European Economic Letters
ISSN 2323-5233
Vol 15, Issue 4 (2025)
http://eelet.org.uk

Examining Millennial Intelligence: Utilizing the Joyce Martin Tool to Harness Multiple Intelligences from Job Experience

[1]Dr. Seema Sant, [*2]Dr. Mrinali Tikare, [3]Prof. Seva Ranganekar

[1]Professor & Associate Dean HR, Vivekanand Education Society Institute of Management Studies and Research, Mumbai, Maharashtra, India Email - seema.sant@ves.ac.in
[*2]Associate Professor, Chetana's Institute of Management and Research, Mumbai, Maharashtra, India Email - mrinali.tikare@cimr.in ORCID -0000-0001-5629-3971
[3]Asst. Professor, Chetana's Institute of Management and Research, Mumbai, Maharashtra, India Email - seva.ranganekar@cimr.in

Abstract
In the early 21st century, Artificial Intelligence ignited fascination, overshadowing our diverse human intelligence. Amid the excitement, our innate cognitive gifts often went unnoticed. This study probes millennial intelligence levels, employing Joyce Martin's tool with 135 items across nine types. Utilizing Varimax rotation, it uncovered robust scale loadings. Focused on Mumbai and Maharashtra, the research targeted tech-savvy millennials with stratified sampling. Descriptive analysis highlighted elevated *Interpersonal, Intrapersonal, Naturalistic, and Philosophical-Ethical Intelligences*. Pearson correlations unveiled significant positive links among these variables. While 'job experience' and 'no job experience' groups showed no significant intelligence score differences, a marked contrast emerged in *Philosophical-Ethical Intelligence* within job experience groups. The study emphasizes consistent intelligence scores across job experiences, offering HR and academic insights, despite acknowledging sampling and self-report biases.

Keywords: *Multiple Intelligence, Job Experience, Millennial Generation, Validity of the Scales*

1. INTRODUCTION

The term Industry 4.0 encompasses a promise of a new industrial revolution—one that marries advanced manufacturing techniques with the Internet of Things (IoT) to create manufacturing systems that are not only interconnected, but communicate, analyze, and use information to drive further intelligent action back in the physical world. Artificial Intelligence (AI) and Industry 4.0 work together to contribute to the revolution that is currently underway in practically every area. AI is crucial to Industry 4.0 because it provides the intelligence required to make sense of massive amounts of data received from IoT devices and other sources. Artificial intelligence is the **simulation of human intelligence processes by machines**, especially computer systems. Specific applications of AI include expert systems, natural language processing, speech recognition, and machine vision. AI and multiple intelligences connect in fascinating ways, highlighting the complex nature of human and computer capabilities. AI, the embodiment of machine intelligence, is inspired by Howard Gardner's concept of multiple intelligences. This link emphasizes the changing relationship between human intellect and computing capabilities. Multiple intelligences refer **to a theory describing the different ways individuals learn and acquire information**. These multiple intelligences range from the use of words, numbers, pictures, and music to the importance of social interactions, introspection, physical movement and being in tune with nature.

AI represents specific types of intelligence, notably logical-mathematical intelligence, but also, increasingly, linguistic, and visual-spatial intelligence. Machine learning algorithms mimic human cognitive processes by learning patterns from large datasets. Natural language processing allows machines to understand and synthesise human language, like linguistic intelligence. By allowing robots to recognise and interpret visual information, computer vision replicates feature of visual-spatial intelligence. However, artificial intelligence currently lacks key types of intelligence, such as emotional and interpersonal intelligences, which are inherently human characteristics. While AI can recognise emotions through sentiment analysis, it falls short of full emotional comprehension. Interpersonal intelligence, which is essential for empathy and efficient communication, is outside the capabilities of AI. AI and multiple intelligences are collaborating in areas such as personalised education and human-AI collaboration. AI-powered education platforms adjust to pupils' learning patterns, similar to how different intelligences are addressed. Humans and AI collaborate in collaborative environments, leveraging their respective strengths—AI's analytical power and humans' emotional and social intelligences. Nonetheless, the uniqueness of human intelligences is unrivalled. Despite its prowess, artificial intelligence is a tool produced by human intellect, and while it may mimic certain elements, it lacks the comprehensive knowledge that comes from the diversity of human intelligences.

In essence, the relationship between AI and various intelligences represents the complex dance of human cognition and technology progress. Recognising the range of intelligences—both human and artificial—as AI evolves provides insight on the intricacy of intelligence itself and the distinct contributions that each brings to the table. The multiple intelligence theory **can draw individuals back into learning**. Using the different intelligences to teach a concept allows each of your diverse learners a chance to succeed at learning. The learner with strength in the visual-spatial intelligence will do well with drawing and puzzles.

Current study aims to understand the disparity in multiple intelligence levels between individuals with job experience and those without. This difference holds significant importance due to its potential implications for education, career development, and workforce effectiveness. This exploration could shed light on whether prior work exposure influences the development and expression of diverse cognitive strengths. Recognizing such disparities might prompt educational institutions, employers, and policymakers to tailor learning methods, training programs, and recruitment strategies to accommodate the varied cognitive profiles of individuals entering the workforce. Moreover, addressing this disparity could contribute to creating more inclusive and supportive work environments that harness a diverse range of intelligences, thereby enhancing collaboration, problem-solving, and overall organizational success.

