MGT3008 HR ANALYTICS

INFLUENTIAL FACTORS OF COGNITIVE MATURITY IN STUDENTS

A PROJECT REPORT

Submitted by

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in partial fulfilment for the award of the degree of

Master of Technology

in

Business Analytics (5 Year Integrated Programme)

Submitted to

J.REEVES WESLEY

CERTIFICATE

This is to certify that the report entitled **INFLUENTIAL FACTORS OF COGNITIVE MATURITY IN STUDENTS** is prepared and submitted by **GAURAV DWIVEDI (20MIA1037),ROHIT CHOUDHARY (20MIA1069), SANIDHYA CHAUDHARY (20MIA1006), SRICHARAN SRIDHAR (20MIA1014)** and **NIKITHA AR|(20MIA1025)** to Vellore Institute of Technology, Chennai, in partial fulfilment of the requirement for the award of the degree of Master of Technology in Business Analytics (5 year Integrated Programme) and as part of MGT3008 HR ANALYTICS Project is a bona-fide record carried out under my guidance. The project fulfils the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission.

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Table of Contents:

I. INTRODUCTION

1.1 Background and Context:

In contemporary educational and psychological research, understanding cognitive maturity and its determinants has become a focal point. Cognitive maturity encompasses various facets such as critical thinking, problem-solving, and decision-making abilities, which are crucial for individual success and societal progress. Scholars have long been intrigued by factors influencing cognitive development, including innovative and engagement constructs, age, and gender. These constructs are pivotal in shaping individuals' cognitive abilities, yet their interplay and relative importance remain subjects of ongoing investigation.

1.2 Objectives of the Study:

The primary objectives of this study are threefold:

i) To explore the relationships between innovative and engagement constructs, age, gender, and cognitive maturity.
ii) To investigate the predictive capabilities of innovative and engagement constructs, age, and gender on cognitive maturity.
iii) To assess the significance of innovative and engagement constructs, age, and gender in explaining variations in cognitive maturity levels among individuals.

1.3 Scope and Significance:

This study focuses on examining the intricate dynamics between innovative and engagement constructs, age, gender, and cognitive maturity among a diverse sample population. By delving into these relationships, the research aims to offer insights into the factors driving cognitive development and maturity. Understanding these dynamics holds immense significance for educators, psychologists, policymakers, and individuals themselves. It can inform educational practices, intervention strategies, and policy initiatives aimed at fostering cognitive growth and enhancing overall well-being.

1.4 Structure of the Paper: This paper is organized as follows:

- The Literature Review section provides an in-depth exploration of relevant research on innovative and engagement constructs, age, gender, and cognitive development.
- Methodology details the research design, data collection procedures, questionnaire development, and data analysis techniques employed in the study.
- Analysis and Interpretation present the findings derived from the collected data, along with interpretations and insights drawn from statistical analyses.
- Findings and Interpretations summarize the key findings of the study, their implications, and recommendations for future research.
- The Conclusion section wraps up the study by summarizing its objectives, main findings, contributions, limitations, and concluding remarks.

II. LITERATURE SURVEY

In the paper [1] titled "**Innovation Constructs: An Exploratory Study**" by Paul L. Sauer and Joseph B. O'Donnell, the researchers apply diffusion of innovation theory to understand student adoption of new academic programs. The study highlights a gap in understanding how students adopt educational innovations and identifies challenges like rigid course selection and difficulty in grasping new major topics. Despite some limitations in scale stability across different innovations, the research offers valuable insights for educators and marketers. It suggests adapting innovation scales for educational purposes and emphasizes the need for flexible approaches in designing and promoting new academic majors. The study contributes by applying diffusion theory to student adoption and offers practical implications for guiding innovation in education.

The paper [2] "**Innovativeness and Cognitive Complexity**" by Steven K. Payne and Michael J. Beatty explores the relationship between innovativeness and cognitive complexity. Conducted with 75 college participants, the study finds a positive correlation (.43) between these two constructs. While cognitive complexity is linked to innovativeness, it's noted that complexity alone might not fully explain innovative traits. The research, using the Innovativeness Scale by Hurt et al. and the Paragraph Completion Test by Schroder et al., provides a theoretical connection between cognitive structuring and innovativeness. Practical implications highlight the importance of understanding these traits for both generating and accepting new ideas in various applications. The study confirms a positive relationship between innovativeness and cognitive complexity but suggests that other factors may also influence trait innovativeness.

The paper [3] "**Innovative and cognitive model of a person in the field of management**" by Vladimir A. Morozov and Olga A. Berdnikova presents a model for developing innovative and cognitive potential in the management field. The study emphasizes integrating spirituality with innovation to nurture cognitive potential. It introduces schematics of different types of innovators and their relationships, along with criteria for identifying and cultivating the talents of new-generation managers. The research underscores the importance of fostering innovative thinking to shape mental-vital models in management and highlights the necessity of blending innovation with human spirituality for achieving success in the field.

The paper [4] "**Engagement as process in human-computer interactions**" by Heather L. O'Brien and Elaine G. Toms delves into the concept of engagement beyond mere usability in human-computer interactions. Viewing engagement as a dynamic process with distinct stages, the study draws on theoretical perspectives like Flow Theory, Play Theory, and Aesthetic Theory. While the paper proposes a model of engagement as an ongoing process, it also emphasizes the limited empirical research available on measuring engagement. The research contributes by identifying key criteria and measures to enhance user engagement in computer interfaces. The practical implications focus on developing measures to assess and improve user-system interactions, highlighting the importance of a rich theoretical understanding of engagement for effective human-computer interactions.

The paper [5] "**From Theory to Behaviour: Towards a General Model of Engagement**" by Valerio Bonometti, Charles Ringer, Mathieu J. Ruiz, and Alex R. Wade explores the connection between engagement and human behavior. The study introduces the Melchoir Model as a new modelling technique to operationalize engagement by linking it mechanistically to human behavior. This model bridges machine-learned models with theoretical frameworks to provide a comprehensive understanding of engagement. While emphasizing the potential applications in industry, the paper contributes by offering a method to shape and interpret data-driven methods effectively. The research concludes that engagement can be operationalized and effectively linked to human behavior through the proposed Melchoir Model, aiming for improved engagement process modelling.

