of Intelligence (IQ) and Learning Styles on Mathematics Learning Motivation and Achievement in Secondary School Students

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ABSTRACT

This study aims to examine the influence of intelligence quotient (IQ) and learning styles on students' learning motivation and mathematics achievement among tenth-grade high school students. The research employed a quantitative approach using an ex post facto design. A total of 83 students participated in the study, selected through a census sampling technique, as the entire population of tenth-grade students was included. Instruments used in this study included an IQ test, a learning style questionnaire (covering auditory, visual, and kinesthetic styles), a motivation questionnaire, and a mathematics achievement test. Data analysis involved instrument validity and reliability testing, classical assumption tests (normality and homogeneity), and multivariate analysis (MANOVA) to assess both the direct and interaction effects of IQ and learning styles on learning motivation and mathematics achievement. The results showed that IQ had a significant impact on mathematics achievement ($p < 0.05$), but no significant effect on learning motivation. Learning styles did not significantly influence either mathematics achievement or learning motivation. Furthermore, there was no significant interaction between IQ and learning styles in relation to either outcome. The coefficient of determination (R^2) indicated that the model explained 26.3% of the variance in mathematics achievement and 16.5% of the variance in learning motivation. It can be concluded that IQ contributes to students' success in mathematics, while learning motivation and performance are also shaped by other factors beyond IQ and learning styles. These findings highlight the importance of instructional strategies that consider students' intellectual capacities along with affective and contextual factors.

Keywords: *Academic Achievement, Intelligence Quotient, Learning Styles, Mathematic Education, Student Motivation*

Pengaruh Peran Kecerdasan (IQ) dan Gaya Belajar dalam Membentuk Motivasi Belajar dan Prestasi Belajar Matematika pada Siswa Sekolah Menengah

ABSTRAK

Penelitian ini bertujuan untuk mengkaji pengaruh Intelligence Quotient (IQ) dan gaya belajar terhadap motivasi belajar dan prestasi belajar matematika pada siswa kelas X SMA. Pendekatan penelitian yang digunakan adalah pendekatan kuantitatif dengan desain *ex post facto*. Sebanyak 83 siswa terlibat dalam penelitian ini, yang dipilih melalui teknik *census sampling* karena seluruh populasi siswa kelas X dijadikan sampel. Instrumen yang digunakan dalam penelitian ini meliputi tes IQ, angket gaya belajar (mencakup gaya auditori, visual, dan kinestetik), angket motivasi belajar, dan tes prestasi belajar matematika. Analisis data mencakup uji validitas dan reliabilitas instrumen, uji asumsi klasik (normalitas dan homogenitas), serta analisis multivariat (MANOVA) untuk menilai pengaruh langsung maupun interaksi antara IQ dan gaya belajar terhadap motivasi belajar dan prestasi matematika. Hasil penelitian menunjukkan bahwa IQ berpengaruh signifikan terhadap prestasi belajar matematika (p < 0,05), namun tidak berpengaruh signifikan terhadap motivasi belajar. Gaya belajar tidak berpengaruh signifikan baik terhadap prestasi belajar matematika maupun motivasi belajar. Selain itu, tidak ditemukan interaksi yang signifikan antara IQ dan gaya belajar terhadap kedua variabel tersebut. Koefisien determinasi (R²) menunjukkan bahwa model menjelaskan 26,3% varians prestasi belajar matematika dan 16,5% varians motivasi belajar. Dapat disimpulkan bahwa IQ berkontribusi terhadap keberhasilan siswa dalam matematika, sementara motivasi dan kinerja belajar juga dipengaruhi oleh faktor-faktor lain di luar IQ dan gaya belajar. Temuan ini menekankan pentingnya strategi pembelajaran yang mempertimbangkan kapasitas intelektual siswa secara bersamaan dengan faktor afektif dan kontekstual

1. Background

Education is one of the key factors in developing high-quality human resources. In the learning process, students' academic achievement is influenced not only by external factors, such as the learning environment and teachers' instructional strategies, but also by internal factors within the students themselves. Two significant internal factors are intelligence level and learning styles (Sternberg, 2019; Chairuddin et al., 2025). Both are believed to contribute to how students comprehend subject matter, motivate themselves in learning, and achieve academic success, particularly in challenging subjects like mathematics.

Mathematics is widely regarded as a challenging subject, as it demands both strong cognitive abilities and high levels of learning motivation. Interestingly, students with similar levels of intelligence often demonstrate varying academic performance (Gottfredson, 2018), which may be influenced by differences in learning preferences (Sternberg, 2019). Understanding the interaction between intelligence and learning styles enables educators to design instructional strategies that are tailored to the unique needs of individual learners (Woolfolk, 2022).

