Northern Economic Review
ISSN: 0262-0383
Vol. 16, No. 1 (2025)
DOI: https://doie.org/10.10399/NER.2025592102

Multiple Intelligences in Management Education: A Path Analysis for Sustainable Leadership

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Abstract:

This study explores the role of Multiple Intelligences (MI) in management education, emphasizing their importance in shaping sustainable educational and professional outcomes. Employing a quantitative design, the Multiple Intelligence profiles of management students were analyzed in relation to their academic performance (CGPA). Factor Analysis was initially used for dimensionality reduction, identifying three key intelligence factors: Intrapersonal Skills, Logical Reasoning, and Spatial Coordination. Subsequently, Path Analysis—a streamlined variant of Structural Equation Modeling (SEM) appropriate for modest sample sizes—was utilized to examine direct and indirect relationships among these factors and academic performance, applying a 90% confidence interval to accommodate the exploratory nature of the study. Results revealed a significant predictive relationship between Logical Reasoning and Spatial Coordination; however, direct relationships between the intelligence factors and academic performance were positive but not statistically significant. These outcomes highlight the potential practical significance of MI in enhancing professional adaptability and leadership capabilities, suggesting that educational institutions could benefit from integrating personalized, intelligence-focused strategies into curricula. The findings provide educators and policymakers with evidence-based recommendations to cultivate human-centric skills, ensuring students' professional resilience and adaptability in increasingly AI-driven workplaces.

Keywords: Multiple Intelligences, Academic Performance, Management Education, Factor Analysis, Path Analysis, Sustainable Leadership, Personalized Education

Introduction:

In the evolving field of management education, there is a need to develop sustainable practices that not only enhance academic performance but also prepare students to tackle challenges of the modern business world. As AI increasingly transforms workplaces, management education must develop skills such as emotional intelligence, creativity, and critical thinking to prepare students for sustainable leadership roles. Sustainable management education aims to cultivate a diverse set of skills. These include cognitive and interpersonal abilities that are crucial for success in academic and professional settings (Dereje, Lamba, Gemechu, & Kenea, 2025). This paper examines the intricate relationships between multiple intelligences and their influence on academic performance in management education. To achieve this, Path Analysis is employed, a statistical method uniquely suited for analyzing interactions between variables, such as intrapersonal skills, logical reasoning, and spatial coordination, and their observable outcomes, such as Cumulative Grade Point Average (CGPA).

The urgency for integrating sustainability into management education stems from the demand that a workplace requires leaders to be not only adept at navigating current markets but also capable of anticipating and mitigating future challenges. In this context, sustainability refers to developing educational practices that foster skills essential for long-term viability—skills that contribute to a student's ability to perform academically and succeed professionally in a sustainable manner.

This study leverages Path Analysis to provide a comprehensive analysis of factors created by combining multiple intelligences contribute to achieving high Cumulative Grade Point Average (CGPA) which a key indicator of academic success in management education. With the help of factor analysis, three factors are created. One focuses on intrapersonal skills, one on logical reasoning and one on spatial coordination. Intrapersonal Skills, which involve self-awareness and emotional intelligence are crucial for personal development and leadership (Mehta, 2025). Logical reasoning serves as the foundation of critical thinking and decision-making, essential for effective strategic management and problem-solving in complex scenarios (Incebacak & Tungac, 2024). Meanwhile, spatial coordination, though more specialized, significantly impacts fields such as project management and logistics by facilitating institutional and logistical integration within dynamic operational environments (Franco et al., 2025). Given the relatively small sample size (N=52), Path Analysis was chosen due to its methodological suitability for limited datasets (Kline, 2015).

By examining the direct impacts of these skills on CGPA, the paper will assess their relative importance in predicting academic performance and provide insights into how management education programs can be structured to enhance these capabilities. The ultimate goal is to not only improve immediate academic outcomes but also equip students with the skills necessary to thrive in sustainable business practices. As artificial intelligence (AI) revolutionizes industries with its efficiency in logical reasoning and data-driven decision-making (Brynjolfsson & McAfee, 2014), uniquely human abilities like emotional intelligence, ethical reasoning, and creativity (Goleman, 1995) have become indispensable in maintaining the relevance of human contributions. Sustainable management education must therefore focus on nurturing these "AI-resistant" intelligences to prepare students for roles that leverage human strengths alongside AI capabilities(Mittal, Vashist, & Chaudhary, 2024). As AI continues to excel in tasks requiring logical reasoning and data-driven decision-making, uniquely human capabilities—such as empathy, ethical decision-making, and innovative thinking—become even more vital (Holmes & Wheeler, 2024). These traits underscore the need for a paradigm shift in management education, where curricula must prioritize the development of these "AI-resistant" intelligences to prepare future leaders for indispensable roles in AI-augmented environments.

By offering evidence-based recommendations, this study contributes significantly to the discourse on educational sustainability within management education. The findings provide actionable insights for educators and policymakers to design curricula that emphasize the development of multiple intelligences—such as intrapersonal skills, logical reasoning, and spatial coordination—that are essential for academic success and professional resilience. These recommendations align with the evolving demands of AI-augmented workplaces, ensuring that future graduates are not only academically prepared but also equipped with the "AI-resistant" skills necessary to excel in dynamic, technology-driven environments. This research ultimately supports the broader goal of fostering sustainable educational practices that empower students to thrive in the face of modern and future business challenges.

Literature Review:

Theoretical Foundations of Multiple Intelligences

Howard Gardner's seminal *Frames of Mind* (1983) challenges the traditional notion of intelligence as a singular, IQ-dominated measure. Instead, Gardner proposes a pluralistic framework of Multiple Intelligences (MI), encompassing diverse cognitive abilities such as logical-mathematical, linguistic, spatial, musical, bodily-kinesthetic, interpersonal, intrapersonal, and naturalistic intelligences. This groundbreaking theory redefines intelligence as a spectrum of distinct capabilities, each contributing uniquely to individual learning and problem-solving.

In management education, MI theory provides a robust foundation for personalized learning approaches, enabling curricula to cater to diverse learner profiles. By integrating MI theory, educators can nurture skills such as intrapersonal intelligence, which supports emotional intelligence and self-awareness, and logical-mathematical intelligence, which underpins critical thinking and decision-making. These intelligences are critical for navigating the challenges of both academic and professional settings.