2. REVIEW OF LITERATURE

Multiple intelligences refer to a theory describing the different ways students learn and acquire information. These multiple intelligences range from the use of words, numbers, pictures and music, to the importance of social interactions, introspection, physical movement and being in tune with nature. Accordingly, an understanding of which type(s) of intelligence a student may possess can help teachers adjust learning styles, and suggest certain career paths for learners. **'Multiple intelligences'** is a theory first posited by Harvard developmental psychologist Howard Gardner in 1983 that suggests human intelligence can be differentiated into eight modalities: visual-spatial, verbal-linguistic, musical-rhythmic, logical-mathematical, interpersonal, intrapersonal, naturalistic and bodily-kinesthetic. Gardner's work differs from the traditional psychometric framework in that his theory of multiple intelligences (MI) adds a number of novel notions in both theory and intelligence assessment. Gardner's research deviates from the usual psychometric approach by involving the construction of tasks based on individuals' ordinary experiences. This method seeks to improve real-world applicability and the link between knowledge and practical performance. The assessment of cognitive ability takes place in a classroom context, with practise tasks that use interesting materials and have no time limits. This method allows youngsters to interact with the materials in a meaningful way. The evaluation process gathers insights into people's abilities to deliver relevant and important information that supports learning, shifting the emphasis away from outcomes (Almeida et al., 2010; Gardner, 1999b).

The Multiple Intelligence theory (MI) investigates and evaluates two types of brain activities: mental capabilities and learning and knowledge acquisition processes (Gardner, 1983). The theory challenges the idea of a single IQ, where human beings have one central "computer" where intelligence is housed. Howard Gardner, the Harvard professor who originally proposed the theory, says that there are multiple types of human intelligence, each representing different ways of processing information:

- Verbal-linguistic intelligence refers to an individual's ability to analyze information and produce work that involves oral and written language, such as speeches, books, and emails.
- Logical-mathematical intelligence describes the ability to develop equations and proofs, make calculations, and solve abstract problems.
- Visual-spatial intelligence allows people to comprehend maps and other types of graphical information.
- Musical intelligence enables individuals to produce and make meaning of different types of sound.
- Naturalistic intelligence refers to the ability to identify and distinguish among different types of plants, animals, and weather formations found in the natural world.
- Bodily-kinesthetic intelligence entails using one's own body to create products or solve problems.
- Interpersonal intelligence reflects an ability to recognize and understand other people's moods, desires, motivations, and intentions.
- Intrapersonal intelligence refers to people's ability to recognize and assess those same characteristics within themselves

Madkour & Mohamed (2016) in their study on ‘Identifying college students’ multiple intelligence to enhance motivation and learning proficiency’ had concluded that students’ awareness regarding their multiple intelligence profiles not only enhance their motivation level but improves their language skills. The study further adds that use of teaching pedagogies based on multiple intelligence approach will help in developing social and cultural skills among students, which ultimately help students in dealing with others in a job scenario. The study cites the use of research-based theories like multiple intelligence to improve students’ performance and achievements. Under the study, researchers have conducted quasi-experimental research by collecting the data from the students of English at the College of Languages and Translation, Al-Imam Mohammad Ibn Saud Islamic University in Saudi Arabia and dividing them into two groups. While the first group learned in traditional classroom setting through memorization of language rules, second group used multiple intelligence concept to learn. The study concluded that use of multiple intelligence theory in teaching may improve students’ academic results, performance, and achievements.

Krishnan & Awang (2017) have addressed the problem of unemployment in their study and how awareness of one’s multiple intelligence can help management graduates to get a job. They have stressed on the role of multiple intelligence in the field of employment. As per them, students with understanding on their multiple intelligence (MI) profile can explore multiple aspects of a job and choose which one is best for them. A fair knowledge about MI can even help in boosting self-esteem, confidence, and performance at workplace. Application of MI theory can assist Human Resources to choose the right candidate by gauging candidates’ MI profile. The study was based on secondary data collected on Multiple Intelligences in Employability among Universiti Teknikal Malaysia Melaka

(UTeM) management graduates. Researchers have applied psychometric test (Ability Test in Employment or ATIEm) to gauge the graduates' perception on their intelligence strengths and weaknesses as per the Howard Gardner's MI theory. The results of study through the application of Structural Equation Modelling concludes that management graduate at UTeM though possesses all types of MI, the extent to which each is developed differs from one person to another. It suggests that universities should nurture and expose students with all MI to ensure their successful career.

Bayram & Özge Yüceloğlu Keskin (2020) examined the multiple intelligence types based on Academic Success, Age, Gender, and Job Experience of Physical Education Teachers. The study was based on the data collected from 110 physical education teachers residing in four cities of Turkey which include Istanbul, Ankara, Samsun, Gaziantep. The study came out with several findings females rank higher than males in bodily-kinesthetic intelligence, social-intelligence points of the older population (34-42) are higher as compared to younger ones, and students prefer to communicate with younger teachers aged 22-28 and consider them as their role models than the older ones. The study has also highlighted the intelligence type points based on the job experience which is also the focus of the current study. Researchers have proved that there is no significant difference between intelligence points and job experience a teacher possesses. However, it pointed out that teachers with experience of 10-14 years scored higher on social intelligence points. It can, therefore, be concluded that the social intelligence points are bound to be higher as the amount of time spent on a job, job experience, and communication skills increases.