One of the most popular models for understanding learning preferences is the VAK framework (Visual, Auditory, and Kinesthetic) which classifies learners based on their dominant sensory modalities (Pritchard, 2017). Visual learners tend to comprehend material more effectively through images and diagrams, auditory learners through spoken explanations, and kinesthetic learners through direct physical engagement. Although this approach has been

widely applied in educational settings, the use of learning styles for personalized instruction (Fleming & Mills, 1992) has drawn criticism from contemporary research. For instance, Rogowsky et al. (2020) and Pashler et al. (2008) argue that aligning teaching methods with students' preferred learning styles does not consistently improve learning outcomes. These findings highlight the importance of adopting more flexible and evidence-based pedagogical approaches.

In addition to learning styles, cognitive factors such as intelligence also play a crucial role in the learning process. Intelligence affects how students absorb and process information. Students with high cognitive ability may prefer abstract, visual tasks, while others may benefit more from concrete, experiential approaches (Chan & Chan, 2023; Zeng et al., 2022). However, a mismatch between instructional strategies and students' cognitive profiles can reduce engagement and hinder academic achievement. To address this issue, Gardner's (2011) theory of multiple intelligences advocates for diverse instructional strategies that accommodate different intellectual strengths, thereby fostering a more inclusive and motivating learning environment. Collectively, many studies indicate that the integration of multiple intelligences into instructional design tends to produce a positive impact on students' mathematics achievement and related outcomes, particularly when it is systematically embedded within structured pedagogical approaches such as problem-based learning or differentiated instruction, although the magnitude of its effect may vary depending on educational context and research design (Hidayat & Mahmudi, 2025; Murtafiah et al., 2024; Siddiq, 2023).

Furthermore, although the VAK model continues to be widely used in educational practice, several recent studies have questioned its practical validity. Rogowsky et al. (2020) found that learning style preferences do not necessarily correlate with academic performance. Likewise, Pashler et al. (2008) emphasized the lack of strong empirical support for the effectiveness of learning style-based instruction. Therefore, educators are advised to exercise caution and avoid over-reliance on the VAK model, instead adopting pedagogical strategies that are evidence-based and contextually responsive.

As a practical implication, integrating data on students' intelligence levels, learning styles, academic performance, and motivation may serve as a foundation for designing adaptive, student-centered instructional strategies (Bhardwaj et al., 2025; Pashler et al., 2008; Rico-Juan et al., 2024; Shemshack & Spector, 2020). Teachers are expected to be sensitive and flexible in identifying students' learning needs to create an inclusive, productive, and supportive learning environment that fosters both academic achievement and cognitive development, including the classification of students' IQ levels.

Several previous studies have provided important insights regarding the influence of intelligence levels and learning styles on students' motivation and academic achievement. Mulyani & Lubis (2024) demonstrated that intellectual intelligence has a significant positive effect on the mathematics achievement of high school students. This finding reinforces the assumption that cognitive ability is a key factor in academic success, particularly in mathematics, which requires deep conceptual understanding. In addition, research by Suciani et al. (2022) emphasized that learning styles aligned with students' preferences can significantly enhance learning motivation. Students who can adapt their learning strategies to their preferred learning styles tend to exhibit higher motivation, which in turn positively influences their academic achievement.

However, both studies examined these variables separately, highlighting the need for further research that integrates both variables simultaneously. The present study aims to address this gap by employing a two-way MANOVA analysis to investigate the combined effects of intelligence levels and learning styles on students' learning motivation and mathematics achievement. This research was conducted with tenth-grade students at a senior high school

involving a total of 83 participants. It is expected that the findings of this study will contribute theoretically to the field of educational psychology and provide practical guidance for teachers and school administrators in designing more personalized and effective instructional approaches tailored to students' individual needs.

2. Methods

This study employed a quantitative approach with a correlational research design, as described by Creswell (2024), which is suitable for examining statistical relationships between variables without manipulating them. Sugiyono (2017) also notes that correlational studies aim to determine the degree of association between two or more variables. The primary objective of this research was to analyze the relationship between intelligence quotient (IQ) and learning styles with students' mathematics learning motivation and mathematics achievement at the senior high school level. The population in this study consisted of all tenth-grade students at a selected public senior high school in Indonesia. A census sampling technique (total sampling) was employed, as the total number of students (N = 83) was relatively small and manageable (Arikunto, 2021). This method allowed all members of the population to be included as respondents. However, the use of total sampling resulted in small subgroups, such as the low IQ group (n = 6), which may have increased the risk of Type II errors in the statistical analysis, where true effects might remain undetected due to limited sample size per category.

The study involved two independent variables, namely IQ and learning styles, and two dependent variables, namely learning motivation and mathematics achievement. IQ was classified into seven standard categories: very low, borderline, low average, average, high average, very high, and superior. Learning styles were categorized based on the Visual, Auditory, and Kinesthetic (VAK) model, as adapted by Chairuddin et al., (2025). Although the VAK model is commonly used in educational practice, the study acknowledges its limitations. Rogowsky et al. (2020) argued that learning style preferences do not necessarily correlate positively with academic performance, a concern also raised by Pashler et al. (2008), who concluded that there is insufficient empirical evidence supporting the effectiveness of learning styles-based instruction.

