**Learning Styles of Mathematics Majors in Davao Central College: Basis for Intervention Plan**

**ABSTRACT**

This study investigates the learning styles of Mathematics majors at Davao Central College (DCC) as a foundation for developing an empirically driven intervention plan. Grounded in the Grasha-Riechmann Learning Styles Model (1974), the study employed a descriptive-comparative quantitative research design, systematically examining the learning styles of 106 Mathematics major students by utilizing the mean, standard deviations, independent sample t-tests, and ANOVA to determine statistical differences across gender, age, and year level. Findings indicate that the most preferred learning styles of the math majors are collaborative, with a mean of 4.24 categorized as high. Subsequently, the results revealed no significant difference in the learning styles among the respondents when analyzed according to gender, age, and year level. However, a significant difference in competitive learning styles was observed across year levels, with first-year students being more competitive compared to other year levels, yielding a p-value of 0.013 This trend aligns with theories of academic motivation and socio-cognitive development, suggesting that exposure to competitive academic environments and career-related pressures contributes to heightened performance-driven behaviors (Zimmerman & Schunk, 2011; Bandura, 1986). The study highlights the importance of adaptive instructional frameworks that incorporate both collaborative and competitive learning strategies to foster student engagement, resilience, and academic motivation. Recommendations include peer-assisted learning models, structured mentorship programs, and institutional interventions to promote balanced cognitive development across academic years. Future research should explore longitudinal assessments of competitive learning, examining the role of institutional culture, self-efficacy, and environmental influences in shaping students' evolving learning preferences.

**Keywords: learning styles of Mathematics, Intervention Plan, academic environments, academic motivation, learning strategies**

**1. INTRODUCTION**

Learning is a continuous cognitive process that allows individuals to acquire knowledge, enhance problem-solving skills, and adapt to new challenges. In mathematics education, students display diverse learning styles, which directly impact their ability to comprehend and apply mathematical concepts effectively. Studies emphasize that aligning instructional methods with students' preferred learning styles can significantly improve academic performance. However, many students struggle with mathematics due to the traditional one-size-fits-all approach, highlighting the need for personalized learning interventions (Clouder et al., 2020).

Globally, the issue of mismatched teaching strategies and students' learning preferences persists. Research by Sun et al. (2023) suggests that the absence of adaptive learning frameworks in mathematics education negatively affects student engagement and mastery of concepts. Additionally, the increasing complexity of mathematics curricula requires educators to tailor teaching techniques to accommodate different cognitive processing styles. Despite advancements in technology-enhanced learning, mathematics instruction in many educational systems remains rigid, limiting student success.

In the Philippines, challenges in mathematics education remain evident, particularly in addressing students' varied learning preferences. A study by Dela Cruz et al. (2023) found that Filipino students often struggle with mathematics due to the lack of differentiated instruction and support programs. Traditional lecture-based teaching methods continue to dominate, with limited efforts to integrate individualized learning approaches. This gap in instructional strategies underscores the need for empirical research on mathematics learning styles within the Philippine context.

Despite extensive research on learning styles, recent studies focusing on mathematics majors remain limited, particularly within Philippine higher education institutions. Many existing studies rely on qualitative approaches, introducing subjective biases in the assessment of learning preferences.

This study aims to bridge this research gap by employing a purely quantitative approach to assess the predominant learning styles of mathematics majors at Davao Central College. The findings will contribute to the development of an intervention program designed to enhance mathematics learning based on empirical data.

The primary objective of this study was to determine the Learning Styles of mathematics majors at Davao Central College, providing a basis for an Intervention Program. Specifically, it sought to answer the following questions:

1. What is the profile of the respondents in terms of:
   1. Gender;
   2. Age;
   3. Year Level;
2. What is the level of the learning styles of the students in terms of:
   1. Independent;
   2. Avoidant;
   3. Collaborative;
   4. Dependent;
   5. Competitive;
   6. Participant;
3. Is there a significant difference in the level of learning styles of the respondents when analyzed according to demographic profile?
4. What intervention program can be proposed based on the findings of the study?