Cognitive Skills in Management Education

Northern Economic Review
ISSN: 0262-0383
Vol. 16, No. 1 (2025)
DOI: https://doie.org/10.10399/NER.2025592102

The application of MI theory in management education highlights the growing recognition of cognitive skills—especially intrapersonal and logical-mathematical intelligences—as vital components of leadership and strategic decision-making. Marks (2023) emphasizes the increasing significance of cognitive abilities in shaping educational and labor market outcomes, signaling a shift in the skills that modern educational systems must prioritize. These findings align with McGregor and Frodsham's (2023) concept of "Scientific Intelligence," which underscores the role of targeted skill development in fostering academic and professional advancement.

Empirical studies also highlight the practical relevance of MI theory in educational outcomes. For example, research by the University of Minnesota (2023) identifies strong correlations between cognitive abilities, personality traits, and life outcomes, reinforcing the importance of cultivating a range of intelligences. Similarly, the Center for College Workforce Transitions (CCWT) demonstrates how workplace training programs can enhance intrapersonal and interpersonal skills, crucial for collaboration, communication, and job satisfaction. Furthermore, regression-based analytical approaches, including Path Analysis, have previously demonstrated robustness in examining relationships among educational and psychological variables in management education contexts, particularly when working with moderate sample sizes (D'Silva, Shaikh, & D'Silva, 2022).

Integration of Intrapersonal Skills and Logical Reasoning

Intrapersonal skills involve self-awareness and emotional intelligence, crucial for personal development and leadership (Mehta, 2025). The relationship between intrapersonal skills and logical reasoning is grounded in their mutual enhancement of cognitive processing. Emotional regulation, a core component of intrapersonal skills, facilitates clearer logical analysis by managing distractions and emotional biases, thereby enhancing decision-making capabilities (Goleman, 1995).

Spatial Coordination and Cognitive Development

Further, spatial coordination supports the ability to visualize and manipulate data, enhancing understanding in subjects requiring spatial judgment. The development of spatial skills is often linked to improved logical reasoning, as both require abstract and systematic thinking (Newcombe & Stieff, 2012).

Bridging Cognitive Skills and Workplace Relevance

With AI increasingly automating routine tasks and data-driven analyses, uniquely human traits—such as empathy, ethical judgment, and adaptability—become indispensable. McGregor and Frodsham (2023) argue that while AI excels in logical-mathematical and spatial tasks, it lacks the capacity for emotional intelligence and ethical reasoning. These findings underscore the need for education systems to focus on developing complementary human skills that align with AI capabilities.

Moreover, sustainable management education must prioritize leadership skills that thrive in dynamic and uncertain environments. Reeves and Whitaker (2020) highlight creativity and emotional intelligence as critical for fostering human-AI collaboration, ensuring that individuals remain indispensable in technology-driven workplaces. This perspective aligns with the broader goals of MI-based education, which seeks to future-proof students for sustainable career paths.

Sustainable Education and Multiple Intelligences

Sustainable management education extends beyond immediate academic outcomes to equip students with the skills necessary for long-term professional resilience. By embedding MI theory into curricula, educational institutions can holistically develop diverse intelligences that address the complexities of global business environments. Gardner's (1983) framework serves as a guiding principle for cultivating cognitive, interpersonal, and intrapersonal skills essential for leadership and adaptability.

As AI transforms industries, sustainable education must focus on nurturing "AI-resistant" intelligences—such as creativity, ethical reasoning, and empathy—to complement AI capabilities. For example, Goleman (1995) emphasizes the role of emotional intelligence in effective leadership, while McGregor and Frodsham (2023) advocate for curricula that prioritize human traits over replicable AI competencies. By fostering these intelligences, MI-based education ensures that students are prepared to collaborate with AI systems, driving innovation and sustainability in the workplace.

Implications for Management Education

The empirical evidence presented in this study underscores the transformative potential of integrating MI theory into management education. Path analysis revealed significant interrelationships among multiple intelligence factors (e.g., Logical Reasoning significantly predicting Spatial Coordination). However, direct predictions of academic performance (CGPA) by these intelligences were positive but statistically non-significant, indicating potential yet unconfirmed influences, highlighting their importance in educational design.

As industries continue to evolve, sustainable management education must adapt by focusing on human strengths that complement AI capabilities. This strategy ensures that students are not merely competitive in the labor market but also equipped to lead in an increasingly digital and complex business landscape.

Research Objectives and Hypotheses

Research Objectives

This study aims to analyze the relationship between multiple intelligences (MI) and academic performance in management education. The specific objectives are to:

1. **Extract Latent Factors from MI Data**: Use factor analysis (FA) to identify and combine latent dimensions of multiple intelligences.
2. **Examine the Relationship Between Identified Factors and CGPA**: Apply Structural Equation Modeling (SEM) to evaluate how the extracted factors relate to academic performance, as measured by Cumulative Grade Point Average (CGPA).
3. **Determine the Predictive Strength of Each Factor**: Assess which of the identified MI factors most significantly influences academic success in management education.

Research Hypotheses:

1. H1: Factor analysis will identify distinct dimensions of multiple intelligences from the dataset.
2. H2: The identified intrapersonal factor impacts CGPA.
3. H3: The identified logical reasoning factor impacts CGPA.
4. H4: The identified spatial coordination factor impacts CGPA.
5. H5: The combination of the identified factors has a greater influence on CGPA than any single factor.

Methodology:

Research Design and Analytical Approach

This study adopts a quantitative, cross-sectional research design to examine the relationship between multiple intelligences (MI) and academic performance among management students. Data were collected from 52 students enrolled in a management program using the validated *Multiple Intelligence Profiling Questionnaire III* (MIPQ III) to assess their MI profiles. Academic performance was captured through each student's Cumulative Grade Point Average (CGPA).

Northern Economic Review
ISSN: 0262-0383
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While Structural Equation Modeling (SEM) theoretically provides a comprehensive analytical framework to simultaneously evaluate complex relationships involving latent constructs and observed variables, it typically requires larger sample sizes (usually 200 or more observations) to ensure stable parameter estimates and adequate statistical power (Kline, 2015). Given the limited sample size in this study (N=52), SEM was not feasible due to potential estimation instability, convergence issues, and low statistical power. Consistent with previous methodological decisions within management education research involving similar sample constraints (D'Silva, Shaikh, & D'Silva, 2022), this study employed Path Analysis, a simpler form of SEM involving only observed composite scores, which reduces model complexity and enhances interpretability with smaller datasets (Weston & Gore, 2006).