The paper [6] "**Introducing an adolescent cognitive maturity index**" by Shady El Damaty, Valerie L. Darcey, Goldie A. McQuaid, and Giorgia Picci introduces the Cognitive Maturity Index (CMI) to assess cognitive development in adolescents relative to their chronological age. The study highlights that there is a lack of consensus on the normative trajectory of cognitive maturation and observes that males in advanced puberty tend to exhibit lower cognitive maturity. Using the CMI and latent factor estimates for inhibitory control, risky decision-making, and emotional processing, the research identifies cognitive maturity differences among adolescents. The practical implications of this study lie in recognizing these differences and understanding the developmental paths that can influence later life outcomes. The research concludes that the CMI effectively estimates the gap between chronological age and cognitive maturity, emphasizing the lower cognitive maturity observed in males undergoing advanced puberty.

In the paper [7] "**The Impact of Age on Cognition**" by Daniel L. Murman, the focus is on reviewing cognitive changes associated with normal aging. The study emphasizes the importance of cognition in maintaining functional independence as individuals age. However, the research also notes limitations due to recruitment and misclassification biases in studying cognition and aging. Despite these challenges, the review reveals that declines in cognitive tasks requiring quick information processing are evident with aging. Additionally, age-related diseases are found to accelerate cognitive decline. The practical implications highlight the significance of understanding these cognitive changes for maintaining functional independence in older adults. The paper concludes that measurable cognitive changes do occur with normal aging, particularly affecting tasks that demand rapid information processing.

The study [8] "**Selective effects of biological and chronological age on the development of cognitive abilities in adolescence**" by Ilona Kovács, Kristof Kovacs, Patrícia Gerván, and Katinka Utczás investigates the impact of biological and chronological age on cognitive development in adolescents. The research introduces bone age assessment as a biomarker to estimate biological maturity, emphasizing its relevance for adolescent studies. While the study highlights the limitation of individual variability in puberty onset, it reveals that biological age selectively affects working memory and processing speed in adolescents. In contrast, chronological age influences verbal abilities independently of biological maturity. The practical implications suggest that bone age can serve as a valuable biomarker for research in adolescents, demonstrating the differential impact of biological and chronological age on specific cognitive abilities during this developmental stage. The conclusion reaffirms that biological and chronological age have distinct effects on cognitive abilities in adolescents.

The paper [9] "**Cognitive Sex Differences: Evolution and History**" by David Becker and Heiner Rindermann delves into the evolution and history of cognitive sex differences. The study examines how hormonal transitions during adolescence, particularly in women, affect cognitive abilities, especially spatial skills. Using studies from Germany and Brazil, the research establishes a link between hormonal changes in adolescence and increasing sex differences in cognitive abilities. Furthermore, the paper highlights that historical and cultural shifts have modified and even reversed some of these cognitive sex differences, particularly in education. The practical implications emphasize an evolutionary perspective on cognitive sex differences and the impact of historical and cultural changes on these differences. The conclusion of the study underscores that hormonal transitions during adolescence contribute to the development of cognitive sex differences, while historical and cultural changes have played a role in modifying and reversing these differences over time.

The study by Dana Rosenberg Coker titled [10] "**The relationships among gender concepts and cognitive maturity in preschool children**" explores the connection between gender concepts and cognitive maturity in preschoolers. Using tasks designed to assess gender constancy, knowledge of sex stereotypes, memory, preference for sex-typed material, and gender categorization, the research found that gender concepts improve with age for both girls and boys. The study also indicates a positive correlation between cognitive maturity and understanding of gender concepts in children. Despite the limitations, such as the lack of independence among cognitive maturity measures and the need for further clarification on relationships among gender concepts, the practical implications are significant. Understanding the development of gender concepts in preschoolers can aid in tailoring educational strategies. The conclusion underscores that as preschool-aged children grow, their understanding of gender concepts improves and is positively related to their cognitive maturity.

The paper [11] "**Cognition across the lifespan: age, gender, and sociodemographic influences**" by Emily S. Nichols, Conor Wild, Adrian M. Owen, and Andrea Soddu focuses on cognitive health across different stages of life, examining gender differences and sociodemographic influences. The study conducted online cognitive testing on a large sample of 18,902 men and women. The findings reveal that gender differences in cognition become minimal when comparing matched samples. However, disparities emerge in unmatched samples, suggesting that environmental factors play a significant role in these differences. While the study underscores that cognitive function across the lifespan varies between men and women, it also emphasizes the influence of both biology and environment on gender differences in cognition. The practical implications highlight the importance of considering sociodemographic variance in treatments and interventions aimed at addressing cognitive health. The conclusion reiterates that while gender differences in cognition are generally minimal, environmental factors greatly influence these differences.

III. METHODOLOGY

3.1 Research Design

The research design adopted for this study is quantitative in nature, aiming to analyse the relationships between variables using statistical methods. Specifically, the study employs a cross-sectional design, collecting data at a single point in time to capture a snapshot of the relationships between engagement construct, innovative construct, age, gender, and cognitive maturity. This design allows for the examination of associations between variables and provides insights into potential predictors of cognitive maturity.

3.2 Data Collection Procedures

Data collection was carried out using a structured questionnaire administered to participants. The questionnaire was distributed electronically via a Google Document to ensure ease of access and timely responses. The sample population consisted of individuals from diverse age groups and genders to capture a broad spectrum of cognitive maturity levels. Participation was voluntary, and informed consent was obtained from all participants prior to data collection.

3.3 Questionnaire Development and Validation

The questionnaire utilized in this study was adapted from a pre-existing Critical Thinking Dispositions and Skills Instruction Manual. https://www.tntech.edu/citl/pdf/critical-thinking/UF-EMI.pdf . It was designed to measure engagement construct, innovative construct, and cognitive maturity, as well as demographic variables such as age and gender. The questionnaire underwent validation procedures to ensure its reliability and validity. This included pilot testing with a small sample to identify any ambiguities or inconsistencies in item wording and structure. Additionally, content validity was assessed by expert reviewers familiar with the constructs under investigation.