Ho1: There is no significant difference in the level of learning styles of the respondents when analyzed according to demographic profile.

This study is anchored on Albert Bandura’s Social Learning Theory, which posits that learning occurs through observation, imitation, and social interaction. This theory provides a strong foundation for the Grasha-Riechmann Learning Style Model, which emphasizes how students engage in the learning process—whether independently, collaboratively, competitively, or passively. The six learning styles identified by Grasha and Riechmann reflect the varying degrees of learners' interaction with instructors, peers, and classroom activities. Since Social Learning Theory highlights the importance of environmental and social factors in shaping behavior and learning, it effectively explains how students develop preferred learning styles through classroom dynamics, peer influence, and observed outcomes. Thus, this theory supports the classification and analysis of learning styles to teaching strategies and educational interventions (Fig-1).

**Learning Styles**

* Competitive
* Collaborative
* Avoidant
* Participant
* Dependent
* Independent

**Demographic Profile**

* Gender
* Age
* Year Level

**Fig. 1. Conceptual Framework of the Learning Styles of Mathematics Majors in Davao Central College: Basis for Intervention Plan**

**2. METHODOLOGY**

This study employed the descriptive-comparative quantitative research design to analyze the data. A descriptive-comparative quantitative research design is used to systematically compare two groups without manipulating variables. This approach allows researchers to analyze differences in academic performance based on predefined criteria. A research questionnaire was adopted from the survey scores of the Grasha-Riechmann Learning Styles Scales (GRLSS, 1996) and was cited in the study of Dela Cruz Jr. and Cardino Jr. on their research study published last May 2020.

The study was conducted at Davao Central College, Inc., located at Juan Dela Cruz St., Toril, Davao City, Davao del Sur, Philippines. The study involved the total population of officially enrolled Mathematics Major students in the second semester for the S.Y. 2024–2025. Twenty-five (25) respondents from first year, thirty-three (33) from second year, twenty-five (25) from third year, and twenty-three (23) from fourth year. A total of one hundred six students (106) were selected using total enumeration or census sampling to ensure precise and reliable results among the students.

Prior to the implementation of the study, the researchers sought the approval from the Program head of the College of Education and Liberal Arts. Approval to conduct survey to the students as respondents.

To analyze the data, independent sample t-test, Anova and mean were used to determine whether there is significant difference in the learning styles of the mathematics majors and demographic profile of the students.

The researcher conducted the study within the school premises, ensuring accessibility and relevance. To facilitate the research process, a letter of approval was submitted to the Program Head of CELA, seeking permission to conduct surveys with selected tertiary students. Transparency and accountability were maintained through this formal request. Additionally, the survey questionnaire was presented to the program head of the CELA department before distribution. The researcher ensured that all information provided remained confidential and securely stored, protecting the rights and privacy of the participants. Additionally, ethical guidelines were followed to prevent bias, uphold integrity, and ensure the responsible handling of data throughout the study.

**3. RESULTS**

Table 1 presents the demographic profile of respondents, it reveals a predominance of female respondents (75.5%) compared to males (24.5%), indicating a gender imbalance in the sample. Age distribution highlights that the majority (93.4%) fall within the 18–24 age bracket, with only a small proportion (6.6%) aged 25–32, suggesting a primarily younger respondent pool. Regarding year level, the largest group consists of second-year students (31.1%), while first- and third-year students each comprise 23.6%, and fourth-year students represent the smallest share (21.7%). This composition implies that responses may be predominantly shaped by younger students with varying academic exposures.