1. **Exploratory Factor Analysis (EFA):**

   The first step involved an **Exploratory Factor Analysis (EFA)** to identify latent constructs representing the various intelligences. EFA was conducted on the MI questionnaire data to reduce dimensionality and group the numerous survey items into a smaller number of factors. This analysis revealed underlying factors corresponding to broad intelligence domains. The measurement model for EFA is expressed as

   For observed variables X_{ij} loading onto their respective latent factors F_k:

$$X_{ij} = \lambda_{jk} F_k + \epsilon_{ij}$$

   Where: - X_{ij} denotes observed variables (e.g., ling_1, logi_1), F_k represents latent factors (e.g., intrapersonal, logical, spatial intelligences), λ_{jk} are factor loadings, and ϵ_{ij} denotes residual error. This model allowed us to identify key latent factors that align with theoretical dimensions of MI and explain the variance in observed variables.

Specifically, three latent factors were extracted, each aligning with a theoretical dimension of MI: an Intrapersonal intelligence factor, a Logical Reasoning factor, and a Spatial Coordination factor. These factors were chosen based on eigenvalues, scree plot inspection, and interpretability in the context of MI theory. The EFA ensured that each identified factor captures the shared variance of a set of related MI items, providing composite measures (factor scores) for use in subsequent analysis. This satisfied the first research objective by distilling the multiple intelligence measures into distinct latent dimensions.

In theory, SEM could be applied subsequently.

1. **Structural Equation Modeling (SEM) – Conceptual Model**

   After extracting the MI factors, a conceptual structural model was formulated to illustrate how these latent factors could influence academic performance. Figure 1 presents this hypothetical SEM model, where the three latent MI factors (Intrapersonal, Logical, and Spatial intelligences) are depicted as exogenous constructs predicting the endogenous outcome (CGPA). In a full SEM framework, one would formally link each latent factor to CGPA with path coefficients (while also modeling any inter-factor correlations or mediated paths as theorized). This combined measurement-and-structural model provides a comprehensive theoretical framework for understanding how specific dimensions of intelligence contribute to academic success.

   The structural model is expressed as:

   The SEM model links the latent factors MR_k to the dependent variable $CGPA$:

$$CGPA = \beta_1 MR1 + \beta_2 MR2 + \beta_3 MR3 + \cdots + \beta_k MRk + \zeta$$

   Where: - β_k: Path coefficient for latent factor MR_k. - ζ: Residual error in CGPA.

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Combining both models gives:

$$
\begin{aligned}
X_{ij} &= \lambda_{jk} F_k + \epsilon_{ij} \quad \text{(Measurement Model)} \\
CGPA &= \beta_1 MR1 + \beta_2 MR2 + \beta_3 MR3 + \cdots + \beta_k MRk + \zeta \quad \text{(Structural Model)}
\end{aligned}
$$

Together, these models provide a comprehensive framework for understanding how specific dimensions of intelligence, such as intrapersonal, logical, and spatial intelligences, contribute to academic performance.

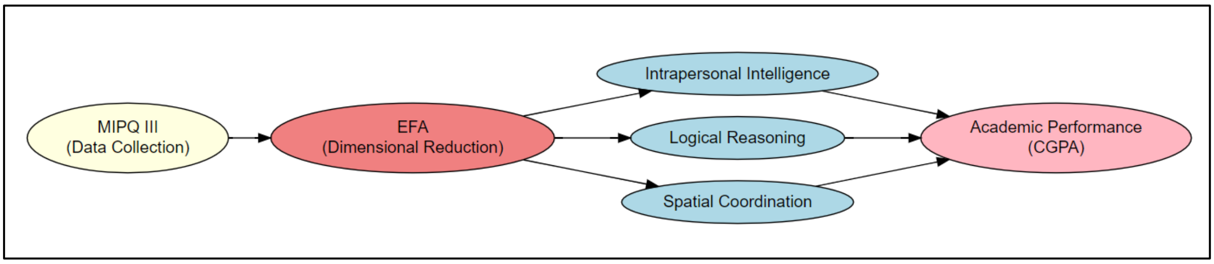

Figure 1: Hypothetical structural model for MI factors impacting CGPA

However, no full SEM was actually estimated in this study. Given the sample size limitations discussed above, implementing the SEM empirically was not feasible. Instead, the SEM diagram and model are presented for theoretical context, whereas the actual statistical testing of relationships was carried out using path analysis with the observed factor scores.

2. Path Analysis

The second step—and primary analytical technique for this study—was a regression-based **Path Analysis** to examine the direct and indirect effects of the three MI factors on academic performance (CGPA). In this path model, each of the three EFA-derived factors serves as an observed predictor variable. The hypothesized relationships tested in the model were as follows:

- **Direct Effects:** Each intelligence factor (Intrapersonal skills, Logical reasoning, and Spatial coordination) was expected to have a direct effect on CGPA (academic performance).
- **Indirect Pathways:** Potential mediation pathways were also considered. In particular, the model allowed for the possibility that Intrapersonal intelligence influences Logical reasoning, and Logical reasoning influences Spatial coordination, thereby creating indirect effects of one factor on CGPA through another.

All paths were estimated using multiple regression techniques appropriate for observed variables (the factor scores) rather than latent constructs. This regression-based path analysis approach enables the assessment of a causal model while maintaining simplicity and interpretability. By using the factor score composites in place of latent variables, the analysis substantially reduces the number of parameters to be estimated, which is advantageous for a smaller dataset. This approach aligns with recommendations for handling small samples, as it forgoes the complexity of a full SEM in favor of a more parsimonious model. In summary, path analysis allowed us to test the study's hypotheses about the influence of multiple intelligences on academic performance in a statistically rigorous yet sample-appropriate manner. Each path coefficient in the model was examined for significance and strength, providing insight into both the direct contributions of the intelligence factors to CGPA and any mediated (indirect) effects among the factors themselves. Given the modest sample size (N=52) and to adequately capture potentially meaningful relationships that may be obscured by conventional confidence thresholds, a **90% confidence interval ($p < 0.10$)** was adopted for interpreting statistical significance in this study. The results from this path analysis inform our understanding of which intelligence domains are most predictive of academic success and how they interrelate in the context of management education.