Lei et al. (2021) in their study on the use of multiple intelligences for corporate employees' learning achievement has focussed on the role of multiple intelligences in enhancing learner motivation and achievement. They conducted their experimental research on 314 employees of the high-tech industry in Taiwan through a questionnaire survey. The study has resulted in several important outcomes. Firstly, teaching with MI would enhance learning motivation and achievement among employees in the high-tech industry. Secondly, employees who have experienced MI in the teaching process turned out to be more confident. Thirdly, as compared to traditional teaching MI teaching methods develop an ability among employees to grasp the learning rather than a mere acceptance of learning. It is obvious from this study that irrespective of the experience one has, if employees are trained using MI there are high chances that they will learn to achieve and also be motivated to learn.

Aguayo et al. (2021) have highlighted the importance and application of MI theory in primary education to improve students' creativity, maturation, and performance. They have experimented on 420 students of state-funded schools by dividing them into control and experimental groups. While the experimental group (EG) was taught using Gardner's MI theory, the control group (CG) employed traditional teaching methods. The results reflected that the students in EG have scored higher grades and a greater aptitude than the students with traditional teaching methods. The results also reflected that various intelligences are positively related to academic performance. Creativity and maturity levels among students educated through MI-based methods are better than those of traditional methods. It can be concluded that these students may perform better in their jobs being more creative and mature to handle the situations.

Mendis & Dharmasiri (2019) investigated the role of MI in individual work performance and the role of generations. The researchers conducted a survey using a pre-validated questionnaire on 294 managers in the banking and apparel sector. Using structural equation modelling, the study has concluded that MI and individual work performance are positively related. The study further elaborated on the effect of generations on this relationship. It says that Gen Y has displayed a higher level of this correlation than Gen Y. The study has added to the existing body of research, the role of MI and generations on the work performance of the individuals. This study, thus, suggests that MI should be considered while judging an individual's performance and contribution to the organization.

According to Gonzalez-Trevino et al. (2020), believes that the identification of various types of multiple intelligence offers educators insights into their students' characteristics. Their study aimed to examine the disparities in MI based on gender and school grade among elementary school students in Mexico. To achieve this, a self-administered questionnaire was used for 161 Mexican students. The study's outcomes indicated that the mean scores across the eight MI categories exhibited similarities between genders. Notably, the only significant gender difference was in intrapersonal IQ, where males reported more discrepancies than females. No other significant variations in MI were observed, and no interactions were identified between gender and school grade. In conclusion, these findings suggest that the effective implementation of diverse MI types might not be fully realized among elementary school children.

Multiple intelligence theory in education facilitates tailored learning based on students' dominant intelligence and preferred style. In their study, (Yavich & Rotnitsky, 2020) conducted their research on Israeli middle school (158 seventh-graders) and explored the link between dominant intelligences and academic achievement. High-performing classes showed 80.9% dominance in logical intelligence, compared to 48.4% in regular classes. Notably, excellent classes had more students with multiple dominant intelligences, including spatial, musical, and kinesthetic. This suggests that while logical-mathematical intelligence significantly influences achievement, other intelligences also contribute, predicting students' success.

2.1 Gap Analysis

A conspicuous gap in the landscape of multiple intelligence theory research becomes evident when we observe that most investigations have been confined to the realm of school students. While extensive attention has been directed towards understanding the dynamics of multiple intelligences within educational settings, there remains a significant dearth of exploration concerning the translation of this theory into practical applications within the workplace. This notable oversight highlights the untapped potential and uncharted territory that exists in comprehending how multiple intelligence theory could play a pivotal role in predicting and understanding the cognitive profiles of individuals in professional contexts. In essence, the extensive body of research focusing on school students has yielded invaluable insights into how the theory of multiple intelligences can influence learning approaches and academic outcomes. However, this concentration has inadvertently overshadowed the unexplored prospects within workplaces. It is essential to recognize that the skills and intelligence that contribute to success in educational contexts are not isolated from those that enable success in professional environments.

The workplace, with its diverse challenges and multifaceted demands, is an arena where the theory of multiple intelligences could potentially shine as a predictive tool. The ability to discern the predominant intelligence among individuals with varying degrees of work experience, juxtaposed with those who are relatively inexperienced, holds the promise of shedding light on the cognitive attributes that drive professional success. This gap in research represents a missed opportunity to harness the theory's potential in aiding talent acquisition, employee development, and the optimization of team dynamics. In addressing this gap, this research endeavors to bridge the divide between the theory's academic foundations and its practical implications for the workforce. By delving into the realm of multiple intelligences within the context of the workplace, the current study has unraveled a nuanced understanding of how individuals' cognitive strengths influence their performance, problem-solving approaches, and overall efficacy within professional settings. Such investigations could potentially transform the landscape of recruitment strategies, training methodologies, and organizational structures, fostering an environment that truly capitalizes on the diverse spectrum of cognitive abilities.

