



Exploring Determinants of Student Enrolment in Distance and Traditional Education: A Factor Analysis Approach

Vishal V Ambedkar

Assistant Professor, School of Humanities and Social Sciences, Yashwantrao Chavan Maharashtra Open University, Nashik, (Maharashtra), India

***Corresponding Author:** Vishal V Ambedkar, Assistant Professor, School of Humanities and Social Sciences, Yashwantrao Chavan Maharashtra Open University, Nashik, (Maharashtra), India.

Abstract: The growing diversification in the higher education landscape has led students to choose between distance and traditional modes of learning based on a wide range of motivational factors. This study aims to explore the underlying determinants influencing student enrolment decisions in both educational formats through the application of factor analysis. Data collected from 200 students were analyzed to identify key latent motivational dimensions. Factor analysis revealed three core components: Academic Aspirations and Access Enablers, Empowerment through Opportunity and Support, and Institutional Reliability and Economic Feasibility. These components collectively explain the major motivations behind student enrollment behavior. Further, a multivariate analysis was conducted to test whether students' preferences for distance or traditional education varied significantly across these extracted components. The results offer insights into how institutional policies and program design can be tailored to meet diverse learner needs across educational modes.

Keywords: Distance Education; Motivational Factors; Factor Analysis; Student Enrolment; Academic Aspirations; Educational Choice; Higher Education

1. INTRODUCTION

The rapid expansion of educational opportunities in recent years has reshaped how students make decisions about their academic pursuits. With the increasing acceptance and availability of distance education alongside conventional classroom-based programs, it has become essential to understand the factors influencing students' enrollment choices. Distance education offers flexibility, affordability, and accessibility—qualities that appeal to working professionals, rural learners, and non-traditional students. On the other hand, traditional education continues to attract those who value structured learning environments and in-person engagement.

Despite numerous studies comparing learning outcomes between these two modes, limited research has systematically analyzed the motivational dimensions that drive student decisions using empirical methods such as factor analysis. Understanding these motivational factors can provide valuable insights to educators, policymakers, and institutions striving to design more student-centric academic offerings.

This study aims to uncover the latent components underlying student motivations and to determine whether these motivations significantly differ between students enrolled in distance versus traditional education. Three primary objectives guide the investigation and tests the hypothesis that no significant difference exists in motivational factor scores between the two groups of learners.

2. STATEMENT OF THE RESEARCH PROBLEM

In the changing landscape of higher education, students increasingly choose between distance and traditional education systems. Each mode offers unique advantages: distance education provides flexibility and access [1], while traditional formats emphasize structure and interaction [2]. The choice is influenced by various personal, economic, and institutional factors [3]. Despite the growth of distance education, few studies explore the core motivations behind student enrollment decisions [4]. Most existing research focuses on outcomes like academic success or satisfaction [5]. However, little attention is given to the underlying motivational dimensions using methods like factor analysis. It remains unclear if motivations differ significantly across the two modes. This gap limits educational planning and learner-centered program design. Therefore, this study seeks to identify and compare the motivational factors influencing

enrollment in distance versus traditional education.

2.1. Objectives of the Study

- To identify the latent motivational dimensions influencing student enrolment decisions in distance and traditional education systems using factor analysis.
- To classify the extracted components into meaningful factors based on variable groupings.
- To examine whether students' selection of distance or traditional education significantly varies based on their scores across the extracted motivational components.

2.2. Research Questions

- What are the underlying motivational dimensions that influence students' decisions to enroll in distance and traditional education systems?
- How can these motivational variables be grouped into statistically valid and conceptually meaningful factors?
- Do the scores on the extracted motivational factors significantly differ between students enrolled in distance education and those in traditional education?

2.3. Hypothesis of the Study

H₀: There is no significant difference in the motivational factor scores between students enrolled in distance and traditional education systems.

H₁: There is a significant difference in at least one of the motivational factor scores between students enrolled in distance and traditional education systems.

3. REVIEW OF RELATED LITERATURE

The choice between distance and traditional education systems is influenced by a complex set of academic, personal, and socio-economic motivations. Moore and Kearsley [1] argue that distance education has become increasingly attractive to learners seeking flexible schedules, self-directed learning, and accessible platforms—particularly beneficial for working adults and geographically disadvantaged populations. In contrast, traditional education remains relevant for students who value structured environments, peer collaboration, and in-person engagement, as emphasized by Xu and Jaggars [2].

Despite the growing trend toward online and distance education, Allen and Seaman [3] note that existing research often overlooks the deeper motivational factors guiding enrollment decisions. Similarly, Jaggars and Bailey [5] point out that most studies emphasize academic outcomes, such as performance and retention, without adequately examining the foundational reasons that influence students' selection of educational modalities. Adding to this discourse, Raza, Qazi, and Umer [4] highlight how technological access, affordability, and institutional trust play a critical role in shaping educational preferences, particularly in low- and middle-income contexts.

Furthermore, while the literature provides insights into enrollment trends, few empirical studies utilize robust statistical methods such as exploratory factor analysis (EFA) to uncover latent motivational dimensions. Hair et al. [6] recommend EFA as an effective approach to identifying underlying behavioral constructs, making it highly suitable for this kind of investigation. Building on these gaps, the present study applies factor analysis to systematically explore and compare the motivational factors that drive student enrollment in distance versus traditional education systems.