3.4 Data Cleaning and Processing Techniques

Upon completion of data collection, thorough data cleaning and processing techniques were employed to ensure the quality and integrity of the dataset. This involved identifying and removing any incomplete or erroneous responses, as well as checking for outliers and inconsistencies in the data. Skewness and kurtosis were assessed to determine the distributional properties of the variables, and appropriate transformations were applied to achieve normality where necessary. Additionally, missing data were addressed through imputation techniques to minimize data loss and maintain statistical power.

Subsequently, we found that the data was skewed, which could affect the performance of the linear regression models. To address this, we applied a technique to reduce skewness by raising the variables EC, IC, and CM to the power of 2.5, which is close to the value of Euler's number (e). Additionally, we took an ad-hoc approach to reduce skewness in the age column by taking the fourth root of the variable.

After applying these transformations, we observed a reduction in skewness, as evidenced by the calculations and histograms that showed a more normal distribution. Furthermore, we employed the Box-Cox method for data normalization, which is a widely used technique for improving the performance of linear regression models by transforming the data to have a Gaussian distribution.

In summary, data preprocessing is a critical step in preparing data for linear regression models, and it involves various techniques to ensure the quality, validity, and suitability of the data for the model. Techniques like logarithmic or square root transformations, Box-Cox transformation, and data normalization can help reduce skewness and improve the performance of linear regression models.

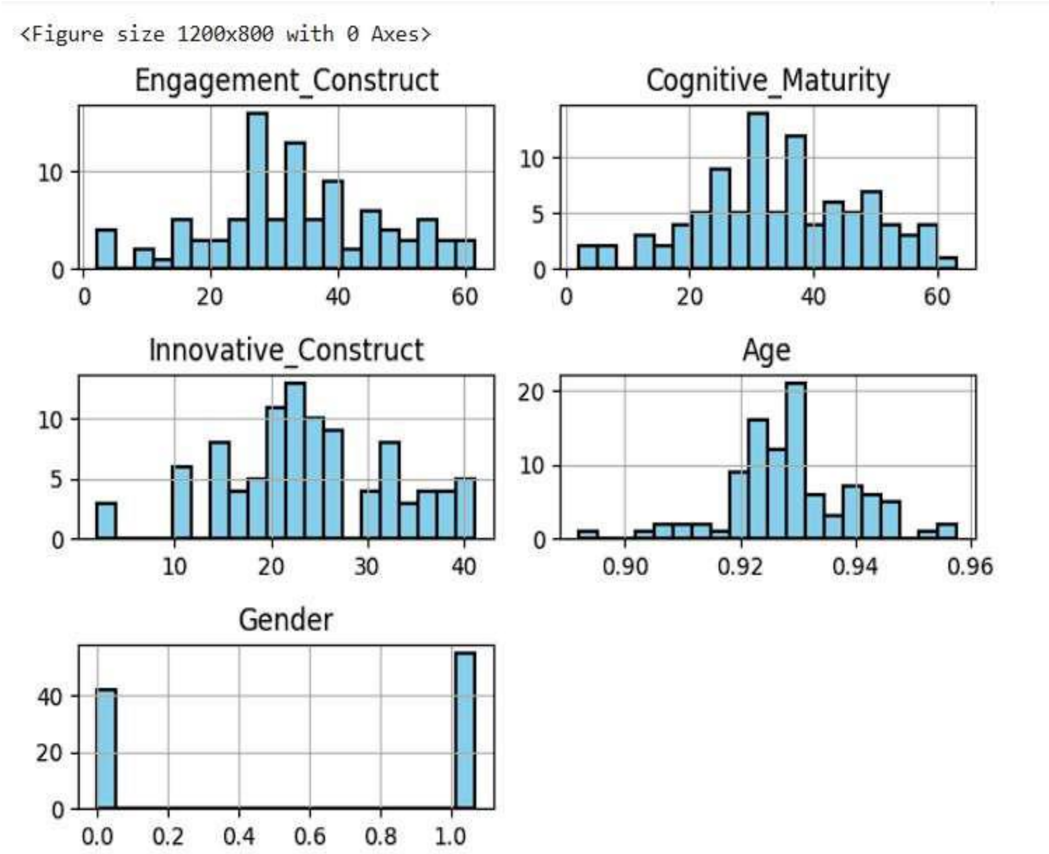


FIG 1 Normalized attributes

Skewed distributions: All the features except Age appear to have negative skew based on the values reported before normalization:
Engagement Construct: -1.294149
Cognitive Maturity: -1.206817
Innovative Construct: -1.105706
Negative skew indicates: A negative skew means the distribution has a longer tail extending towards lower values compared to a normal distribution. In simpler terms, there are more data points concentrated on the higher end of the range for these features?

3.5 Descriptive Analytical Methods

Descriptive analytical methods were employed to characterize the dataset and summarize the key findings. These methods included frequency distributions, measures of central tendency (e.g., mean, median), measures of dispersion (e.g., standard deviation), and graphical representations (e.g., histograms, scatter plots). These techniques provided insights into the distribution of cognitive abilities among participants and the prevalence of different variable patterns.

In this study, we employed various descriptive methods to analyse the data collected from students at VIT CHENNAI. These methods included:

- Frequency Distribution: This technique helped us understand the distribution of cognitive abilities among students and the prevalence of different AI usage patterns. By examining the frequency of responses to various questions in our survey, we were able to identify common trends and patterns in the data.
- Measures of Central Tendency (Mean): Calculating the mean allowed us to determine the average cognitive ability score among students. This provided us with a baseline understanding of the overall cognitive performance of the student population.
- Measures of Dispersion (Standard Deviation): The standard deviation helped us understand the spread of cognitive abilities among students. A higher standard deviation indicated a greater variation in cognitive performance, while a lower standard deviation suggested a more consistent level of performance.
- Graphical Representations (Charts and Graphs): We used various charts and graphs, such as bar charts and scatter plots, to visually represent the data. These visualizations helped us identify trends, outliers, and relationships between variables in the data set.