Four main research instruments were used. First, IQ was measured using an adapted version of Raven's Progressive Matrices (RPM), a nonverbal assessment of abstract reasoning and problem-solving skills (Raven, 2000; John & Raven, 2003). Second, the Learning Style Questionnaire was developed based on the VAK framework, validated through expert judgment and pilot testing (Chairuddin et al., 2025). Third, the Learning Motivation Questionnaire was constructed based on motivation theory indicators from Santrock (2023), covering dimensions such as attention, relevance, confidence, and satisfaction. Fourth, a Mathematics Achievement Test consisting of multiple-choice and essay questions was designed in alignment with the basic competencies of the tenth-grade mathematics curriculum.

The validity and reliability of the Learning Motivation and Learning Style questionnaires were tested prior to deployment. Item validity was evaluated using the Pearson Product-Moment correlation coefficient (Arikunto, 2021), and instrument reliability was tested using Cronbach's Alpha (Azwar, 2015). Results confirmed that all instruments met the required standards of validity and reliability for use in empirical educational research. Before data collection, formal approval was obtained from the school administration, and informed consent was secured from student participants. The research complied with ethical standards in educational research, including voluntary participation and the confidentiality of respondents' identities.

Data analysis was conducted using SPSS, following several statistical procedures. First, normality was assessed using the Kolmogorov-Smirnov test (Santrock, 2023). Second, homogeneity of variance was examined using Levene's Test (Santrock, 2023). Third, Multivariate Analysis of Variance (MANOVA) was employed to assess the simultaneous effects of IQ and learning styles on the two dependent variables (Creswell, 2024). Finally, an interaction effect test was performed to determine whether there was a significant interaction between IQ and learning styles in influencing students' motivation and achievement (Sugiyono, 2017). All tests were conducted at a significance level of 0.05, with results interpreted based on p-values, Wilks' Lambda, and effect size indicators appropriate for multivariate data.

3. Results and Discussion

3.1 Result

The data collection for this study was conducted in April 2025, focusing on tenth-grade students at the senior high school level, with a total of 83 participants. A Learning Motivation Questionnaire was administered to measure each student's motivation score. This was followed by a mathematics test consisting of 40 questions to assess the students' mathematics achievement scores. Data analysis was performed using SPSS version 29, including variability tests on the items of the learning motivation questionnaire to ensure the validity and reliability of the instrument (Cuevas, 2015).

Table 1. Motivation Questionnaire Score Pearson Correlation

No.	Statement	Pearson Correlation	Sig. (2-tailed)	Description
1	I enjoy learning Mathematics	0.783	< 0.001	Valid
2	I find learning Mathematics interesting	0.807	< 0.001	Valid
3	I like challenging Mathematics problems	0.775	< 0.001	Valid
4	I try hard when studying Mathematics	0.498	< 0.001	Valid
5	When I struggle with Mathematics, I try to find the cause	0.503	< 0.001	Valid
6	I use strategies to truly understand Mathematics	0.536	< 0.001	Valid
7	I prepare well for Mathematics tests and quizzes	0.468	< 0.001	Valid
8	I am confident I will get good scores on Mathematics assignments/ projects	0.695	< 0.001	Valid
9	I am confident I will do well on Mathematics exams	0.794	< 0.001	Valid
10	I believe I can master the materials and skills in Mathematics	0.790	< 0.001	Valid
11	I believe I can achieve an A grade in Mathematics (above the passing grade)	0.706	< 0.001	Valid
12	I believe I can achieve an A grade in Mathematics (above the passing grade)	0.666	< 0.001	Valid
13	I feel that Mathematics lessons will be useful for me	0.460	< 0.001	Valid
14	I think learning Mathematics can help me get a good job	0.359	< 0.001	Valid
15	I think learning Mathematics will support my future career	0.548	< 0.001	Valid
16	I feel anxious before taking Mathematics exams	0.664	< 0.001	Valid
17	I feel nervous about Mathematics exam results	0.584	< 0.001	Valid
18	I worry about failing Mathematics exams	0.652	< 0.001	Valid
19	I worry that my classmates are better at Mathematics	0.431	< 0.001	Valid

The validity test was conducted to determine the extent to which each item in the motivation questionnaire (items 1 to 19 in Table 1) was significantly correlated with the total motivation score. The analysis technique used was the Pearson Product Moment correlation. The results of the validity test showed that most items had significant Pearson correlation (r) values with the total moti vation score at both the 5% ($p < 0.05$) and 1% ($p < 0.01$) significance levels. The

critical value for the correlation coefficient (r table) was determined to be 0.217, based on 19 items and 83 participants. The analysis of SPSS revealed that all items had correlation coefficients greater than 0.217, indicating that the questionnaire items had strong correlations with the total score and could therefore be considered valid. Subsequently, a reliability test was conducted on the questionnaire administered to the students that be seen in Table 2.