**Table 1. Demographic Profile of the Respondents**

|  |  |  |
| --- | --- | --- |
| **Indicators** | **Frequency** | **Percent** |
| **GENDER** |  |  |
| Male | 26 | 24.5 |
| Female | 80 | 75.5 |
| **AGE** |  |  |
| 18 – 24 | 99 | 93.4 |
| 25 – 32 | 7 | 6.6 |
| **YEAR LEVEL** |  |  |
| First Year | 25 | 23.6 |
| Second Year | 33 | 31.1 |
| Third Year | 25 | 23.6 |
| Fourth Year | 23 | 21.7 |

Table 2 presents the respondents' learning style preferences based on mean scores and standard deviation (SD). The Collaborative learning style has the highest mean (4.25), indicating strong agreement among respondents in favor of working with peers. The Dependent (4.02) and Participant (3.93) styles also show moderately high agreement, suggesting that learners benefit from structured guidance and active engagement. Meanwhile, the Independent learning style (3.86) reflects moderate agreement, implying that students appreciate autonomy in their studies but still value external input. The Avoidant (3.34) and Competitive (3.04) styles fall under an undecided stance, indicating variability in respondents' attitudes toward self-directed or performance-driven learning. The highest standard deviation (SD) (1.001) for the Competitive learning style suggests greater variability in responses, whereas the Collaborative (0.529) and Dependent (0.530) styles exhibit more consistency.

**Table 2. Descriptive Table**

|  |  |  |  |
| --- | --- | --- | --- |
| **LEARNING STYLE** | **SD** | **Mean** | **Description** |
| Independent | 0.584 | 3.86 | High |
| Avoidant | 0.750 | 3.34 | Moderate |
| Collaborative | 0.529 | 4.25 | Very High |
| Dependent | 0.530 | 4.02 | High |
| Competitive | 1.001 | 3.04 | Moderate |
| Participant | 0.590 | 3.93 | High |

Table 3 presents the independent samples t-test results, it indicates that there are no statistically significant differences in learning styles between male and female respondents. All p-values exceed the conventional significance threshold of 0.05, with the lowest p-value being 0.331 for the avoidant learning style and the highest being 0.679 for the independent learning style. The t-values range from 0.416 (independent) to 0.976 (avoidant), suggesting minimal variation between gender groups. The overall mean scores (male: 3.819, female: 3.716, t = 0.828, p = 0.410) further reinforce the conclusion that gender does not significantly influence learning style preferences. Thus, the null hypothesis is consistently accepted across all categories, indicating homogeneity in learning style distributions between male and female participants.

**Table 3. T-test Table for Gender**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Learning Styles** | **Gender** | | **t-value** | **p-value** | **Decision on Ho** |
| **Male** | **Female** |
| Independent | 3.900 | 3.845 | 0.416 | 0.679 | Accepted |
| Avoidant | 3.465 | 3.300 | 0.976 | 0.331 | Accepted |
| Collaborative | 4.304 | 4.238 | 0.554 | 0.581 | Accepted |
| Dependent | 4.073 | 4.001 | 0.598 | 0.551 | Accepted |
| Competitive | 3.189 | 2.995 | 0.855 | 0.395 | Accepted |
| Participant | 3.985 | 3.918 | 0.502 | 0.617 | Accepted |
| **Overall Mean** | **3.819** | **3.716** | **0.828** | **0.410** | **Accepted** |

Table 4 presents the independent samples t-test results, it shows no statistically significant differences in learning styles between the two age groups (18–24 and 25–32). All p-values exceed the significance threshold of 0.05, with the lowest at 0.295 (collaborative learning style) and the highest at 0.711 (avoidant learning style). The t-values range from -0.372 (avoidant) to -1.053 (collaborative), indicating that any variations in learning styles between age categories are not meaningful. The overall mean scores (18–24: 3.729, 25–32: 3.921, t = -0.893, p = 0.374) further confirm the homogeneity in learning preferences across age groups. Consequently, the null hypothesis is accepted for all categories, reinforcing that age does not significantly influence learning style preferences.