3. RESEARCH METHODOLOGY

3.1 Research Objectives

a) To identify multiple intelligence levels of participants of the millennial generation.
b) To find out the correlation between nine types of intelligence
c) To compare multiple intelligence levels of work experience participants and non-work experience participants.

3.2 Research Hypothesis

a) There is no significant correlation among the nine types of intelligence.
b) There is no significant difference in the level of the population mean scores on the composite dependent variables with reference to work experience participants and non-work experience participants.

3.3 Major Variables under Study

The study encompasses independent variables that pertain to demographic aspects, specifically Education, Experience, Gender, and Region. These variables are crucial factors that can potentially influence the multiple intelligence levels under investigation. On the other hand, the dependent variables central to the study are the nine distinct types of intelligence levels. These cognitive attributes collectively represent the focal points of examination, aiming to uncover potential patterns and relationships between these intelligence types and the aforementioned demographic factors. By analyzing how these independent and dependent variables interplay, the study aims to contribute valuable insights into the intricate connections between human cognitive abilities and demographic characteristics.

3.4 Sampling Design

The study focuses on the Millennial generation, specifically individuals aged 20 to 27 years. The sample comprises individuals who have successfully completed their Graduate Degree and are aspiring to pursue a Master's or Post-Graduate degree. These participants are drawn from urban areas in Maharashtra, characterized by their familiarity with computer usage. The technique employed for sample selection is Stratified Random Sampling, ensuring representation across various subgroups within the population. The chosen sample size is 205, offering a comprehensive view of the targeted cohort's perspectives and experiences.

Sample Size Estimation

Sample Size Determination Based on Continuous Variable	Estimated by using the Confidence Interval Method $$n = \frac{z^2 \times \hat{p}(1-\hat{p})}{\varepsilon^2}$$ where	Sample estimation – 267 300 Questionnaire Distributed 240 Response Received 205 Used for Study Response Rate – 68%

	z is the z score : 1.96 **ε** is the margin of error :6% **N** is population size: 267 **p̂** is the population proportion: 50%	

The Likert Scale used for the data collection where score 5 indicated for Strongly Agree and 1 assigned for Strongly Disagree. There are 15-items for each scale of intelligence therefore, the minimum mean score is expected 15 and maximum mean score is expected 75. If there is more than 55 mean score then it should be interpreted as higher level of intelligence and vice versa.

3.5 Details of Tools

Before 1939, the Army Alpha test was conducted for soldiers, and it consisted of verbal and problem-solving assessments. In 1939 David Weschler published the more sophisticated Stanford–Binet test of adult intelligence (Weschler Adult Intelligence Scale) to measure general intelligence. A new framework for describing intelligence was proposed by Professor Howard Gardner of Harvard University in 1983 based on evidence derived from research in neurophysiology and psychology. The theory of multiple intelligences was outlined in his groundbreaking book ***'Frames of Mind'***. Evidence were presented that the multiple intelligences theory could be utilized not only to explain intelligence but also, in a practical sense, to promote and develop it. Martin Joyce worked on applying multiple intelligence at work in 2000, drawing inspiration from Gardner's work. In his book, ***'Profiting from Multiple Intelligence in the Workplace'*** by mapping job-related skills or competencies, he created the 9 types of intelligence scale. According to him, the initial step in implementing the concept of multiple intelligence is to create personal database profiles. Each intelligence type has 15 items that consist of 'importance' and 'competence' of intelligence. By assigning weight, it is measured on a scale of 1 to 5 which starts from low to high. However, for the present study, the level of multiple intelligences was measured using the 'Likert Scale' from 1 to 5, starting from strongly disagree to strongly agree.

3.6 Construct Reliability & Validity

Cronbach's Alpha values are used to examine the measurement model's internal consistency and reliability. The degree to which an instrument produces the same results when measured under the same conditions is referred to as its reliability.

Table 1: Construct Reliability

SR. No.	Dependent Variable – Nine Types of Intelligence	Number of Items	Cronbach Alpha
1	Linguistic Intelligence	15	0.876
2	Mathematical Technical Logical Scientific Intelligence	15	0.887
3	Visual Intelligence	15	0.882
4	Auditory Intelligence	15	0.779
5	Kinaesthetic Motor Intelligence	15	0.792
6	Interpersonal Intelligence	15	0.839
7	Intrapersonal Intelligence	15	0.865
8	Naturalistic Intelligence	15	0.892
9	Philosophical Ethical Intelligence	15	0.869

Cronbach's alpha scores should be at least 0.70 for the questionnaire to be considered credible (J F Hair et al., 2019). The current study reflects the Cronbach Alpha values of all the variables are above 0.7 as reflected in Table 1. A higher value of Cronbach's alpha indicates better internal consistency of the items measuring the construct.

To check the validity of the constructs, the 135-item multiple intelligence scales were subjected to Principal Components Analysis (PCA) using SPSS version 21 (Table 2). Prior to performing PCA, the suitability of data for factor analysis was assessed. Inspection of the correlation matrix revealed the presence of many coefficients of 0.3 and above in both scales.