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Analysis:

Measure	*Mean*	*Median*	*Min*	*Max*	*SD*
Linguistic	3.375	3.250	1.75	5.00	0.686887
Logical	3.308	3.250	1.00	5.00	0.883697
Spatial	3.471	3.500	1.75	5.00	0.697778
Bodily_Kinesthetic	3.519	3.625	1.75	5.00	0.893668
Musical	3.327	3.500	1.00	5.00	0.987096
Interpersonal	3.505	3.500	1.00	5.00	0.916208
Intrapersonal	3.620	3.750	1.00	5.00	0.756492
Naturalistic	4.090	4.000	1.00	5.00	0.855879
Spiritual	3.947	4.000	1.00	5.00	0.880531
CGPA	3.540	3.590	2.74	3.92	0.283573

Table 1: Descriptive Statistics of MI Profile and CGPA

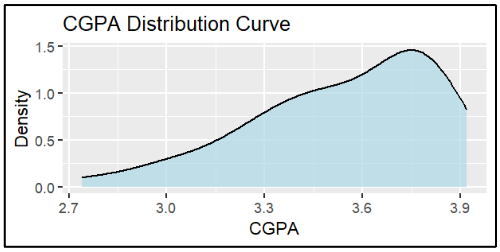

Figure 2: Distribution of CGPA

The data reveals that participants scored highest in Naturalistic intelligence (mean: 4.09) and Spiritual intelligence (mean: 3.95), indicating these are their strongest domains, while Logical intelligence (mean: 3.31) is among the lower averages, suggesting room for improvement in reasoning skills. Musical intelligence shows the highest variability (SD: 0.99), indicating significant differences in participants' abilities in this area. CGPA, with a mean of 3.54 and low variability (SD: 0.28), reflects consistent academic performance across participants. Overall, the data suggests strengths in observational and ethical reasoning, with potential for targeted development in reasoning and creativity-focused areas like Logical and Musical intelligences. The CGPA distribution curve shows a right-skewed pattern with most values concentrated between 3.3 and 3.9, reflecting strong academic performance among participants. The density peaks around 3.7, indicating it is the most frequent CGPA score. This highlights the overall consistency and high academic standing within the group.

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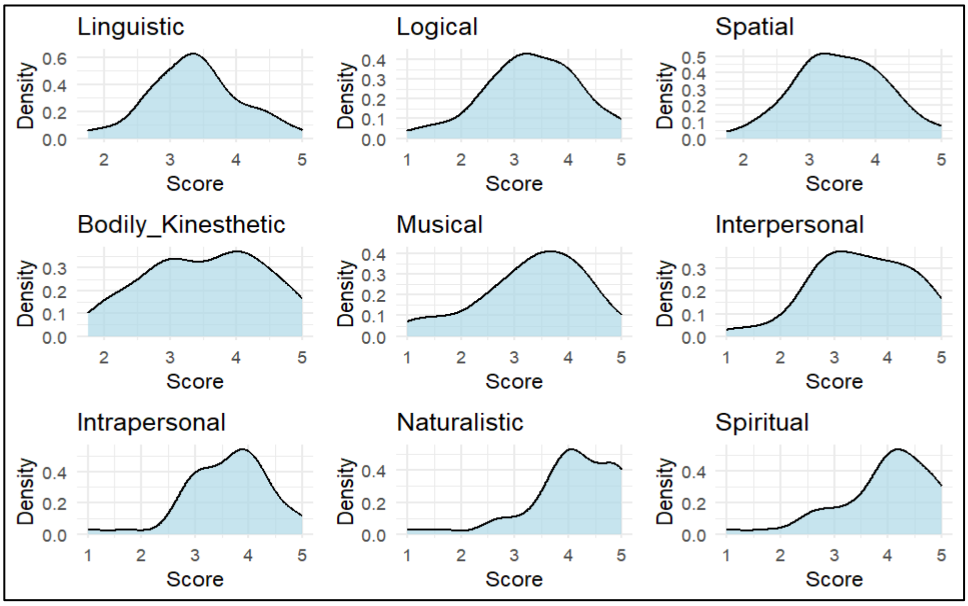

Figure 3: Distribution of Multiple Intelligences

The density plots for the multiple intelligences show varied distributions across the nine categories. Most intelligences, such as Linguistic, Logical, and Spatial, have a balanced spread with peaks around scores of 3 to 4, indicating moderate to high proficiency. Naturalistic and Spiritual intelligences exhibit a shift toward higher scores, suggesting strengths in these domains for the group. In contrast, Musical intelligence displays a broader distribution with higher variability, reflecting significant differences in participants' musical abilities. These plots highlight the diverse skill profiles within the dataset.