Table 2. Reliability Test (Cronbach's Alpha)

Cronbach's Alpha	Cronbach's Alpha based on standardized	N of items
0,908	0,91	19

A reliability test was conducted using the Cronbach's Alpha method to determine the internal consistency of the learning motivation instrument. This test ensures that the questionnaire items provide stable and consistent results in measuring learning motivation. Based on the SPSS output, the Cronbach's Alpha value obtained was 0.908 with 19 items. According to the reliability criteria proposed by Guilford (1956) and George & Mallery (2003), the interpretation of Cronbach's Alpha values is as follows: (1) > 0.90 = Excellent, (2) 0.80–0.90 = Good, (3) 0.70–0.80 = Acceptable, (4) < 0.70 = Poor (requires revision). With a Cronbach's Alpha value of 0.908, this learning motivation instrument is categorized as having excellent reliability. This indicates that all items in the questionnaire consistently measure the intended aspects of learning motivation and can be reliably used for further research.

The next step to ensure that the research data is suitable for further analysis is to conduct a normality test. The normality test aims to determine whether the data follows a normal distribution. A normal distribution is typically shaped like a "symmetrical bell curve" (Gaussian curve), essential in parametric statistical analysis. The normality test in this study was conducted to examine whether each independent variable (learning style and IQ) is normally distributed about the dependent variables (academic achievement and learning motivation). The first normality test was carried out to assess the relationship between learning style and both academic achievement and learning motivation that can be seen in Table 3.

Table 3. Normality Test Table of Learning Styles on Academic Achievement and Learning Motivation

Learning Style (X)	N	Asymp. Sig. Y1 (Academic Achievement)	Y1 Distribution	Asymp. Sig. Y2 (Motivation)	Y2 Distribution
Auditory	30	0.374	Normal	0.667	Normal
Kinesthetic	23	0.974	Normal	0.692	Normal
Visual	30	0.108	Normal	0.291	Normal

Based on the results of the Kolmogorov–Smirnov normality test for the variables of academic achievement (Y1) and learning motivation (Y2), grouped by students' learning styles (Auditory, Kinesthetic, and Visual), the obtained significance values (Asymp. Sig. 2-tailed) are as follows: (1) For the Auditory learning style group, the significance value for academic achievement is 0.347, and for learning motivation, it is 0.667. (2) For the Kinesthetic learning style group, the significance value for academic achievement is 0.974, and for learning motivation, it is 0.680. (3) For the Visual learning style group, the significance value for academic achievement is 0.108, and for learning motivation, it is 0.291. All significance values are greater than 0.05, indicating that the data for both academic achievement and learning motivation in each learning style category are typically distributed. The next normality test will

examine the relationship between IQ/intelligence and academic achievement and learning motivation.

Table 4. Normality Test Table for IQ Categories in Relation to Academic Achievement and Motivation

IQ Category (X)	N	Asymp. Sig. Y1 (Academic Achievement)	Y1 Distribution	Asymp. Sig. Y2 (Motivation)	Y2 Distribution
Low	6	0.702	Normal	0.985	Normal
Average	29	0.657	Normal	0.891	Normal
High	18	0.544	Normal	0.546	Normal
Very High	22	0.608	Normal	0.753	Normal
Superior	8	0.153	Normal	0.669	Normal

Based on the results of the Kolmogorov–Smirnov normality test in Table 4, it was found that all data for academic achievement (Y1) and learning motivation (Y2) within each IQ category (low, average, high, very high, and superior) had significance values (Sig. > 0.05). Therefore, it can be concluded that the data are normally distributed within each IQ group, thus meeting the requirements for further parametric analysis such as the Homogeneity Test.

Box's M test was conducted to examine the equality of covariance matrices of the dependent variables across groups. This test is essential before performing MANOVA because one of MANOVA's assumptions is that the covariance matrices among groups must be homogeneous or equal. Based on the results of Box's M test (Table 5), a significance value of 0.502 (> 0.05) was obtained. This indicates no significant difference between the covariance matrices of the groups. Thus, the assumption of covariance homogeneity is met, allowing subsequent analyses such as MANOVA to be conducted without violating statistical assumptions (Ghozali, 2016).

Table 5. Box's M Test for Homogeneity

Statistics	Value
Box's M	40.939
F	0.979
df1	33
df2	1,754
Sig. (p-value)	0.502

Before conducting further analysis such as MANOVA, it is necessary to perform the Levene's Test. This test is used to check whether the variances of each group in the dependent variables are homogeneous (equal). Homogeneity of variance is one of the critical assumptions in MANOVA/ANOVA analysis. The general criterion is as follows: if the p-value (Sig.) is greater than 0.05, the variances are considered homogeneous, meaning the assumption is met. Conversely, if the p-value (Sig.) is less than or equal to 0.05, the variances are considered not homogeneous, indicating that the assumption is violated (Ghozali, 2016). For further clarity, the results are presented in Table 6.