Table 2: Construct Validity using Principal Components Analysis

Variables N = 205	**KMO Measures Of Sampling Adequacy With P Value**	**Initial Presence of Number of Components**	**Decision to use Component**	**The Total of Factor Loading in Rotation**	**Eigen Values**	**Total Variance Explained**	**Specific Observation**
Linguistic Intelligence (15 Items)	0.877 P = 0.000	3	1	9.085	5.641	37.604	
Mathematical Technical Logical Scientific Intelligence (15 Items)	0.876 P = 0.000	3	1	8.651	5.973	39.819	Note: 2 Items has small coefficient
Visual Intelligence (15 Items)	0.841 P = 0.00	4	1	9.264	5.819	38.793	
Auditory Intelligence (15 Items)	0.779 P = 0.00	5	1	7.216	3.923	26.152	Note: 1 Item has small coefficient
Kinaesthetic Motor Intelligence (15 Items)	0.763 P = 0.00	4	1	7.316	3.982	26.543	Note: 1 Item has small coefficient
Interpersonal Intelligence (15 Items)	0.836 P = 0.00	4	1	8.466	4.904	32.695	
Intrapersonal Intelligence (15 Items)	0.852 P = 0.00	4	1	8.868	5.399	35.991	
Naturalistic Intelligence (15 Items)	0.888 P = 0.00	3	1	9.496	6.098	40.655	
Philosophical Ethical Intelligence (15 Items)	0.861 P = 0.00	4	1	9.012	5.502	36.682	

Note: Only loadings above .3 computed for the Total of Factor Loading

The Kaiser-Meyer-Olkin value exceeded the recommended value of 0.6 (Kaiser 1970, 1974 & Bartlett's Test of Sphericity (Bartlett 1954) and reached statistical significance, supporting the factorability of the correlation matrix. Principal components analysis revealed the presence of 3 to 5 components for multiple scales of intelligence with eigenvalues exceeding 1. However, with the objectives of this study, it was decided to retain one component for each intelligence scale for further investigation. By using Varimax rotation the one-component solution explained a total of the variances indicated in Table No. 2. It is also observed that there is strong loading for each component. The results of this analysis support the use of a unidimensional scale of each multiple intelligence for further inferential statistics.

4. DATA ANALYSIS AND INTERPRETATION

4.1 Demographic Analysis

As previously mentioned, this study's scope is confined to the state of Maharashtra, with participants falling within the age range of 20 to 27 years. All participants hold Bachelor's Degrees, comprising 56.6% males and 43.4% females. Notably, the analysis reveals that 47.3% of respondents possess job experience, while the remaining 52.7% lack any prior work experience.

Table 3: Descriptive Statistics

SR. No.	Dependent Variable – Nine Types of Intelligence	Mean	Standard Deviation
1	Linguistic Intelligence	54.2537	6.93415
2	Mathematical Technical Logical Scientific Intelligence	52.9073	8.06567
3	Visual Intelligence	52.0488	7.73188
4	Auditory Intelligence	50.8049	6.31222
5	Kinaesthetic Motor Intelligence	52.1366	6.40472
6	Interpersonal Intelligence	59.5366	6.06863
7	Intrapersonal Intelligence	59.5171	6.55714
8	Naturalistic Intelligence	53.8634	7.67993
9	Philosophical Ethical Intelligence	58.7171	6.99986

Table 3 shows the average scores and how much the scores vary for different types of intelligence. For example, in linguistic intelligence, people scored around 54.25 on average, and their scores varied by about 6.93 points. In subjects like interpersonal and intrapersonal intelligence, where we understand and manage our own emotions and others, the average scores were higher at about 59.54, with smaller variations. On the other hand, in auditory intelligence, which is about understanding sounds and patterns, the average score was about 50.80, and the scores didn't vary much, with only about 6.31 points of difference. This information helps us understand how people's abilities in these areas differ and how consistent or spread out their scores are. Among the respondents, the highest average scores were observed in Interpersonal Intelligence and Intrapersonal Intelligence, both with an average score of around 59.54. These types of intelligence pertain to understanding and managing emotions within oneself and in relationships with others. This suggests that, on average, the participants demonstrated relatively strong abilities in perceiving and navigating social and emotional aspects. Similarly, Participants exhibited an average score of about 58.72 in Philosophical Ethical Intelligence. This type of intelligence involves contemplating abstract concepts, ethical dilemmas, and philosophical questions. The relatively high average score suggests that respondents, on average, possess a certain level of proficiency in grappling with moral and philosophical matters, indicating a capacity for thoughtful and reflective consideration of ethical and philosophical aspects.

Thus, from above table it can be interpreted that all the respondents indicated higher level of Interpersonal Intelligence, Intrapersonal Intelligence, Naturalistic Intelligence and Philosophical Ethical Intelligence.

4.2 Inferential Statistics

4.2.1 Pearson Correlations

To accomplish objective 2 i.e. to find out the correlation among multiple intelligence, Pearson Correlation Technique was performed as reflected in Table 4.