Table 1: Factor Loadings (Pattern Matrix) based upon Correlation Matrix

Variable	*MR1*	*MR2*	*MR4*	*MR3*	*MR5*	*MR7*	*MR6*	*MR8*	*Communalities*	*Uniqueness*
logi_1	0.05	0.85	0.16	0.00	0.09	0.13	0.02	-0.02	0.77	0.2313
logi_2	-0.02	0.76	0.11	0.15	0.25	0.13	-0.12	-0.05	0.70	0.2970
logi_3	0.23	0.70	-0.15	0.04	0.14	0.04	-0.01	-0.08	0.60	0.4015
logi_4	0.48	0.42	-0.05	0.26	0.02	0.01	-0.08	0.24	0.54	0.4568
ling_1	0.04	-0.04	-0.02	-0.05	-0.02	0.12	0.98	0.16	1.00	0.0041
ling_2	0.15	-0.69	-0.02	0.25	-0.05	0.25	0.11	0.11	0.65	0.3518
ling_3	-0.01	0.21	0.01	-0.08	0.04	0.37	0.09	0.12	0.21	0.7919
ling_4	0.26	-0.06	0.00	-0.03	0.06	0.30	0.09	0.65	0.59	0.4061
spat_1	0.10	0.52	0.04	0.52	-0.13	-0.22	0.24	0.10	0.69	0.3131
spat_2	0.02	0.50	0.19	0.48	-0.02	0.10	0.11	0.11	0.56	0.4402
spat_3	0.23	0.09	-0.03	0.45	0.11	-0.07	-0.15	0.09	0.31	0.6914
spat_4	0.13	-0.08	0.20	0.10	-0.12	0.13	0.07	0.38	0.25	0.7470
body_1	0.04	-0.07	0.02	0.23	0.06	0.81	0.04	0.17	0.75	0.2465
body_2	0.08	-0.08	0.15	0.79	0.23	0.12	0.02	-0.12	0.73	0.2651
body_3	0.33	0.03	0.09	0.59	0.03	0.43	-0.04	0.02	0.65	0.3498
body_4	0.09	0.04	0.29	0.68	0.21	0.04	0.03	-0.01	0.61	0.3913
musi_1	0.24	0.10	0.02	0.17	0.69	0.12	-0.04	-0.12	0.60	0.3954
musi_2	0.10	0.25	0.38	0.16	0.59	-0.15	-0.10	0.19	0.65	0.3498
musi_3	0.14	0.33	0.17	0.21	0.78	0.09	0.10	-0.02	0.83	0.1693
musi_4	0.13	-0.02	0.47	0.42	0.33	0.05	0.06	0.20	0.56	0.4361
inter_1	0.21	0.00	0.69	0.25	0.17	-0.08	0.12	0.04	0.63	0.3654
inter_2	0.42	0.08	0.79	0.05	0.03	0.05	-0.14	0.06	0.84	0.1572
inter_3	0.29	0.17	0.81	0.14	0.12	0.09	0.03	0.02	0.80	0.1967
inter_4	0.63	0.10	-0.07	-0.01	0.17	-0.16	-0.05	0.27	0.54	0.4564
intra_1	0.77	0.05	-0.07	0.06	0.34	-0.16	-0.16	0.15	0.79	0.2117
intra_2	0.63	-0.03	0.15	0.23	0.06	0.02	0.02	0.15	0.49	0.5069
intra_3	0.61	0.21	0.03	-0.03	0.18	0.12	0.06	-0.15	0.49	0.5079
intra_4	0.28	-0.16	0.17	0.25	0.37	0.11	0.37	-0.28	0.57	0.4343
natur_1	0.73	0.02	0.24	0.07	0.16	0.05	0.00	0.23	0.67	0.3298

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natur_2	0.77	-0.02	0.24	0.14	0.05	-0.04	0.13	0.10	0.70	0.2961
natur_3	0.64	0.10	0.11	0.11	-0.01	-0.10	0.30	-0.10	0.55	0.4504
spirit_1	0.67	-0.11	0.31	0.19	0.08	0.11	0.19	0.06	0.64	0.3551
spirit_2	0.72	0.07	0.36	0.17	-0.06	0.21	-0.07	0.12	0.75	0.2540
spirit_3	0.76	-0.07	0.19	0.11	0.03	0.27	-0.10	0.00	0.72	0.2800
spirit_4	0.68	0.00	0.48	0.00	-0.05	0.07	-0.01	-0.17	0.73	0.2660

Table 2: Factor Summaries

Factor	*SS Loadings*	*Proportion Var*	*Cumulative Var*	*Proportion Explained*	*Cumulative Proportion*
MR1	6.36	0.18	0.18	0.29	0.29
MR2	3.37	0.10	0.28	0.15	0.44
MR4	3.08	0.09	0.37	0.14	0.58
MR3	2.96	0.08	0.45	0.13	0.71
MR5	2.19	0.06	0.51	0.10	0.81
MR7	1.56	0.04	0.56	0.07	0.88
MR6	1.49	0.04	0.60	0.07	0.95
MR8	1.19	0.03	0.63	0.05	1.00

Measure	*Value*
RMSR	0.05
df Corrected RMSR	0.06
Tucker Lewis Index	0.879
RMSEA	0.038
RMSEA 90% CI	0-0.069
BIC	-979.3
Fit based on Off-Diagonal Values	0.98

Table 3: Statistical and Fit Indices of Factor Analysis

To determine the optimal number of factors for analysis, a scree plot was generated (Figure X). The plot shows a clear elbow point after the third factor, indicating that only three factors explain most of the variance in the data. Based on this, we retained three factors (MR1, MR2, MR3) for further analysis and excluded the remaining factors due to their low eigenvalues and limited explanatory power.

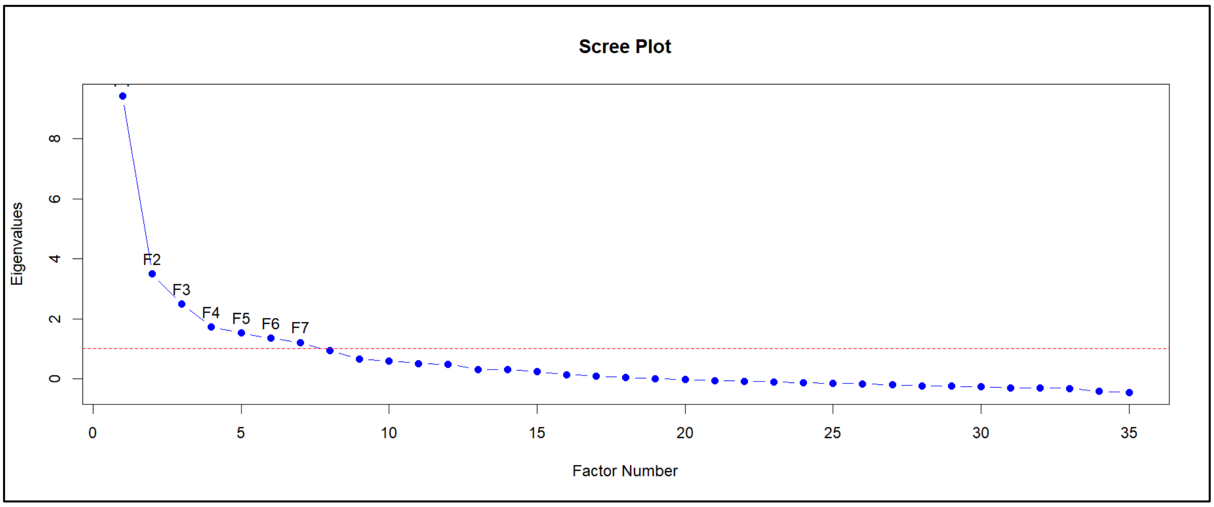

Figure 4: Scree Plot for Factor Analysis

Factor Loadings Interpretation

MR1 (Intrapersonal Skills Factor):

- Dominated by variables intra_1, intra_2, intra_3, and natur_1, natur_2, natur_3, which suggest this factor encapsulates elements related to personal self-awareness and a connection to nature. High loadings on intra_1 (0.77), natur_1 (0.73), and natur_2 (0.77) indicate strong intrapersonal skills and an understanding or appreciation of natural elements.