**Table 4. T-test Table for Age**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Learning Styles** | **Age Category** | | **t-value** | **p-value** | **Decision on Ho** |
| **18 - 24** | **25 - 32** |
| Independent | 3.852 | 3.957 | -0.461 | 0.646 | Accepted |
| Avoidant | 3.333 | 3.443 | -0.372 | 0.711 | Accepted |
| Collaborative | 4.239 | 4.457 | -1.053 | 0.295 | Accepted |
| Dependent | 4.005 | 4.214 | -1.009 | 0.315 | Accepted |
| Competitive | 3.021 | 3.343 | -0.820 | 0.414 | Accepted |
| Participant | 3.921 | 4.114 | -0.835 | 0.405 | Accepted |
| **Overall Mean** | **3.729** | **3.921** | **-0.893** | **0.374** | **Accepted** |

Table 5 presents the ANOVA results, it indicates that for most learning styles, there are no statistically significant differences across year levels. All p-values, except for the competitive learning style, exceed the 0.05 threshold, confirming that learning preferences remain stable regardless of academic standing. The highest p-value is 0.943 for the independent learning style (F = 0.129), suggesting minimal variance across year levels. However, the competitive learning style shows a significant difference (F = 3.767, p = 0.013), leading to the rejection of the null hypothesis. This suggests that year level influences students’ preference for competitive learning, with first-year students scoring the highest (3.548) and third-year students scoring the lowest (2.740). The overall mean scores (first-year: 3.885, second-year: 3.724, third-year: 3.622, fourth-year: 3.740, F = 0.969, p = 0.411) reinforce the conclusion that learning styles are largely unaffected by year level, except for competitive learning tendencies.

**Table 5. ANOVA Table for Year Level**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Learning Styles** | **Year Level** | | | | **F-value** | **p-value** | **Decision on Ho** |
| **1st year** | **2nd year** | **3rd year** | **4th year** |
| Independent | 3.900 | 3.827 | 3.800 | 3.857 | 0.129 | 0.943 | Accepted |
| Avoidant | 3.512 | 3.267 | 3.396 | 3.200 | 0.853 | 0.468 | Accepted |
| Collaborative | 4.244 | 4.176 | 4.216 | 4.417 | 1.019 | 0.387 | Accepted |
| Dependent | 4.040 | 4.033 | 3.872 | 4.135 | 1.028 | 0.384 | Accepted |
| Competitive | 3.548 | 3.082 | 2.740 | 2.765 | 3.767 | 0.013 | Rejected |
| Participant | 4.068 | 3.912 | 3.708 | 4.065 | 2.112 | 0.103 | Accepted |
| **Overall Mean** | **3.885** | **3.724** | **3.622** | **3.740** | **0.969** | **0.411** | **Accepted** |

**3.1 Propose an Intervention Plan for Mathematics Majors at Davao Central College**

Objective: To address the diverse learning styles of Mathematics majors at Davao Central College (DCC), a structured intervention plan should focus on three key areas: enhancing collaborative learning, balancing competitive pressures, and providing academic and institutional support. This approach ensures that students receive a learning experience tailored to their cognitive preferences, fostering both engagement and academic success.

1. Collaborative Learning Enhancement

Research indicates that collaborative learning is the preferred style among Mathematics majors (mean = 4.25). To maximize this strength, the following strategies should be implemented:

* Peer-Assisted Study Groups: Organize structured peer tutoring sessions, where upper-year students’ mentor lower-year students in mathematical problem-solving. This approach not only strengthens conceptual understanding but also fosters a supportive learning community (Vygotsky, 1978).
* Team-Based Learning Activities: Implement collaborative projects, case-based learning, and group discussions to encourage student interaction and cooperative problem-solving (Felder & Silverman, 1988).
* Mathematical Inquiry Workshops: Host interactive seminars that focus on inquiry-based learning, allowing students to work collaboratively on complex mathematical theories and applications.

2. Balancing Competitive Learning Pressures

Findings indicate that competitive learning significantly differs across year levels, particularly among 3rd-Year students, where competitiveness increases (p = 0.037). To ensure students benefit from healthy competition without excessive academic pressure, institutions should implement the following:

* Structured Academic Competitions: Organize friendly mathematics challenges, such as problem-solving contests and logic puzzle tournaments, to foster constructive competitiveness without stress (Zimmerman & Schunk, 2011).
* Self-Regulated Learning Strategies: Conduct workshops focused on self-monitoring, strategic planning, and performance reflection, helping students develop independent study habits and regulate their learning styles (Zimmerman, 2002).
* Growth Mindset Training: Implement resilience-building programs, using Dweck’s (2006) growth mindset framework, encouraging students to view challenges as opportunities for mastery rather than obstacles.