Table 4: Pearson Correlations

Correlations									
Variables	Linguistic Intelligence	Mathematical Technical Intelligence	Visual Intelligence	Audio Intelligence	Kinaesthetic Intelligence	Interrelationship Intelligence	Intrarelationship Intelligence	Naturalistic Intelligence	Philosophical Intelligence
Linguistic Intelligence	1	.303**	.400**	.474**	.430**	.551**	.498**	.433**	.505**
Mathematical Technical Logical Scientific Intelligence		1	.535**	.311**	.487**	.378**	.318**	.408**	.428**
Visual Intelligence			1	.591**	.520**	.458**	.419**	.604**	.493**
Auditory Intelligence				1	.560**	.505**	.499**	.598**	.506**
Kinaesthetic Motor Intelligence					1	.531**	.569**	.513**	.508**
Interpersonal Intelligence						1	.726**	.587**	.699**
Intrapersonal Intelligence							1	.596**	.687**
Naturalistic Intelligence								1	.627**
Philosophical Ethical Intelligence									1
**. Correlation is significant at the 0.01 level (2-tailed).									

The relationship among multiple intelligence was investigated using Pearson Product-Moment Correlation Coefficient. Preliminary analyses were performed to ensure no violation of the assumptions of normality, linearity, and homoscedasticity. The provided table represents the Pearson Correlations among various intelligence variables. Each cell displays the correlation coefficient between the respective intelligence variables, ranging from Linguistic Intelligence to Philosophical Intelligence. The table indicates significant correlations at the 0.01 level (2-tailed).

The correlation coefficients in the table represent the strength and direction of the relationships between different types of intelligence variables. Correlation values range from -1 to +1, where -1 indicates a perfect negative correlation, +1 indicates a perfect positive correlation, and 0 indicates no correlation.

In this specific correlation matrix:

- Linguistic Intelligence has moderate to strong positive correlations with Mathematical Technical Logical Scientific Intelligence (r = 0.303**), Visual Intelligence (r = 0.400**), Auditory Intelligence (r = 0.474**), Kinaesthetic Intelligence (r = 0.430**), Interrelationship Intelligence (r = 0.551**), Intrarelationship Intelligence (r = 0.498**), Naturalistic Intelligence (r = 0.433**), and Philosophical Intelligence (r = 0.505**). This suggests that individuals with higher linguistic intelligence tend to also have higher levels of these other intelligences.

- Mathematical Technical Logical Scientific Intelligence shows moderate to strong positive correlations with Visual Intelligence (r = 0.535**), Auditory Intelligence (r = 0.311**), Kinaesthetic Intelligence (r = 0.487**), Interrelationship Intelligence (r = 0.378**), Intrarelationship Intelligence (r = 0.318**), Naturalistic Intelligence (r = 0.408**), and Philosophical Intelligence (r = 0.428**).
- Visual Intelligence displays strong positive correlations with Auditory Intelligence (r = 0.591**), Kinaesthetic Intelligence (r = 0.520**), Interrelationship Intelligence (r = 0.458**), Intrarelationship Intelligence (r = 0.419**), Naturalistic Intelligence (r = 0.604**), and Philosophical Intelligence (r = 0.493**).
- Auditory Intelligence is strongly positively correlated with Kinaesthetic Intelligence (r = 0.560**), Interpersonal Intelligence (r = 0.505**), Intrarelationship Intelligence (r = 0.499**), and Naturalistic Intelligence (r = 0.598**), indicating that those with higher auditory intelligence tend to have higher scores in these other intelligence domains.
- Kinaesthetic Intelligence has strong positive correlations with Interpersonal Intelligence (r = 0.531**), Intrarelationship Intelligence (r = 0.569**), and Naturalistic Intelligence (r = 0.513**).
- Interpersonal Intelligence demonstrates a very strong positive correlation with Intrarelationship Intelligence (r = 0.726**).
- Intrapersonal Intelligence has a very strong positive correlation with Naturalistic Intelligence (r = 0.596**).

These correlation values provide insights into the extent to which different types of intelligence are related to each other among the variables being studied. Strong positive correlations suggest that individuals who excel in one type of intelligence often tend to do well in others as well. The significance level of 0.01 indicates that these correlations are statistically significant.

Since there was a moderate, positive and significant correlation among these nine variables, therefore, the Null Hypothesis - 'There is no significant correlation among the multiple intelligence level', is rejected.

4.2.2 Multivariate Analysis of Variance

To accomplish objective 3 – 'To compare multiple intelligence level of work experience participants and non-work experience participants, the multivariate analysis of variance was performed.

Table 5: Box's Test

Box's Test of Equality of Covariance Matrices[a]	
Box's M	58.188
F	1.233
df1	45
df2	132205.922
Sig.	.136
Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.	
a. Design: Intercept + JOBEXP	

The Box's Test of Equality of Covariance Matrices (Table 5) was conducted to assess whether the observed covariance matrices of the dependent variables are equal across groups. The calculated Box's M statistic is 58.188 (Table 5). The associated F statistic is 1.233, and the degrees of freedom (df1) are 45. The test also involves a large value for df2 (132205.922). The p-value (Sig.) resulting from the test is 0.136. From the above table of Box's Test of Equality of Covariance Matrices, it is observed that sig. value is larger than 0.001, therefore assumption of homogeneity of variance was not violated.