MR2 (Logical Reasoning Factor):

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ISSN: 0262-0383
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- Strongly loads on logi_1 (0.85), logi_2 (0.76), and logi_3 (0.70). This factor represents logical and analytical thinking skills. High loadings indicate inclination towards logical reasoning and problem solving.

MR3 (Spatial Coordination Factor):

- Features significant loadings from spat_1 (0.52), spat_2 (0.50), and body_2 (0.79), suggesting this factor is characterized by spatial awareness and physical coordination. It implies an ability to manage physical space and body movements effectively.

Statistical and Fit Indices Interpretation

- Root Mean Square of the Residuals (RMSR) at 0.05 and df corrected RMSR at 0.06 suggest a reasonably good fit, indicating minor discrepancies between the observed and predicted data.
- Tucker Lewis Index of 0.879 is below the preferred threshold of 0.95 but still indicates an acceptable fit.
- RMSEA (Factors Analysis) of 0.038 with confidence intervals ranging from 0 to 0.069 signifies a good fit, as values below 0.05 are generally considered excellent.
- BIC of -979.3 suggests the model is highly effective relative to other potential models, given the negative value indicating a strong preference over more complex or simpler models.

Using the three latent factors, the adjusted structural model is as follows:

Structural Equation:

$$CGPA = \beta_1 MR1 + \beta_2 MR2 + \beta_3 MR3 + \zeta$$

Where: - $\beta_1, \beta_2, \beta_3$: Path coefficients representing the effect of each latent factor on CGPA. - ζ: Residual error term representing unexplained variance in CGPA.

The Table: Summary of Path Analysis Results

Category	*Item*	*Estimate*	*Standard Error*	*Z-value*	*P-value*	*Standardized Loading (Std.lv)*
Fit Indices						
	Chi-square	75.685			0.098	
	Degrees of Freedom	61				
	CFI	0.938				
	TLI	0.921				
	RMSEA	0.068				
	SRMR	0.089				
Latent Variables Intrapersonal Skills	intra_1	1.000	0.223	4.453	0.000	0.752
	intra_2	0.995	0.214	4.146	0.000	0.634
	intra_3	0.888	0.220	6.054	0.000	0.592
	natur_1	1.330	0.189	5.922	0.000	0.851
	natur_2	1.118	0.226	4.348	0.000	0.831
	natur_3	0.981	0.323	3.859	0.000	0.620
Logical Reasoning	logi_1	1.000	0.143	5.699	0.000	0.799
	logi_2	0.816	0.152	4.409	0.000	0.862
	logi_3	0.669	0.183	4.515	0.000	0.627
Spatial Coordination	spat_1	1.000	0.193	4.111	0.000	0.643
	spat_2	1.247	0.175	2.455	0.014	0.943
	body_2	0.612	0.266	4.979	0.000	0.369

Northern Economic Review
ISSN: 0262-0383
Vol. 16, No. 1 (2025)
DOI: https://doie.org/10.10399/NER.2025592102

Regressions						
	LogicalReasoning ~ IntrprsnlSklls	0.286	0.263	1.089	0.276	0.174
	SpatialCoordination ~ LogicalReasnng	0.442	0.147	3.018	0.003	0.647
CGPA Regressions						
	CGPA ~ IntrprsnlSklls	0.066	0.062	1.071	0.284	0.156
	CGPA ~ LogicalReasnng	0.047	0.054	0.871	0.384	0.184
	CGPA ~ SpatialCordntn	0.015	0.076	0.191	0.848	0.039

Table 4: Statistical and Fit Indices of Path Analysis

Model Fit

- **Chi-square Test**: A non-significant chi-square (p = 0.098) suggests a good fit of the model to the data. In Path Analysis, a non-significant chi-square value indicates that the model does not significantly deviate from the observed data, supporting the hypothesized model structure.
- **CFI and TLI**: Both the Comparative Fit Index (CFI = 0.938) and Tucker-Lewis Index (TLI = 0.921) are close to 1, indicating an excellent fit. Values above 0.90 are typically considered indicative of a well-fitting model, suggesting that the model provides a good representation of the underlying data structure.
- **RMSEA**: The Root Mean Square Error of Approximation (RMSEA = 0.068) of Path Analysis falls below the 0.08 threshold, further suggesting a reasonable fit. The confidence interval (0.000, 0.114) and the P-values associated with RMSEA thresholds suggest moderate uncertainty in model precision, warranting cautious interpretation.
- **SRMR**: The Standardized Root Mean Square Residual (SRMR = 0.089) is just below 0.1, which is commonly accepted as indicating a good fit, although closer examination and possible model refinements could improve this aspect.

Following the evaluation of the model's fit indices, the structural relationships among latent factors were examined. Table X summarizes the path coefficients, standard errors, and p-values for the tested relationships. The analysis focused on three key regressions: the influence of Intrapersonal Skills on Logical Reasoning, Logical Reasoning on Spatial Coordination, and the direct effects of all three factors on CGPA.