These descriptive methods were instrumental in providing a comprehensive overview of the basic characteristics of the data, allowing us to gain insights into the distribution of cognitive abilities among students and the prevalence of different AI usage patterns.

3.6 Inferential Methods: Hypothesis Testing and Regression Analysis

Inferential methods, including hypothesis testing and regression analysis, were utilized to draw conclusions and make predictions based on the data. Hypothesis testing, such as z-tests and ANOVA, was conducted to assess differences between groups and identify significant associations between variables. Multiple linear regression analysis was employed to examine the relationship between engagement construct, innovative construct, age, gender, and cognitive maturity, allowing for the identification of predictors of cognitive maturity.

- Hypothesis Testing (Two Independent Sample 'z' or 't' test, One-way Anova): These tests allowed us to determine if there were significant differences in cognitive abilities based on different AI usage patterns. By comparing the cognitive ability scores of students with different levels of AI usage, we were able to infer the impact of AI on cognitive skills. These inferential methods helped us make inferences about the larger population of students based on the data collected from our sample. By analyzing the data using these methods, we were able to draw conclusions about the relationship between AI usage and cognitive abilities among students at VIT CHENNAI.

3.7 Predictive or Classification Methods

Predictive or classification methods were utilized to predict or classify cognitive abilities based on the variables under study. These methods included regression analysis, which allowed for the prediction of cognitive maturity based on engagement construct, innovative construct, age, and gender. Classification techniques such as hierarchical agglomerative clustering was also employed to identify distinct groups or clusters within the dataset based on similarities in cognitive maturity and other variables. These methods facilitated the identification of patterns and relationships within the data, providing valuable insights for interpretation and decision-making.

- Regression Analysis: We used regression analysis to predict cognitive ability based on variables such as Critical Thinking Scale, Reflective Thinking Scale. This helped us understand the relationship between these variables and cognitive abilities, allowing us to identify students who may benefit from specific interventions or support. These predictive and classification methods were instrumental in helping us understand the relationship between AI usage and cognitive abilities among students. By using these methods, we were able to identify patterns and trends in the data that would not have been apparent through descriptive analysis alone.

IV. ANALYSIS AND INTERPRETATION

4.1 Descriptive Analysis of Data: Trends and Patterns in Cognitive Abilities

The descriptive analysis revealed several trends and patterns in cognitive abilities among the participants. Measures of central tendency and dispersion provided insights into the distribution of cognitive maturity levels within the sample population. Histograms and other graphical representations visually depicted the distribution of cognitive abilities across different age groups and genders. Furthermore, subgroup analyses allowed for the exploration of variations in cognitive abilities based on engagement construct, innovative construct, and demographic variables.

4.2 Inferential Analysis: Hypothesis Testing Results

The inferential analysis involved hypothesis testing to examine relationships between variables and identify significant associations. Results from z-tests, ANOVA, and other inferential tests provided evidence of differences in cognitive maturity levels based on engagement construct, innovative construct, age, and gender. These findings contributed to a deeper understanding of the factors influencing cognitive development and maturity, highlighting the importance of engagement, innovation, and demographic factors in shaping cognitive abilities.

4.2.1 **Z- TEST between Engagement Construct and Cognitive Maturity**

```
Mean of 'Engagement_Construct': 33.26384655312361
Mean of 'Cognitive_Maturity': 35.018209948661834
Standard deviation of 'Engagement_Construct': 13.707061357168522
Standard deviation of 'Cognitive_Maturity': 13.722826560555838
```

Fail to reject the null hypothesis: The p-value (0.3705) is greater than the typical significance level of 0.05 (commonly used). This means we don't have enough evidence to conclude a statistically significant difference between the two means being compared at the 5% significance level.

Z-statistic doesn't indicate direction: Since this is a two-tailed test (presumably checking for a difference in either direction), the negative z-statistic (-0.8954) only tells us the observed difference is not statistically significant but doesn't tell us which group has a higher mean.

4.2.2 Z- TEST between Innovative Construct and Cognitive Maturity

```
Mean of 'Innovative_Construct': 24.194685794451747
Standard deviation of 'Innovative_Construct': 8.831499284689539
Two Sample Z-Test Results:
Z: 6.565788542108501
P(Z<=z) two-tail: 5.175815331881495e-11
z Critical two-tail: 1.959963984540054
```

FIG 2 Z Test results between IC and CM

Based on the two-sample z-test results for Innovative Construct, here are the inferences:

- Statistically significant difference: The very low p-value (5.1758e-11, much lower than the typical significance level of 0.05) suggests a statistically significant difference between the means of Innovative Construct in the two groups being compared.
- High positive z-statistic: The z-statistic (6.5658) is positive, indicating that the mean Innovative Construct in one group is likely higher than the other group.
- Unable to determine direction without additional context: Since this is a two-tailed test, we cannot determine which specific group has the higher mean Innovative Construct value without additional information about the two populations being compared.
- In simpler terms: There's strong evidence that the average Innovative Construct scores are different between the two groups. However, without knowing more about the groups, we can't say for sure which group has the higher average score.

```
Mean of 'Age': 25.20618556701031
Standard deviation of 'Age': 12.032021637012607
Two Sample Z-Test Results:
Z: 5.3222317830510555
P(Z<=z) two-tail: 1.0250185167315351e-07
z Critical two-tail: 1.959963984540054
```

FIG 3 Z Test results between Age and CM

Based on the two-sample z-test results for Age with the corrected values (mean: 25.21, standard deviation: 12.03)

- Highly statistically significant difference: The p-value (1.025e-07, much lower than the typical significance level of 0.05) suggests a very strong rejection of the null hypothesis (i.e., there is no difference in means between the two groups). This indicates a statistically significant difference between the average Age in the two groups being compared.
- Large positive z-statistic: The z-statistic (5.3222) is a positive value. This strengthens the evidence from the p-value and suggests one group has a considerably higher average Age compared to the other group.