Table 6. Levene's Test for Error Variance

Variable	Test Method	Levene Statistic	df1	df2	Sig. (p-value)
Learning Outcomes (Y1)	Based on Mean	1.150	12	68	0.337
Motivation (Y2)	Based on Mean	0.796	12	68	0.653

Based on the results of Levene's test in Table 6, the significance values (Sig.) for all calculation methods base on mean for both dependent variables, Learning Outcomes and Motivation, are greater than 0.05. These significance values indicate no significant differences

in variances between groups (based on either IQ or learning style). Therefore, the assumption of homogeneity of variances is met. This condition reinforces that the data meet the requirements for further MANOVA analysis, as the error variances across groups are considered homogeneous. In line with the main objective of this study, which is to determine whether there is a relationship between the independent variables (IQ and Learning Style) and the dependent variables (Learning Outcomes and Motivation), a multivariate test needs to be conducted, starting with descriptive statistical analysis of each variable.

Table 7. Mathematics Learning Outcomes

Learning Style	IQ Category	Mean	Std. Dev.	N
Auditory	Low	72.50	19.53	3
	Very High	85.56	9.34	3
	Superior	86.25	12.67	4
	High	82.50	8.66	8
	Total Average	78.89	8.40	9
Kinesthetic	Low	70.00	3.54	2
	Very High	73.00	15.43	5
	Superior	93.33	3.82	3
	High	85.88	8.93	8
	Total Average	79.33	14.21	5
Visual	Low	75.00	–	1
	Very High	79.06	11.80	8
	Superior	95.00	–	1
	High	80.00	10.75	5
	Total Average	75.33	9.25	15

From the descriptive data in Table 7 above, the overall mean of Learning Outcomes (Y1) is 77.75, with a standard deviation of 10.28, and a total sample size of 83 students. It can be concluded that students with a superior IQ category consistently demonstrate the highest average learning outcomes, particularly among those with a visual learning style (95.00) and kinesthetic learning style (93.33). Students with auditory learning styles and IQs in the high and above categories also show relatively high and stable learning outcomes. Meanwhile, the visual learning style group exhibits a somewhat wider distribution, indicated by a relatively high standard deviation, reflecting considerable variation in student performance within this group that showed in Table 8.

From the descriptive data in Table 8, it can be concluded that the overall mean motivation score is 66.00, with a standard deviation of 10.62, and a total sample size of 83 students. Generally, the motivation scores are lower compared to the learning outcomes. The highest average motivation was observed in the auditory learning style group (68.40), followed by kinesthetic (64.39) and visual (61.87) learning styles. The auditory learning style tends to have more stable motivation scores (SD = 10.91) than kinesthetic and visual learning styles. To examine whether there is a relationship or interaction between variables X1 and X2, a Multivariate Test analysis (MANOVA) can be conducted. However, it is important to acknowledge that certain subgroup distributions are highly unbalanced. For example, only one participant was classified as having a Low IQ with a visual learning style. This limited subgroup size poses a risk of unstable or non-generalizable results within the interaction analysis. Therefore, caution must be taken when interpreting the findings related to specific combinations of IQ levels and learning styles, especially in cases where the sample size is too small to support statistical reliability.

Table 8. Mathematics Learning Motivation

Learning styles	IQ Category	Mean	Std. Deviasi	Students (N)
Auditory	Low	67,00	7,93	3
	Very high	70,44	14,38	9
	Superior	64,50	5,00	4
	High	61,40	11,54	5
	Total Average	**68,40**	**10,90**	**30**
Kinestetik	Low	59,50	12,02	2
	Very high	67,20	6,02	5
	Superior	68,66	5,69	3
	High	65,62	15,90	8
	Total Average	**64,39**	**10,89**	**23**
Visual	Low	55,00	-	1
	Very high	67,75	10,47	8
	Superior	69,00	-	1
	High	70,20	7,79	5
	Total Average	**64,83**	**10,03**	**30**

Table 9. Multivariate Test Based on Wilks' Lambda

Effect	Test Statistic	Value	F (calculated)	Hypothesis df	Error df	Sig. (p)	Decision
Learning Style (X2)	Wilks' Lambda	0.98	0.346	4	134	0.847	Not significant
IQ (Category X1)	Wilks' Lambda	0.798	2.001	8	134	0.051	Significant (significant in Hotelling's & Roy's tests)
Learning Style × IQ	Wilks' Lambda	0.813	0.914	16	134	0.555	Not significant

Based on the Table 9, a multivariate test (MANOVA) was conducted to determine whether learning style (X2), IQ category (X1), and their interaction simultaneously affect two dependent variables mathematics learning outcomes (Y1) and learning motivation (Y2). The effect of Learning Style (X2) shows a Wilks' Lambda value of 0.980 with p = 0.847 (> 0.05). This indicates no significant multivariate difference in the combined learning outcomes and motivation among the three learning styles (auditory, kinesthetic, visual). Meanwhile, the effect of IQ (Category X1) shows a Wilks' Lambda p-value of 0.051 (close to 0.05). However, two other statistics, Hotelling's Trace (p = 0.047) and Roy's Largest Root (p = 0.010), indicate significance. Considering the overall evidence, IQ category has a meaningful multivariate effect on the combined Y1-Y2 variables. This means that students' IQ levels influence the combined profile of learning outcomes and motivation.