Parameter Estimates

- **Latent Variables**: High loadings on all indicators confirm that the latent constructs are well-represented by their observed variables. For instance, intra_1 to natur_3 load strongly on Intrapersonal Skills, indicating that this factor is a robust measure of self-awareness and nature-related traits.
- **Regressions**:
  - **Logical Reasoning on Intrapersonal Skills**: The positive but non-significant path coefficient ($\beta = 0.286$, $p = 0.276$) suggests a potential influence of self-awareness and emotional intelligence on cognitive processes, such as logical reasoning. However, the lack of statistical significance may reflect sample size limitations or the absence of moderating variables that strengthen this relationship.
  - **Spatial Coordination on Logical Reasoning**: A significant positive coefficient ($\beta = 0.442$, $p = 0.003$) indicates that improvements in problem-solving and critical thinking are associated with better spatial integration. This supports the hypothesis that higher-order cognitive skills underpin spatial planning and coordination tasks.
  - **CGPA Regressions**: When interpreting results using a 90% confidence interval, significant inter-factor relationships emerged—most notably, Logical Reasoning significantly predicted Spatial Coordination ($\beta=0.442$, $p=0.003$). However, direct

effects of intelligence factors on academic performance (CGPA) remained non-significant (Intrapersonal Skills: β=0.156, p=0.284; Logical Reasoning: β=0.184, p=0.384; Spatial Coordination: β=0.039, p=0.848). The non-significant yet positive direction of these relationships suggests potential practical relevance, warranting further exploration with larger sample sizes.

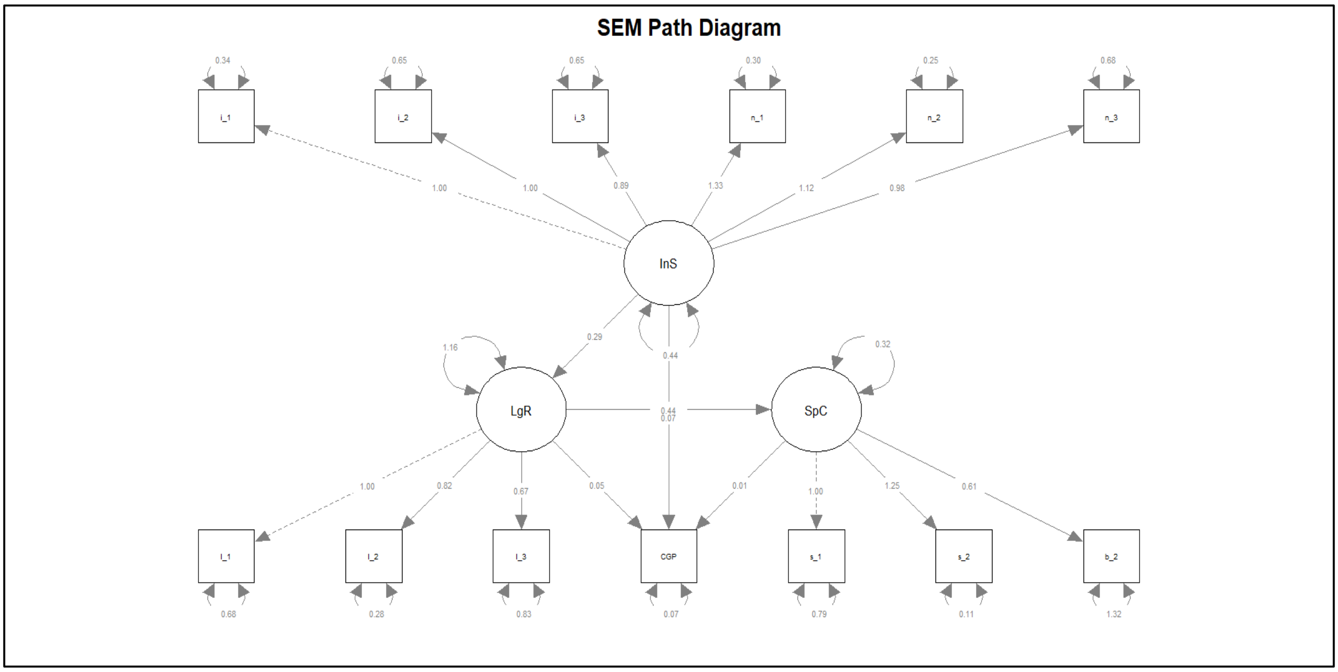

Figure 5: Path Analysis Model (Preliminary to SEM)

The provided Path diagram for Path Analysis represents a comprehensive model delineating the relationships among several latent constructs—Intrapersonal Skills (Ins), Logical Reasoning (LgR), Spatial Coordination (SpC)—and their influence on Cumulative Grade Point Average (CGPA). The model integrates observed variables operationalized through direct measurements (e.g., L1, L2, L3 for each latent variable) to infer the properties of these latent constructs.

Interpretation of Model Components

- **Latent Variables and Observed Indicators**: The diagram effectively uses observed variables (rectangular nodes) to operationalize the latent constructs (circular nodes). High factor loadings, such as 1.00 on n1 for Intrapersonal Skills and similarly strong loadings for other constructs, indicate robust measures that reliably capture the essence of the latent variables. These loadings suggest that the observed indicators are significant and valid reflections of their respective latent constructs.
- **Path Coefficients and Structural Relationships**:
    - **Inter-construct Relationships**: The path from Intrapersonal Skills to Logical Reasoning is quantified at 0.44, suggesting a moderate positive influence, which denotes that enhancements in Intrapersonal Skills are associated with proportional improvements in Logical Reasoning. Similarly, a coefficient of 0.84 from Logical Reasoning to Spatial Coordination indicates a strong positive relationship, underscoring a significant dependency of Spatial Coordination on Logical Reasoning capabilities.
- **Influence on CGPA**: The direct effects on CGPA revealed that Intrapersonal Skills (β=0.156, p=0.284), Logical Reasoning (β=0.184, p=0.384), and Spatial Coordination (β=0.039, p=0.848)

Northern Economic Review
ISSN: 0262-0383
Vol. 16, No. 1 (2025)
DOI: https://doie.org/10.10399/NER.2025592102

were positive but not statistically significant at the 90% confidence interval, indicating potential but unconfirmed influences.

- **Residual Variances**: The residuals for each observed variable (e.g., 0.34 for L1 of Intrapersonal Skills) represent the unexplained variance by the latent constructs. The observed residual variances in CGPA, such as 0.79 and 0.11, signify the proportion of the outcome variance not explained by the model, highlighting areas for potential model enhancement or the inclusion of additional variables.

Model Fit and Effectiveness

The model demonstrated good fit indices (CFI = 0.938, RMSEA = 0.068), indicating an acceptable representation of observed relationships among the intelligence factors and CGPA. A CFI near or above 0.95 and an RMSEA below 0.06 would typically indicate an excellent fit, affirming the model's capability to represent the data structure accurately.