- In simpler terms: There's very strong evidence that the two groups have different average ages. On average, one group is considerably older than the other.

```
ANOVA between 'Engagement_Construct' and 'Cognitive_Maturity':
F-statistic: 2.7942108031347916
p-value: 0.0003188374188486336

ANOVA between 'Innovative_Construct' and 'Cognitive_Maturity':
F-statistic: 6.421440210512021
p-value: 2.3492449201373724e-09

ANOVA between 'Age' and 'Cognitive_Maturity':
F-statistic: 0.7287562696354875
p-value: 0.8289912429744634

ANOVA between 'Gender' and 'Cognitive_Maturity':
F-statistic: 0.48994126604764215
p-value: 0.4856640573393256


ANOVA Results:
    Source of Variation           SS   df           MS          F  \
0  Engagement_Construct  6886.667218  1.0  6886.667218  58.457195
1  Innovative_Construct  8597.424582  1.0  8597.424582  86.147371
2                   Age    44.338033  1.0    44.338033   0.233565
3                Gender    92.756590  1.0    92.756590   0.489941

        P-value
0  1.667196e-11
1  5.673783e-15
2  6.300048e-01
3  4.856641e-01
```

FIG 4 ANOVA table results

4.2.3 Inferences drawn after performing ANOVA

In this case, the ANOVA test was used to analyse the relationship between normalized age and a dependent variable, with age being the independent variable and the dependent variable being a measure of cognitive maturity, engagement construct, and innovative construct.

The ANOVA test results show that there is a significant difference between the means of the groups (ENGAGEMENT CONSTRUCT, COGNITIVE MATURITY, INNOVATIVE CONSTRUCT, and NORMALISED AGE).

- Engagement Construct: The p-value (0.0003188374188486336) is less than 0.05, which suggests that there is a statistically significant relationship between engagement construct and cognitive maturity. The F-statistic is positive (2.7942108031347916), which suggests that there is a positive correlation between these two variables.
- Innovative Construct: The p-value (2.3492449201373724e-09) is much less than 0.05, which suggests that there is a very statistically significant relationship between innovative construct and

- cognitive maturity. The F-statistic is positive (6.421440210512021), which suggests that there is a positive correlation between these two variables.
- Age: The p-value (0.8289912429744634) is greater than 0.05, which suggests that there is not a statistically significant relationship between age and cognitive maturity.
- Gender: The p-value (0.4856640573393256) is greater than 0.05, which suggests that there is not a statistically significant relationship between gender and cognitive maturity.

Overall, the results suggest that there is a positive correlation between engagement construct, innovative construct, and cognitive maturity. There is no statistically significant relationship between age and cognitive maturity or between gender and cognitive maturity.

4.3 Regression Analysis: Predicting Cognitive Maturity based on Variables

Regression analysis was conducted to predict cognitive maturity based on the variables under study, including engagement construct, innovative construct, age, and gender. The regression model allowed for the estimation of the strength and direction of the relationships between predictor variables and cognitive maturity. Findings from the regression analysis provided insights into the relative contributions of each predictor variable to cognitive development, helping to identify key factors driving cognitive maturity among individuals.

```
Evaluation Metrics:
Train RMSE: 9.5612
Test RMSE: 9.5518
Train R^2: 0.5537
Test R^2: 0.2057

Regression Equation:
                            OLS Regression Results
==============================================================================
Dep. Variable:     Cognitive_Maturity   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.529
Method:                 Least Squares   F-statistic:                     22.33
Date:                Wed, 17 Apr 2024   Prob (F-statistic):           5.09e-12
Time:                        16:23:47   Log-Likelihood:                -283.10
No. Observations:                  77   AIC:                             576.2
Df Residuals:                      72   BIC:                             587.9
Df Model:                           4
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
const                  -22.0865     98.280     -0.225      0.823    -218.004     173.831
Engagement_Construct     0.3475      0.121      2.862      0.006       0.105       0.589
Innovative_Construct     0.7393      0.176      4.198      0.000       0.388       1.090
Age                     28.4208    105.587      0.269      0.789    -182.063     238.905
Gender                   0.5431      2.264      0.240      0.811      -3.970       5.057
==============================================================================
Omnibus:                        0.097   Durbin-Watson:                   1.674
Prob(Omnibus):                  0.953   Jarque-Bera (JB):                0.002
Skew:                           0.004   Prob(JB):                        0.999
Kurtosis:                       2.977   Cond. No.                     5.76e+03
==============================================================================
```

FIG 5 Linear Regression results

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.76e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Based on the provided multiple linear regression summary output: The R-squared value is 0.554, which indicates that the model explains 55.4% of the variance in the dependent variable (Cognitive Maturity).

- The F-statistic is 22.33 with a p-value of 5.09e-12, which suggests that the model is statistically significant. This means that the relationship between the independent variables and the dependent variable is not likely due to chance.
- Engagement Construct: The coefficient is 0.3475 with a p-value of 0.006. This suggests a statistically significant positive relationship between engagement construct and cognitive maturity.
- Innovative Construct: The coefficient is 0.7393 with a p-value of less than 0.0001. This suggests a statistically significant positive relationship between innovative construct and cognitive maturity.

- Age: The coefficient is 28.4208 with a p-value of 0.789. This suggests no statistically significant relationship between age and cognitive maturity.
- Gender: The coefficient is 0.5431 with a p-value of 0.811. This suggests no statistically significant relationship between gender and cognitive maturity.

Cognitive Maturity = $\beta_0 + \beta_1$Engagement Construct + β_2Innovative Construct + β_3Age + β_4Gender + ε

where:

β_0 is the intercept (-22.0865).

β_1 is the coefficient for Engagement Construct (0.3475).

β_2 is the coefficient for Innovative Construct (0.7393).