3. Academic Support and Pedagogical Adaptation

To address students who prefer Dependent (4.02) and Participant (3.93) learning styles, tailored instructional approaches should be introduced:

* Personalized Learning Modules: Develop adaptive instruction pathways, ensuring personalized learning experiences for students struggling with mathematical concepts (Felder & Silverman, 1988).
* Faculty Development Initiatives: Train educators to identify student learning styles and adjust teaching methods accordingly, integrating visual, kinesthetic, and participatory techniques into mathematics instruction.
* Gamified Learning Systems: Introduce interactive online learning platforms, such as adaptive quizzes, problem-solving simulations, and AI-driven tutoring, ensuring content delivery caters to different cognitive learning styles (Sun et al., 2023).

4. Institutional Support Initiatives

To ensure long-term effectiveness, institutions must create a supportive academic environment that fosters student engagement and resilience:

* Mentorship and Career Development Programs: Establish mentorship opportunities that connect students with faculty, alumni, and industry professionals, guiding them through academic and career progression (Bandura, 1986).
* Resilience and Stress Management Seminars: Conduct regular workshops focused on academic resilience, mental wellness, and stress-coping mechanisms, helping students navigate competitive learning environments effectively (Dweck, 2006).
* Longitudinal Tracking and Learning Style Assessment: Implement yearly student evaluations to monitor shifts in learning preferences, allowing for dynamic intervention adjustments that meet evolving student needs.

**4. DISCUSSION**

The demographic profile of respondents reveals a substantial gender imbalance, with females comprising 75.5% of the sample, which may influence learning style tendencies (Johnson, 2020). Additionally, the age distribution indicates that the majority (93.4%) are within the 18–24 bracket, reflecting a predominantly younger respondent pool whose cognitive and motivational factors are likely shaped by emerging adulthood (Arnett, 2015). The representation across year levels shows the largest group as second-year students (31.1%), with first- and third-year students each at 23.6%, and fourth-year students the smallest at 21.7%. This uneven distribution suggests that findings may primarily reflect perspectives of early academic cohorts, affecting the interpretation of learning patterns (Tinto, 1993). The demographic structure underscores the need to consider sample composition when generalizing educational insights.

The analysis of learning style preferences suggests that respondents predominantly favor collaborative learning (M = 4.25, SD = 0.529), consistent with Vygotsky’s (1978) socio-cultural theory, which emphasizes peer interaction in knowledge construction. The Dependent (M = 4.02, SD = 0.530) and Participant (M = 3.93) styles further support structured engagement, aligning with Bandura’s (1986) social learning principles. Meanwhile, the Independent style (M = 3.86) reflects a balanced preference for autonomy, reinforcing self-regulated learning perspectives (Zimmerman, 2002). The Avoidant (M = 3.34) and Competitive (M = 3.04) styles indicate indecisiveness, with the Competitive learning style exhibiting the highest variability (SD = 1.001), suggesting diverse motivational orientations (Dweck, 1986). These findings highlight the predominance of socially driven learning preferences while underscoring variability in competitive attitudes within the sample.

The independent samples t-test results reveal no statistically significant differences in learning styles between male and female respondents, as all p-values exceed the standard threshold of 0.05, confirming homogeneity across gender (Pashler et al., 2008). The lowest p-value (0.331) for avoidant learning and the highest (0.679) for independent learning indicate minimal variance, with t-values ranging from 0.416 to 0.976, suggesting weak gender-based differentiation. The overall mean scores (male: 3.819, female: 3.716, t = 0.828, p = 0.410) reinforce this conclusion, indicating that gender does not significantly influence learning style preferences, aligning with prior research that questions the role of biological sex in cognitive learning patterns (Hyde, 2005). Consequently, the null hypothesis is upheld, confirming that learning style distributions remain stable across male and female participants.