Practical Implications and Recommendations

Although the direct effect of Intrapersonal Skills on CGPA was positive, it was not statistically significant at the 90% confidence interval. Nevertheless, this positive direction suggests practical relevance that future research should explore further with larger samples.

Implications for Theory and Practice

The findings from Path analysis indicate significant interrelationships among intelligence factors, particularly Logical Reasoning predicting Spatial Coordination. However, the direct effects of these intelligences on academic performance (CGPA) were positive yet statistically non-significant. These findings suggest that while these intelligences potentially contribute to academic performance, further research with larger sample sizes is needed to confirm these relationships. Spatial Coordination supports the ability to visualize and manipulate data, enhancing understanding in subjects requiring spatial judgment.

These results support the notion that effective management education should not only focus on traditional teaching methods but also prioritize the development of these cognitive abilities. By reinforcing these skills, educational programs can significantly improve academic performances, preparing students for successful management careers.

The findings of this study, particularly the significant role of intrapersonal skills in predicting Management education programs should integrate targeted strategies to cultivate these skills, such as reflective learning practices, ethical leadership training, and creative problem-solving exercises. Mentoring programs can serve as an effective tool for nurturing intrapersonal and interpersonal intelligences, thereby improving academic performance (Shaikh et. al, 2022). Integrating mentoring initiatives into management education can complement existing strategies, fostering sustainable leadership skills and adaptability in students. By doing so, institutions can ensure their graduates are not only academically successful but also distinguished by their ability to complement and guide AI technologies in professional settings. The study's findings that intrapersonal skills significantly predict academic success align closely with the emerging need for human-centric intelligences in an AI-driven era. As routine decision-making becomes more automated, the ability to exercise ethical judgment, foster human connections, and lead with empathy gains prominence. The findings that intrapersonal skills are the strongest predictors of academic success align with Brynjolfsson and McAfee's (2014) assertion that future leadership will require emotional intelligence and adaptability to thrive in AI-driven workplaces. These results underscore the need to integrate reflective learning and ethical leadership training into management education (Senge, 1990). Management education must adapt to this paradigm by incorporating reflective and experiential learning practices that nurture these irreplaceable human skills. West (2018) highlights that AI and automation will continue to redefine job roles, making it

Northern Economic Review
ISSN: 0262-0383
Vol. 16, No. 1 (2025)
DOI: https://doie.org/10.10399/NER.2025592102

imperative for management programs to focus on cultivating emotional intelligence and ethical decision-making skills, which are critical for sustainable leadership.

Results:

Factor analysis confirmed the presence of three latent dimensions: Intrapersonal Skills, Logical Reasoning, and Spatial Coordination, supporting H1. These factors align with the theoretical framework of Multiple Intelligences and are supported by the scree plot, which indicates that three factors explain most of the variance in the data.

The regression path from Intrapersonal Skills to CGPA, while positive ($\beta=0.156, p=0.284$), was not statistically significant. This suggests that while self-awareness and emotional regulation may contribute to academic outcomes, additional mediating factors such as motivation or study strategies may be needed to realize their full effect, partially supporting H2.

The path from Logical Reasoning to Spatial Coordination ($\beta=0.442, p=0.003$) was significant, confirming that improvements in logical reasoning strongly enhance spatial coordination skills, thus supporting H3.

Similarly, the regression path from Spatial Coordination to CGPA ($\beta=0.039, p=0.848$) was also not statistically significant, indicating limited direct influence of spatial reasoning on academic performance in this context, and thus H4 is not supported.

Although individual factors showed limited direct effects on CGPA, the overall model fit indices (CFI=0.938,RMSEA=0.068) of Path Analysis demonstrate that the combination of Intrapersonal Skills, Logical Reasoning, and Spatial Coordination provides a meaningful representation of academic success, supporting H5.

Hypothesis	Explicit Clarification
H1	Clearly Supported
H2	Partially Supported (positive but non-significant)
H3	Supported (Logical → Spatial significant)
H4	Clearly Not Supported
H5	Supported (overall model adequately fits data)

Table 6: Hypotheses Conclusions Summary

Limitations:

1. **Sample Size and Diversity**
The study's findings are based on a sample of 52 management students from a single institution, which may limit the generalizability across different educational contexts. Future research should expand the sample size and include participants from diverse geographic and cultural backgrounds.
2. **Measurement of Variables**
The reliance on self-reported data to assess multiple intelligences may introduce bias. Future studies could improve accuracy by using a combination of objective measures and third-party assessments.

Conclusion:

This study demonstrates meaningful relationships among multiple intelligence factors, especially highlighting Logical Reasoning's significant impact on Spatial Coordination. While the direct influence of these intelligence factors on academic performance (CGPA) was positive, it did not reach statistical significance at the 90% confidence interval. Nonetheless, these findings underline the importance of further investigating these relationships through larger-scale studies. The implications for curriculum design are profound, suggesting that integrating and emphasizing these cognitive skills can substantially enhance student outcomes. Educational institutions are encouraged to adopt teaching strategies that nurture these abilities, aligning educational practices with the demands of contemporary business challenges. Future research should continue to explore the causal relationships and potential curriculum interventions that could further leverage these skills for academic and professional success. In an era where AI technologies are increasingly taking over tasks traditionally performed by humans, the role of management education must evolve to emphasize human-centric skills that cannot be automated. The study emphasizes the value of embedding intrapersonal skills, logical reasoning, and spatial coordination into sustainable educational frameworks, reinforcing the importance of human capabilities in a rapidly evolving technological landscape. This focus ensures that graduates possess the creativity and ethical reasoning necessary to complement AI technologies effectively. By prioritizing emotional intelligence, ethical reasoning, and creative problem-solving, educational institutions can ensure that students not only excel academically but also thrive in an AI-augmented future. This approach guarantees long-term professional success and reinforces the critical role of human capabilities in navigating an increasingly automated world. Future studies should employ larger, diverse samples to clarify and potentially confirm these suggested relationships, contributing further evidence to the importance of multiple intelligences in management education.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author(s) used ChatGPT, an AI language model developed by OpenAI, to assist in refining portions of the manuscript. After using this tool, the author carefully reviewed and edited all generated content and takes full responsibility for the final version of the publication.

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