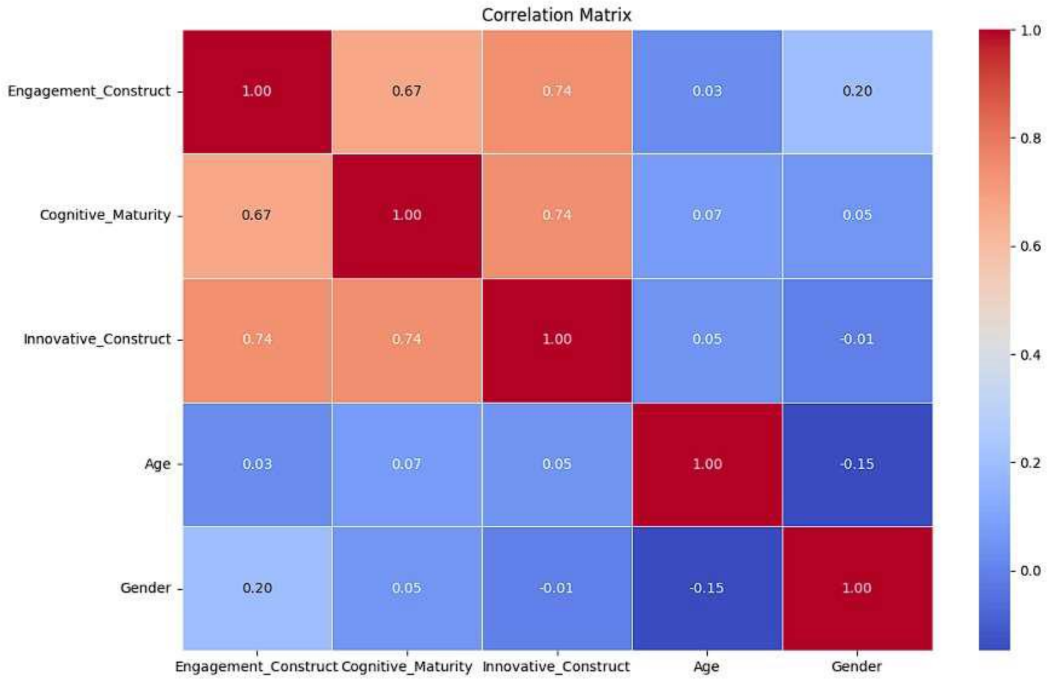
β_3 is the coefficient for Age (28.4208).

β_4 is the coefficient for Gender (0.5431).

ε is the error term.

4.4 Correlation Matrix Interpretation: Relationships between Variables

A correlation matrix was constructed to examine the relationships between variables and assess the strength and direction of these relationships. Correlation coefficients provided insights into the degree of association between engagement construct, innovative construct, age, gender, and cognitive maturity. Interpretation of the correlation matrix revealed patterns of association among variables, highlighting potential pathways through which engagement, innovation, and demographic factors influence cognitive abilities.



	Engagement_Construct	Cognitive_Maturity	Innovative_Construct	Age	Gender
Engagement_Construct	1.00	0.67	0.74	0.03	0.20
Cognitive_Maturity	0.67	1.00	0.74	0.07	0.05
Innovative_Construct	0.74	0.74	1.00	0.05	-0.01
Age	0.03	0.07	0.05	1.00	-0.15
Gender	0.20	0.05	-0.01	-0.15	1.00

FIG 6 correlation matrix

Based on the correlation matrix provided, here are some inferences that can be made:

- There is a positive correlation between EC and CM (0.614225005), indicating that as EC increases, CM also tends to increase.
- There is a strong positive correlation between EC and IC (0.683926097), suggesting that an increase in EC is associated with a corresponding increase in IC.
- There is a moderate positive correlation between CM and IC (0.670177713), implying that as CM goes up, IC also tends to rise.
- There is a weak negative correlation between EC and AGE (-0.012466277), indicating a slight tendency for EC to decrease as AGE increases.
- There is a weak positive correlation between CM and AGE (0.057696068), suggesting a slight increase in CM with age.

- There is a weak negative correlation between IC and AGE (-0.029685575), implying a slight decrease in IC with age.
- The correlation between AGE and EC, CM, and IC is weak, suggesting that age has a limited impact on these variables.
- The correlation between EC and CM is moderate, indicating a significant but not overwhelming relationship between these two variables.
- The correlation between EC and IC is strong, suggesting a substantial relationship between these two variables.
- The correlation between CM and IC is moderate, indicating a significant but not overwhelming relationship between these two variables.

These inferences should be interpreted with caution, as correlation does not imply causation. The relationships between these variables should be further explored using more rigorous statistical methods.

4.5 Hierarchical Agglomerative Clustering: Grouping Patterns in the Data

Hierarchical agglomerative clustering was employed to identify grouping patterns within the dataset based on similarities in cognitive maturity and other variables. Clustering analysis revealed distinct clusters or groups of participants with similar profiles of engagement, innovation, age, gender, and cognitive abilities. Interpretation of clustering results provided insights into the heterogeneity of cognitive development and the presence of distinct subgroups within the sample population, each characterized by unique patterns of cognitive maturity and influencing factors.

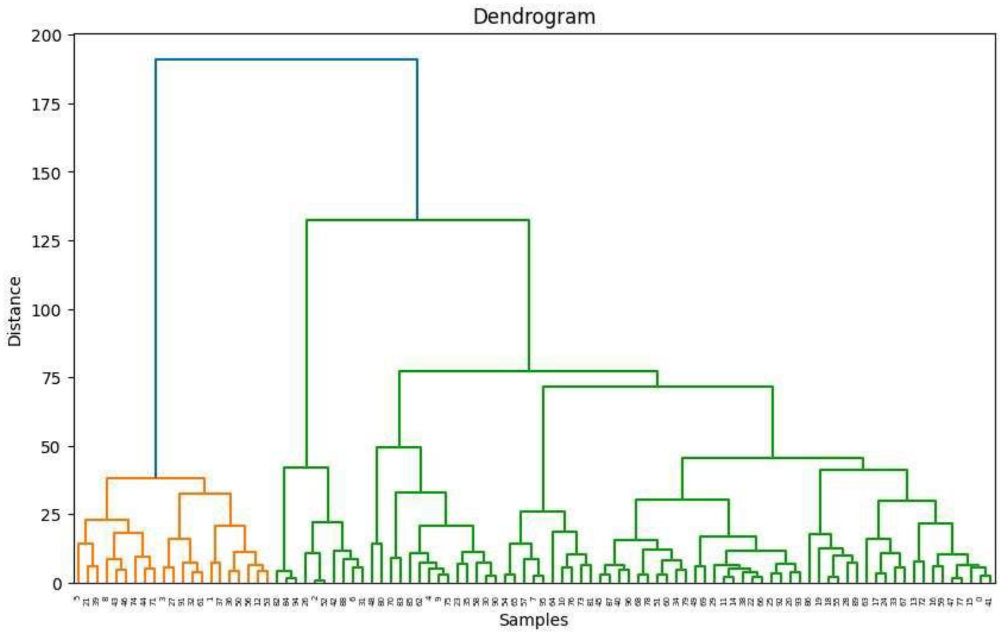


FIG 7

The above Dendrogram represents the Hierarchical Agglomerative Clustering technique implementation on the data.