Table 6: Multivariate Tests

Multivariate Tests[b]							
Effect		**Value**	**F**	**Hypothesis df**	**Error df**	**Sig.**	**Partial Eta Squared**
Intercept	Pillai's Trace	.992	2778.088[a]	9.000	195.000	.000	.992
	Wilks' Lambda	.008	2778.088[a]	9.000	195.000	.000	.992
	Hotelling's Trace	128.219	2778.088[a]	9.000	195.000	.000	.992
	Roy's Largest Root	128.219	2778.088[a]	9.000	195.000	.000	.992
JOBEXP	Pillai's Trace	.081	1.900[a]	9.000	195.000	.054	.081
	Wilks' Lambda	.919	1.900[a]	9.000	195.000	.054	.081
	Hotelling's Trace	.088	1.900[a]	9.000	195.000	.054	.081
	Roy's Largest Root	.088	1.900[a]	9.000	195.000	.054	.081
a. Exact statistic							
b. Design: Intercept + JOBEXP							

A one-way between-groups multivariate analysis of variance was performed to investigate job experience differences in multiple intelligence levels. Nine dependent variables of multiple intelligence were used. The independent variable was job experience. Preliminary assumption testing was conducted to check for normality, linearity, univariate and multivariate outliers, homogeneity of variance and covariance matrices, and multicollinearity with no serious violations noted. There was no statistically significant difference between no job experience and with job experience on the combined dependent variables, F (9, 195) = 0.19, P = 0.054; Wilk's Lambda = 0.919; partial eta squared = 0.081 as mentioned in the Table No. 6.

When the results of dependent variables were considered separately, the only difference to reach statistical significance, using a Bonferroni adjusted alpha level of 0.005, was Philosophical Ethical Intelligence – F (1, 203) = 8.397, p = 0.004, partial eta squared = 0.040 indicated in Table No. 7.

Table 7: Tests of Between-Subjects Effects

Tests of Between-Subjects Effects							
Source	**Dependent Variable**	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
JOB EXPERIENCE	Linguistic Intelligence	114.206	1	114.206	2.391	.124	.012
	Mathematical Technical Logical Scientific Intelligence	281.741	1	281.741	4.403	.037	.021
	Visual Intelligence	40.100	1	40.100	.670	.414	.003
	Auditory Intelligence	61.207	1	61.207	1.540	.216	.008
	Kinaesthetic Motor Intelligence	87.192	1	87.192	2.137	.145	.010
	Interpersonal Intelligence	77.547	1	77.547	2.117	.147	.010
	Intrapersonal Intelligence	179.758	1	179.758	4.247	.041	.020
	Naturalistic Intelligence	1.028	1	1.028	.017	.895	.000
	Philosophical Ethical Intelligence	397.051	1	397.051	8.397	**.004**	.040

Table 8: Estimated Marginal Means

JOB EXPERIENCE					
Dependent Variable	**JOB EXPERIENCE**	**Mean**	**Std. Error**	**95% Confidence Interval**	
				Lower Bound	**Upper Bound**
Linguistic Intelligence	NO JOB EXPERIENCE	53.546	.665	52.235	54.857
	JOB EXPERIENCE	55.041	.702	53.658	56.425
Mathematical Technical Logical Scientific Intelligence	NO JOB EXPERIENCE	51.796	.770	50.279	53.314
	JOB EXPERIENCE	54.144	.812	52.543	55.746
Visual Intelligence	NO JOB EXPERIENCE	51.630	.745	50.161	53.098
	JOB EXPERIENCE	52.515	.786	50.966	54.065
Auditory Intelligence	NO JOB EXPERIENCE	50.287	.607	49.091	51.483
	JOB EXPERIENCE	51.381	.640	50.119	52.643
Kinaesthetic Motor Intelligence	NO JOB EXPERIENCE	51.519	.615	50.307	52.730
	JOB EXPERIENCE	52.825	.648	51.546	54.103
Interpersonal Intelligence	NO JOB EXPERIENCE	58.954	.582	57.805	60.102
	JOB EXPERIENCE	60.186	.614	58.974	61.397
Intrapersonal Intelligence	NO JOB EXPERIENCE	58.630	.626	57.395	59.864
	JOB EXPERIENCE	60.505	.661	59.203	61.808
Naturalistic Intelligence	NO JOB EXPERIENCE	53.796	.741	52.336	55.257
	JOB EXPERIENCE	53.938	.782	52.397	55.479
Philosophical Ethical Intelligence	NO JOB EXPERIENCE	57.398	.662	56.094	58.703
	JOB EXPERIENCE	60.186	.698	58.809	61.562

However, the null hypothesis, ‘There is no significant difference in the level of population mean scores on the composite dependent variables (MI) with reference to work experience of participants and non-work experience participants’ was retained. An inspection of the mean scores indicated that almost both groups were shown (Table 8) similar level of mean for eight dependent variables. However, for Philosophical Ethical Intelligence the mean level is higher for job experience respondents.