For the interaction of Learning Style × IQ, Wilks' Lambda = 0.813 with p = 0.555 indicates no significant interaction. Certain combinations between learning style and IQ do not produce a distinct pattern of differences in learning outcomes and motivation. Therefore, IQ can be considered the primary factor teachers should focus on when aiming to simultaneously improve academic performance and motivation simultaneously. Learning style appears to have no significant simultaneous effect; a differentiated learning style approach may be more relevant only in specific aspects (e.g., teaching methods), rather than on the combined cognitive-motivation achievement. Since there is no interaction, learning strategies based on learning styles do not need to be specifically designed for each IQ level. The focus can be placed on providing support appropriate to the IQ level.

Table 10. Test of Between-Subjects Effects

Source of Variation	Dependent Variable	df	Mean Square	F	Sig. (p)	Description
Learning Style (X2)	Learning Outcomes (Y1)	2	38.676	0.321	0.726	Not significant
	Motivation (Y2)	2	57.429	0.506	0.605	Not significant
IQ Category (X1)	Learning Outcomes (Y1)	4	436.047	3.622	0.010	Significant (affects Y1)
	Motivation (Y2)	4	85.706	0.755	0.558	Not significant
Interaction (X2 × X1)	Learning Outcomes (Y1)	8	100.740	0.837	0.574	Not significant
	Motivation (Y2)	8	121.938	1.074	0.392	Not significant

Based on the results of the Test of Between-Subjects Effects (MANOVA analysis) in Table 10, information was obtained regarding the influence of each independent variable on the two dependent variables, namely mathematics learning outcomes (Y1) and mathematics learning motivation (Y2) is : (1) Effect of Learning Style (X2)**:** There was no significant effect of learning style on either learning outcomes (Y1) or motivation (Y2), as the significance values were greater than 0.05 (p = 0.726 for Y1 and p = 0.605 for Y2). This indicates that differences in students' learning styles (auditory, visual, kinesthetic) did not significantly differ in mathematics learning outcomes or motivation. (2) Effect of IQ (X1)**:** IQ had a significant effect on mathematics learning outcomes (Y1), with an F value of 3.622 and p = 0.010 (< 0.05). However, it did not significantly affect mathematics learning motivation (Y2), with p = 0.558. This shows that students' IQ levels significantly contribute to their learning outcomes but not to their motivation. (3) Interaction between Learning Style and IQ: These two independent variables did not significantly influence learning outcomes or motivation (p = 0.574 for Y1 and p = 0.392 for Y2). This means that the combination of students' learning styles and IQ levels does not create an interactive effect on their academic performance or motivation.

To enhance the interpretive depth of the findings, an effect size analysis was conducted based on the coefficient of determination (R^2), which conceptually corresponds to eta squared (η^2). The results indicated that the independent effect of IQ on mathematics learning outcomes (Y1) yielded an η^2 value of 0.431, which is classified as a moderate effect. Meanwhile, the combined model, including IQ, learning styles, and their interaction, produced an η^2 value of 0.696, indicating a large effect. For learning motivation (Y2), the η^2 value reached 0.510, also reflecting a substantial effect. These findings suggest that the research model accounts for a meaningful proportion of variance in both dependent variables, thereby offering a richer understanding of the practical implications beyond mere statistical significance.

For Y1 (Mathematics Learning Outcomes), the coefficient of determination is $R^2 = 0.263$. This means that 26.3% of the variation in students' learning outcomes can be explained by the combined influence of IQ, learning style, and their interaction. The remaining 73.7% (100% - 26.3%) is explained by factors outside the model, such as intrinsic motivation, teacher quality, home environment, teaching methods etc. For Y2 (Learning Motivation), the coefficient of determination $R^2 = 0.165$. This means that IQ, learning style and interaction can explain only 16.5% of the variation in students' learning motivation. Therefore, 83.5% of the variation in learning motivation is still influenced by other factors not included in the model, such as psychological factors, social relationships, academic pressure, or family conditions. This is common in educational research, as human behavior is complex and influenced by numerous variables. Therefore, it is recommended to conduct further multivariate testing, where for each effect, SPSS reports four tests (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, Roy's Largest Root). The common practice is to use Wilks' Lambda; if uncertainty arises, decisions should be based on agreement among at least three of the four tests.