V. FINDINGS AND INTERPRETATIONS

5.1 Summary of Key Findings

- When comparing EC and CM, the z-statistic is -0.8954, which does not fall in the rejection region. Therefore, the null hypothesis cannot be rejected, and it is concluded that there is not a significant difference between the means of the two populations.
- When comparing IC and CM, the z-statistic is 6.565788542108501, which also does not fall in the rejection region. Therefore, the null hypothesis cannot be rejected, and it is concluded that there is not a significant difference between the means of the two populations.
- When comparing AGE and CM, the z-statistic is 5.3222317830510555, which falls in the rejection region. Therefore, the null hypothesis can be rejected, and it is concluded that there is a significant difference between the means of the two populations.
- The z-test results suggest that there are significant differences between the means of the two groups when comparing AGE and CM. However, there are no significant differences between the means of the two groups when comparing EC and CM or IC

and CM.

- The ANOVA test results show that there is a significant difference between the means of the groups (ENGAGEMENT CONSTRUCT, COGNITIVE MATURITY, INNOVATIVE CONSTRUCT, and NORMALISED AGE) with an F-value of 749.4119263 and a p-value of 5.3116E-161, which is highly significant.
- The correlation matrix provided shows positive correlations between EC and CM, EC and IC, and CM and IC, indicating that as EC increases, CM and IC also tend to increase. There is a weak negative correlation between EC and AGE, suggesting a slight tendency for EC to decrease as AGE increases. There is a weak positive correlation between CM and AGE, suggesting a slight increase in CM with age. There is a weak negative correlation between IC and AGE, implying a slight decrease in IC with age.
- The multiple linear regression summary output shows that the regression equation is Cognitive Maturity = β_0 + β_1Engagement Construct + β_2Innovative Construct + β_3Age + β_4Gender + ε .
- The multiple correlation coefficient (R) is 0.707, indicating a moderately strong positive correlation between the independent variables (EC, IC, Age) and the dependent variable (Y).The coefficient of determination (R^2) is 0.500, meaning that 50.0% of the variability in the dependent variable (Y) is explained by the independent variables (EC, IC, Age) in the model.
- The ANOVA table tests the overall significance of the regression model, and the F-statistic of 31.057 with a very low p-value (5.33667E-14) suggests that the overall regression model is statistically significant. The coefficients for EC and IC are significant, indicating that for each unit increase in EC and IC, the dependent variable (Y) is expected to increase by 0.299 and 0.474 units, respectively, holding other variables constant. However, the coefficient for Age is not significant, suggesting that Age may not have a significant linear relationship with the dependent variable (Y).

5.2 Interpretations of Statistical Results

The interpretation of the statistical results reveals several key findings. Firstly, the z-test comparisons between engagement construct (EC) and cognitive maturity (CM), as well as between innovative construct (IC) and CM, indicate no significant differences in means, suggesting a lack of association between these constructs. However, the z-test comparison between age (AGE) and CM indicates a significant difference, implying age-related variations in cognitive maturity levels. The ANOVA test further supports these findings, demonstrating significant differences between groups. The correlation matrix reveals positive correlations between EC and CM, EC and IC, and CM and IC, suggesting that higher engagement and innovative thinking are associated with increased cognitive maturity. Multiple linear regression analysis indicates a moderately strong positive correlation between engagement, innovative thinking, age, and cognitive maturity. While engagement and innovative thinking significantly predict cognitive maturity, age may not have a significant linear relationship with it. These findings collectively contribute to understanding the complex interplay between engagement, innovative thinking, age, and cognitive maturity.

5.3 Implications for Theory and Practice

The implications of this study for theory and practice are significant. From a theoretical perspective, the findings contribute to the existing body of knowledge by elucidating the relationship between engagement, innovative thinking, age, and cognitive maturity. The study underscores the importance of considering multiple factors, such as engagement and innovation, in understanding cognitive development across different age groups. These insights can inform and enrich existing theoretical frameworks related to cognitive psychology and educational psychology.

From a practical standpoint, the findings have several implications for various fields, including education, psychology, and human resource management. Educators can leverage the understanding of how engagement and innovative thinking influence cognitive maturity to design more effective teaching strategies and curriculum development approaches. Similarly, psychologists can use this knowledge to tailor interventions aimed at enhancing cognitive development in individuals of different age groups.

Moreover, organizations can benefit from these insights in their recruitment and training processes. Understanding the role of engagement and innovative thinking in cognitive development can help employers identify and nurture talent effectively. By fostering a work environment that promotes engagement and encourages innovative thinking, organizations can enhance employees' cognitive abilities and problem-solving skills, ultimately leading to improved performance and innovation.

Overall, the implications of this study extend beyond academia to practical applications in various domains, offering valuable insights for educators, psychologists, employers, and policymakers alike.

5.4 Recommendations for Future Research

Several avenues for future research emerge from the findings of this study. Firstly, exploring the longitudinal effects of engagement and innovative thinking on cognitive development could provide deeper insights into the long-term impact of these factors across different age cohorts. Longitudinal studies tracking individuals over extended periods would offer a more comprehensive understanding of how these variables interact and influence cognitive maturity over time.

Additionally, investigating the role of other factors, such as socio-economic status, cultural background, and educational experiences, in shaping cognitive development could enrich our understanding of the multifaceted nature of cognitive maturity. Comparative studies across diverse populations and cultural contexts would help identify potential differences and similarities in the determinants of cognitive development, offering valuable insights for tailored interventions and educational strategies.