The independent samples t-test results indicate no statistically significant differences in learning styles between respondents aged 18–24 and 25–32, as all p-values exceed the 0.05 threshold, confirming learning style homogeneity across age groups (Pashler et al., 2008). The lowest p-value (0.295) for collaborative learning and the highest (0.711) for avoidant learning suggest negligible age-based variance, with t-values ranging from -0.372 to -1.053, reinforcing weak differentiation. The overall mean scores (18–24: 3.729, 25–32: 3.921, t = -0.893, p = 0.374) further support this conclusion, aligning with research indicating that learning preferences are influenced more by contextual and pedagogical factors than age alone (Illeris, 2007). Thus, the null hypothesis is retained, affirming that learning styles remain stable across these age categories.

The ANOVA results reveal that learning styles remain largely consistent across year levels, with all p-values exceeding the 0.05 significance threshold except for the competitive learning style (F = 3.767, p = 0.013), which indicates a statistically significant difference (Pashler et al., 2008). The highest p-value (0.943) for independent learning and the lowest (0.013) for competitive learning suggest that academic standing has minimal impact on most learning preferences, aligning with prior findings that emphasize contextual over structural influences on learning behaviors (Illeris, 2007). Notably, first-year students exhibit the highest competitive learning preference (M = 3.548), while third-year students report the lowest (M = 2.740), supporting theories that competition may diminish as students progress through their academic journey (Deci & Ryan, 2000). The overall mean scores (first-year: 3.885, second-year: 3.724, third-year: 3.622, fourth-year: 3.740, F = 0.969, p = 0.411) confirm that learning styles remain generally stable across year levels, reinforcing the acceptance of the null hypothesis in all cases except for competitive learning.

The findings suggest that learning style preferences are largely consistent across gender, age, and year level, reinforcing the idea that individual learning tendencies are shaped more by contextual and pedagogical factors than demographic variables (Illeris, 2007; Pashler et al., 2008). The dominance of collaborative, dependent, and participant learning styles underscores the importance of structured and socially driven learning environments, aligning with Vygotsky’s (1978) and Bandura’s (1986) theories. However, the significant variation in competitive learning across year levels (F = 3.767, p = 0.013) suggests that academic progression influences motivation and engagement strategies (Deci & Ryan, 2000). These insights highlight the need for educational frameworks that accommodate diverse learning orientations while fostering adaptive instructional approaches to enhance student engagement.

**5. CONCLUSION AND RECOMMENDATIONS**

To optimize the learning experience of Mathematics majors at Davao Central College (DCC), educators may incorporate collaborative learning strategies, as students demonstrated a strong preference for peer-assisted environments. Implementing group problem-solving activities, peer tutoring, and structured discussions will foster a deeper understanding of mathematical concepts, aligning with Vygotsky’s (1978) socio-cultural learning theory that emphasizes knowledge construction through social interactions. Given the observed increase in competitive learning styles among upper-year students, institutions should introduce mentorship programs and formative assessments to ensure that competitiveness remains constructive rather than stress-inducing. These strategies can support self-regulated learning, helping students balance performance-driven motivation with adaptive study techniques (Zimmerman & Schunk, 2011). Additionally, universities should cultivate institutional support systems that encourage intrinsic motivation, integrating academic resilience workshops and psychological interventions to help students navigate academic pressures effectively (Dweck, 2006). Future research should explore longitudinal trends in students’ learning preferences, examining the role of institutional culture, peer influences, and psychological factors in shaping competitive learning behaviors over time. By integrating evidence-based strategies and adaptive pedagogical frameworks, institutions can enhance student engagement while fostering a balanced and supportive learning environment.

**Ethical Approval:**

The researchers sought the approval from the Program head of the College of Education and Liberal Arts. Approval to conduct survey to the students as respondents.

**Disclaimer (Artificial intelligence)**

Option 1:

Author(s) hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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