3.2   Discussion

The findings of this study indicate that Intelligence Quotient (IQ) has a significant influence on students' mathematics learning outcomes, consistent with the results reported by Mulyani & Lubis (2024) and Sikhah (2017), which confirmed that students with higher intellectual intelligence tend to achieve better academic performance. These findings are also strongly supported by international empirical evidence demonstrating that intelligence remains one of the most stable and powerful predictors of academic achievement across domains, particularly in mathematics. For example, Peng et al. (2019), in a comprehensive meta-analysis published in *Psychological Bulletin*, reported a strong and consistent correlation between intelligence and mathematics achievement across developmental stages. Similarly, Lozano-Blasco et al. (2022) found that general intelligence significantly predicts academic outcomes even after controlling for demographic variables.

Theoretically, this relationship can be explained by the cognitive demands inherent in mathematics learning. Mathematics requires abstract reasoning, logical deduction, working memory capacity, and the ability to manipulate symbolic representations. These cognitive processes are closely aligned with constructs of fluid intelligence and quantitative reasoning. Students with higher IQ levels typically demonstrate greater efficiency in processing complex information, identifying patterns, and solving multistep problems. Therefore, the present findings reinforce the conceptualization of intelligence as a structural cognitive resource that facilitates higher-order mathematical thinking.

However, this study differs from several previous studies in that it did not find any significant influence of learning styles or learning motivation, either directly or through interaction with IQ. For instance, Suciani et al. (2022) and Muslimah (2024) found that learning styles significantly affected students' learning motivation at the elementary school level. In contrast, this study, focusing on senior high school students, found that learning styles (visual, auditory, and kinesthetic) did not significantly influence either learning motivation or academic achievement. Rogowsky et al. (2020) found that matching instruction to students' preferred learning styles did not lead to improved learning outcomes, providing no empirical support for the learning styles hypothesis. These contrasting results suggest that the effectiveness of learning styles may indeed be context-dependent, influenced by factors such as educational level, student maturity, and instructional complexity.

From a developmental perspective, younger students may rely more heavily on sensory-based instructional input due to limited metacognitive and self-regulation skills. As students progress into adolescence, they typically develop more advanced executive functioning and learning strategies, reducing their dependence on specific sensory modalities. This interpretation aligns with critical evaluations of the learning styles hypothesis in international literature. Newton & Salvi (2020) reported that although belief in learning styles remains widespread among educators, empirical evidence supporting the instructional matching hypothesis is limited. Likewise, Rogowsky et al. (2020) concluded that providing instruction tailored to students' preferred learning styles does not significantly improve learning outcomes.

Therefore, the present findings contribute to the ongoing debate by suggesting that learning styles may not function as independent predictors of mathematics achievement in more cognitively demanding educational contexts. Mathematics learning at the senior high school level requires integrated processing of symbolic, spatial, and verbal information. As Howard-Jones (2014) explained, learning involves distributed neural networks rather than isolated sensory channels. Consequently, modality-based categorization may oversimplify the integrative nature of mathematical cognition.

Furthermore, this study employed a Multivariate Analysis of Variance (MANOVA) approach to examine variables' direct and interaction effects, which is relatively uncommon in similar studies. This presents a methodological advantage, as MANOVA allows researchers to simultaneously evaluate the relationships between multiple independent and dependent variables while accounting for covariance among outcome variables. This differs from previous studies, such as those by Mulyani (2020) and Hidayat & Mahmudi (2025), which generally relied on simple correlational analysis or linear regression. By applying MANOVA, the present study reduces the risk of inflated Type I error and provides a more comprehensive assessment of interaction effects. The absence of significant interaction between IQ and learning styles further strengthens the conclusion that modality preference does not moderate the intelligence–achievement relationship in this context.

Interestingly, this study also found that IQ or learning styles did not significantly influence learning motivation. This result contradicts the findings of Handarini et al. (2021) and Hertanti et al. (2024), who concluded that cognitive intelligence and learning styles affect students' motivation and academic performance. Sengodan & Iksan (2012) found that students' learning styles were significantly related to their intrinsic motivation in learning mathematics, indicating that certain learning style preferences were associated with higher levels of internal motivation. The discrepancy suggests that learning motivation may be shaped by broader environmental and contextual variables rather than internal cognitive traits alone.

Contemporary motivational theories support this interpretation. Self-Determination Theory posits that motivation arises from the satisfaction of psychological needs for autonomy, competence, and relatedness (Ryan & Deci, 2020). Intelligence alone does not guarantee fulfillment of these needs. A student with high cognitive ability may still exhibit low motivation if classroom practices do not support autonomy or provide meaningful feedback. Similarly, Control-Value Theory emphasizes that students' motivation depends on perceived control over learning tasks and the subjective value assigned to them (Murayama et al., 2013; Pekrun, 2024). These perceptions are strongly influenced by contextual and relational factors.

One significant external factor is the availability of learning resources and access to educational technology. Alphonce & Mwantimwa (2019) found that students with greater access to digital learning resources demonstrate higher academic motivation because such access enhances self-efficacy and perceived autonomy. Digital tools can provide immediate feedback, flexible pacing, and interactive learning experiences, which strengthen students' engagement independent of their IQ levels.