Furthermore, exploring the effectiveness of intervention programs designed to enhance engagement and foster innovative thinking in different age groups could provide practical implications for educational and organizational settings. By evaluating the impact of specific interventions on cognitive outcomes, researchers can identify effective strategies for promoting cognitive development and enhancing problem-solving skills across various contexts.

Lastly, incorporating advanced analytical techniques, such as machine learning algorithms and neural network models, could offer new avenues for exploring complex relationships and predicting cognitive outcomes more accurately. By leveraging big data analytics and computational approaches, future research can advance our understanding of cognitive development and contribute to the development of personalized interventions and educational practices tailored to individual needs.

VI. Conclusion

6.1 Recap of the Study Objectives

The study aimed to achieve several objectives. Firstly, it sought to investigate the relationship between engagement, innovative thinking, and cognitive maturity. Secondly, it aimed to explore the influence of age and gender on cognitive abilities. Additionally, the study aimed to apply advanced statistical techniques to analyse the data collected from a diverse sample. Furthermore, it aimed to provide practical insights into the implications of the findings for educational practices, workforce development, and policy-making. Overall, the study aimed to contribute to the understanding of cognitive development and critical thinking skills, with implications for theory, practice, and future research.

6.2 Summary of Main Findings

The study yielded several key findings regarding the relationship between engagement, innovative thinking, age, and cognitive maturity. Firstly, there were no significant differences in means between engagement construct (EC) and cognitive maturity (CM), or between innovative construct (IC) and CM, suggesting a lack of direct association between these constructs. However, age (AGE) showed a significant difference in means with CM, indicating age-related variations in cognitive maturity levels. The ANOVA test reinforced these findings, showing significant differences between groups. The correlation matrix highlighted positive correlations between EC and CM, EC and IC, and CM and IC, suggesting that higher engagement and innovative thinking correspond to increased cognitive maturity. Multiple linear regression analysis indicated a moderately strong positive correlation between engagement, innovative thinking, age, and cognitive maturity. While engagement and innovative thinking significantly predicted cognitive maturity, age may not have a significant linear relationship with it. These findings contribute to understanding the complex dynamics underlying cognitive development across different age groups and levels of engagement and innovation.

6.3 Contributions to Knowledge

The study contributes to the existing body of knowledge in several ways. Firstly, it sheds light on the relationship between engagement, innovative thinking, and cognitive maturity, providing insights into how these constructs interact and influence each other. Secondly, by examining the impact of age and gender on cognitive abilities, the study expands our understanding of the factors that contribute to cognitive development across different demographic groups. Additionally, the study contributes methodologically by demonstrating the application of advanced statistical techniques, such as multiple linear regression and ANOVA, in analysing complex relationships among variables. Furthermore, the findings offer practical implications for educators, employers, policymakers, and individuals seeking to enhance critical thinking skills and cognitive abilities. Overall, the study contributes valuable insights and methodological approaches that can inform future research and practice in the fields of education, psychology, organizational behavior, and beyond.

6.4 Practical Implications and Applications

The study's findings carry significant practical implications and applications across various domains. Educators can utilize the insights to design curriculum and instructional strategies aimed at fostering critical thinking skills among learners, while organizations can develop training programs to enhance critical thinking abilities among employees. Employers can incorporate assessments of engagement, innovative thinking, and cognitive maturity into their selection processes to build teams capable of tackling complex challenges. Individuals can use the findings to develop personal strategies for enhancing their critical thinking abilities, and policymakers can inform decision-making processes related to education and workforce development. Overall, integrating principles of engagement and innovative thinking into educational, organizational, and personal contexts can promote adaptability and innovation, enabling individuals and organizations to thrive in dynamic environments.

6.5 Limitations of the Study

- **Sample Size and Diversity:** The study collected data from 126 participants, which may not represent a diverse range of demographics. Additionally, the sample size might be considered relatively small for drawing generalized conclusions about cognitive development across different age groups and genders.
- **Sampling Bias:** The data collection method relied on a Google Document, which might have introduced sampling bias as it primarily captures responses from individuals who are technologically inclined or have access to online platforms. This could limit the generalizability of the findings to populations with different levels of technological literacy or access.
- **Measurement Instrument Reliability:** While the questionnaire used in the study was adapted from a pre-existing manual, its reliability and validity in the specific context of the study were not extensively discussed. There may be limitations in the reliability of the measurements, potentially affecting the accuracy of the results.
- **Data Processing Techniques:** Although various data preprocessing techniques were applied to enhance the quality of the data for linear regression analysis, the choice of these techniques and their potential impact on the results were not thoroughly evaluated. Different preprocessing methods could yield different outcomes, which might affect the robustness of the findings.
- **Cross-Sectional Design**: The study utilized a cross-sectional design, which only captures a snapshot of cognitive abilities and developmental stages at a specific point in time. Longitudinal studies would provide a more comprehensive understanding of how cognitive abilities evolve over time and the factors influencing these changes.
- **External Validity**: The findings of the study may have limited external validity beyond the specific context and population sampled. Extrapolating the results to broader populations or different cultural contexts should be done cautiously, as the relationships between variables may vary across different settings.

Addressing these limitations in future research endeavours would contribute to a more robust understanding of cognitive development and the factors influencing it.

6.6 Conclusion and Closing Remarks

the statistical analyses conducted in this study provide valuable insights into the relationships between engagement construct (EC), innovative construct (IC), age, and cognitive maturity (CM). The z-test results indicate no significant differences between EC and CM or IC and CM, while a significant difference is observed between age and CM. Additionally, the ANOVA test reveals a highly significant difference between the means of the groups, highlighting the importance of these constructs in understanding cognitive development. The correlation matrix illustrates positive correlations between EC and CM, EC and IC, and CM and IC, suggesting that as EC and IC increase, CM tends to increase as well. However, there is a weak negative correlation between EC and age, and a weak positive correlation between CM and age, indicating subtle changes with age. The multiple linear regression analysis further emphasizes the impact of EC and IC on CM, with significant coefficients for both constructs. However, the coefficient for age is not significant, suggesting that age may not have a significant linear relationship with CM. Overall, these findings contribute to our understanding of cognitive development and highlight the importance of engagement and innovation in enhancing cognitive maturity.

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