5. DISCUSSION OF FINDINGS

The research objectives were multifaceted, and aimed at understanding various aspects of multiple intelligence within the millennial generation. The study primarily sought to identify the different levels of multiple intelligence among participants belonging to this demographic. By doing so, the study aimed to shed light on the diverse cognitive strengths that individuals of the millennial generation possess. Moreover, the research aimed to uncover any potential correlations that might exist between the nine distinct types of intelligence, thereby providing insights into the interconnectedness of these cognitive abilities.

The study's investigation into the impact of work experience on multiple intelligence levels added another layer of complexity to its exploration. By categorizing participants into two groups – those with work experience and those without – the study sought to ascertain whether real-world professional exposure influences individuals' cognitive capabilities. The research hypotheses encapsulated both the potential correlations between the nine intelligence types and the differences in mean scores of multiple intelligences between the two participant groups.

Upon analyzing the data, a notable finding emerged: there existed a moderate, positive, and statistically significant correlation among the nine types of intelligence. This discovery signifies that these cognitive attributes are not isolated from one another but rather tend to coexist and interact in a meaningful manner within individuals. The rejection of the hypothesis related to the lack of significant correlation supports the notion that these cognitive capacities are indeed interlinked and can collectively contribute to an individual's overall cognitive profile.

On the other hand, when it comes to the influence of work experience on multiple intelligence levels, the data indicated that there was no significant difference in the population mean scores for the composite dependent variables (MI) between individuals with work experience and those without. This finding suggests that, overall, work experience might not lead to significant variations in the combined intelligence levels among participants. This could be interpreted to mean that the types of cognitive abilities assessed in this study might not be strongly influenced by exposure to the workforce. However, the analysis did reveal an interesting nuance: participants with job experience showed a higher mean level specifically in Philosophical Ethical Intelligence. This observation indicates that real-world professional exposure might contribute to the development or enhancement of philosophical and ethical reasoning abilities. The specific impact on Philosophical Ethical Intelligence suggests that certain cognitive attributes might be more responsive to work experience compared to others.

In summary, the study's findings underscore the intricate relationships between different types of intelligence within the millennial generation. While correlations among the various cognitive abilities were evident, the impact of work experience on overall multiple intelligence levels appeared to be relatively limited. However, the heightened Philosophical Ethical Intelligence among job experience respondents suggests that certain dimensions of cognitive capacity could indeed be influenced by exposure to the workforce. These insights contribute to a deeper understanding of how cognitive strengths and their interplay can be shaped by real-world experiences.

6. RECOMMENDATION AND FUTURE IMPLICATION

In light of the intriguing insights gleaned from the study's findings and the nuanced discussions that followed, several valuable recommendations can be formulated. These recommendations aim to leverage the newfound understanding of the correlations between various types of intelligence and the potential influence of work experience on cognitive strengths. By translating these insights into actionable strategies, educators, professionals, and researchers can collectively contribute to the enhancement of learning environments, workplace dynamics, and individual growth trajectories. These recommendations encapsulate the essence of the study's implications and propose directions for practical application and future investigation.

- **Educational Approaches**: Given the significance of correlations between different types of intelligence, educators could consider designing more holistic and personalized teaching approaches. Recognizing that these cognitive abilities often coexist, educational methods that leverage multiple intelligences could enhance learning experiences and cater to diverse learning styles.
- **Workplace Training**: While the study didn't find significant variations in overall multiple intelligence levels due to work experience, the heightened Philosophical Ethical Intelligence among job experience respondents suggests an opportunity for workplace training. Organizations could consider integrating ethics-related training and philosophical discussions to harness and foster this cognitive attribute.
- **Individualized Career Development**: The finding that work experience might impact specific types of intelligence underscores the importance of tailored career development. Individuals can reflect on their cognitive strengths, such as Philosophical Ethical Intelligence, to align with roles that capitalize on these capabilities, promoting personal growth and job satisfaction.
- **Longitudinal Studies**: To delve deeper into the influence of work experience, longitudinal studies could be conducted. Tracking participants' cognitive profiles over an extended period of their career

could provide insights into how various types of intelligence evolve with different job experiences and responsibilities.

Looking beyond the present study's horizons, there exist promising avenues for future research that could delve deeper into the intricate relationship between cognitive abilities and real-world experiences. One compelling avenue involves the exploration of cultural and regional variations in how work experience shapes cognitive strengths. By expanding the participant pool to encompass diverse cultural backgrounds, researchers can unravel whether cultural nuances contribute to different types of intelligence responding to professional exposure in distinct ways. Additionally, a more expansive investigation into the impact of work experience on a wider array of intelligence categories could unveil a comprehensive understanding of the extent to which various cognitive attributes are malleable in response to career contexts. A longitudinal approach offers another exciting trajectory, permitting the tracking of participants' cognitive profiles across multiple stages of their careers. Such an approach could illuminate how different types of intelligence evolve and adapt in the face of evolving work environments and responsibilities. Moreover, qualitative research methods like interviews and focus groups offer the potential to unearth rich narratives and personal experiences, providing a textured understanding of how job experiences resonate with specific cognitive capacities. Collectively, these future research directions have the potential to refine and expand upon the present study's insights, contributing to a more nuanced comprehension of the interplay between cognitive strengths and real-world engagement.

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