In addition, parental support plays a crucial role in enhancing students' learning motivation. Parental involvement, whether through supervision, verbal encouragement, or recognition of their children's academic efforts, has been shown to contribute positively to students' motivation (Suharti & Fatimah, 2023). International research further supports this claim. Hill & Tyson (2009) demonstrated that parental academic socialization significantly predicts adolescents' achievement motivation. Pietschnig et al. (2023) found that the general intelligence factor (g) derived from Italian achievement data (2010–2022) remained largely stable over time, with slight age-dependent variations, suggesting no clear overall Flynn effect in achievement-based g. Parental expectations, emotional support, and involvement in academic planning create motivational climates that encourage persistence and resilience.

This support becomes even more effective when complemented by a supportive physical school environment. Widiastuti et al. (2020) emphasized that classroom comfort, learning facilities, and environmental cleanliness significantly affect students' learning atmosphere and enthusiasm. Studies on school climate indicate that students who perceive their classrooms as safe, organized, and supportive show higher engagement and persistence (Wang & Degol,

2016). A conducive learning environment fosters concentration and emotional security, thereby enhancing motivation.

Furthermore, the leadership style of the school principal also influences students' motivation. Principals who are visionary and supportive are able to establish a positive academic culture that shapes the overall learning climate (Leithwood & Azah, 2020; Brauckmann et al., 2023). Effective school leadership promotes teacher collaboration, instructional innovation, and high academic expectations. Such systemic factors indirectly strengthen students' motivational orientation by creating a culture of academic excellence.

In addition, peer influence is a social factor that cannot be overlooked. Peer groups with positive study habits can serve as a source of motivation and encouragement for students to grow academically (Kindermann, 2016; Woreta et al., 2025). Adolescents are particularly sensitive to peer norms, and association with academically engaged peers can enhance motivation, persistence, and self-regulated learning behaviors.

Lastly, cultural expectations and societal norms also help shape students' motivation to learn. In communities with high academic expectations, students are often driven to study harder in order to fulfill those expectations (Nodooshan, 2022). Hussain (2024) found that in a challenge-driven flipped learning environment, students' initial expectations, largely shaped by prior experiences, strongly influenced their engagement, and that effectively managing these expectations can help reduce the gap between theory and practice and create a more balanced and engaging learning experience. Cross-cultural educational research has shown that societal values emphasizing academic achievement can significantly influence student effort and persistence (OECD, 2019). Cultural narratives regarding success, mobility, and educational attainment contribute to students' internalization of achievement goals.

All these external factors interact dynamically to create an educational ecosystem that fosters strong and sustainable learning motivation. This ecosystem perspective explains why IQ and learning styles alone did not significantly predict motivation in the present study. Pizon & Ytoc (2022) found that motivation, attitude, learning styles, and teaching strategies collectively and significantly predict students' mathematics performance, with motivation and attitude exerting the strongest direct effects. Motivation appears to be multidimensional, context-sensitive, and socially constructed rather than purely cognitively determined.

In conclusion, the differences between this study and previous research emphasize that while IQ remains an important predictor of mathematics achievement, learning styles and motivation appear more situational and complex, and therefore cannot be universally generalized across all educational settings. Intelligence functions as a cognitive capacity foundation, whereas motivation emerges from interactions among environmental, relational, institutional, and cultural influences. These findings encourage future research to adopt multilevel and longitudinal approaches to better understand the dynamic interplay between cognitive and contextual determinants of mathematics learning.

4. Conclusion and Suggestions

Based on the data analysis involving 83 high school students, it can be concluded that IQ significantly influences on mathematics learning outcomes. Students with high and superior IQ categories tend to have better average learning outcomes than those with average or low IQ levels. However, learning styles (auditory, kinesthetic, visual) do not significanty influence either learning outcomes or students' learning motivation. Likewise, no significant interaction was found between IQ and learning styles about to these two dependent variables. Furthermore, students' learning motivation was not significantly affected by either IQ or learning styles, suggesting that motivation is likely influenced more by other external factors, such as the

learning environment, teacher approach, or individual interests. These findings highlight the importance of considering cognitive factors such as IQ when designing learning strategies, while variables like learning styles may require more contextual and personalized approaches. Suggestions This study indicates that IQ significantly affects mathematics learning outcomes, while learning styles do not show a meaningful impact. Therefore, for future research, it is recommended to : (1) Explore other factors that may influence students' learning motivation, such as learning environment, teaching methods, or parental education background. (2) Utilize more in-depth instruments for identifying students' learning styles, such as direct observation or interviews, to obtain more accurate results. (3) Increase the sample size and conduct cross-school or cross-regional studies to examine differences across broader educational contexts. (4) Develop adaptive learning models based on artificial intelligence (AI) or digital platforms that can adjust to students' IQ levels and learning characteristics to enhance both learning outcomes and motivation.

By considering these recommendations, future studies are expected to provide more comprehensive contributions to efforts aimed at improving the quality of mathematics education in schools.

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