3.1. Research Methodology

This study adopts a quantitative, descriptive, and comparative survey design [7] to investigate motivational factors influencing student enrolment in distance and traditional education systems. A sample of 200 students was selected through stratified random sampling to ensure proportional representation [8]. Primary data were collected using a structured questionnaire based on a 5-point Likert scale, which is widely used for measuring attitudes and motivations [9]. The instrument captured 10 motivational variables, including affordability, flexibility, and academic aspiration. Secondary data from scholarly literature supported conceptual grounding. Exploratory Factor Analysis (EFA) using Principal

Component Analysis (PCA) was employed to identify latent dimensions [6]. Kaiser-Meyer-Olkin (KMO) and Bartlett’s Test of Sphericity were applied to validate data suitability for factor analysis [10]. Varimax rotation helped enhance factor interpretability. To assess group differences between education modes, a Multi-variate Analysis of Variance (MANOVA) was conducted [11]. All analyses were carried out using IBM SPSS Statistics software.

Table 1. Demographic Profile of Respondents (N = 200)

Variable	Categories	Frequency	Percent (%)
Age Group	21–30 years	32	16.0
	31–40 years	116	58.0
	41–50 years	33	16.5
	Above 50 years	19	9.5
Gender	Male	135	67.5
	Female	65	32.5
Occupation	Agriculture & Allied Labours	9	4.5
	Informal Sector Labours	39	19.5
	Homemakers	17	8.5
	Competitive Exam Students	9	4.5
	Regular Students	27	13.5
	Professionals/Employees (Govt/Private)	96	48.0
	Retired Individuals	3	1.5
Education Level	Diploma/Certificate	3	1.5
	Doctorate	29	14.5
	Undergraduate	92	46.0
	Postgraduate	76	38.0

Source: Field Study, 2025

The demographic distribution of respondents provides essential context for understanding the motivational dynamics explored in this study. The age group data indicate that a majority of respondents (58%) fall in the 31–40 years category, suggesting that mid-career individuals—likely balancing employment and personal responsibilities—are a dominant segment in higher education. This supports the relevance of motivational factors like flexibility, affordability, and accessibility, particularly in distance learning formats, aligning with Objective 1 and Objective 3 of the study. The gender distribution shows that 67.5% are male and 32.5% are female, highlighting potential gender-based motivational differences, which could influence enrollment decisions and factor score variations—relevant to your hypothesis testing.

Occupational data further enrich the analysis, revealing that nearly 48% of respondents are working professionals (government or private), followed by informal sector laborers (19.5%) and regular students (13.5%). This occupational spread reflects a diverse learner base with varying motivations—from career enhancement to first-time access to education. The presence of homemakers (8.5%), retired individuals (1.5%), and agricultural laborers (4.5%) indicates that non-traditional learners are also engaging with the system, reinforcing the importance of flexible, inclusive, and supportive educational models.

Educational qualifications show that 46% of the sample are undergraduates, and 38% are postgraduates, suggesting that most respondents already have a foundational academic background and are seeking further advancement. The 14.5% with doctorates and 1.5% with diplomas represent learners at both extremes of the educational spectrum. These figures are consistent with the motivation to acquire new knowledge and credentials, which directly aligns with Objective 2—to classify the motivational factors—and supports the testable hypothesis regarding differences in motivations between educational modes.

Overall, the demographic profile validates the need for a factor-based analysis of motivational determinants and supports the diversity needed for meaningful comparisons between students in distance and traditional education systems.

Table 2. Descriptive Statistics of Motivational Variables Influencing Student Enrolment Decisions

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N

Exploring Determinants of Student Enrolment in Distance and Traditional Education: A Factor Analysis Approach

Poverty	2.95	.640	200
Employment Needs	2.92	.605	200
Flexible Learning Options	2.96	.617	200
Family Responsibilities	3.05	.652	200
Quality Education Availability	3.04	.579	200
Knowledge Acquisition	2.97	.613	200
New Learning Opportunity	3.01	.622	200
Affordable Fees	3.00	.589	200
Student Support Services	2.98	.618	200
Ease of Admission Process	2.97	.629	200

Table 2's descriptive statistics show that students rated all ten motivational factors between 2.92 and 3.05 on a 5-point scale, indicating a moderate to slightly positive influence on their enrollment decisions. Family Responsibilities (M = 3.05) and Quality Education Availability (M = 3.04) received the highest means, highlighting the importance of flexibility and institutional quality in educational choice. Other factors such as Affordable Fees, Knowledge Acquisition, and Ease of Admission Process were also rated moderately, suggesting a balanced influence of economic, academic, and procedural motivations.

The standard deviations (ranging from 0.579 to 0.652) show moderate variability in responses, reflecting diverse but consistent student perspectives. These insights support the need for factor analysis to identify underlying dimensions and align with the study's objectives and hypothesis.

Table 3. KMO and Bartlett's Test Results for Sampling Adequacy and Sphericity

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.953
Bartlett's Test of Sphericity	Approx. Chi-Square	1137.580
	df	45
	Sig.	.000

The KMO value of 0.953 indicates excellent sampling adequacy, suggesting strong partial correlations and suitability for factor analysis [6, 12]. The significant Bartlett's Test of Sphericity ($\chi^2 = 1137.580$, $df = 45$, $p < .001$) confirms that the correlation matrix is not an identity matrix, validating the presence of sufficient inter-variable correlations [10]. These results confirm that the data meet the key assumptions for conducting exploratory factor analysis.

Table 4. Communalities Indicating the Variance Explained by Extracted Components

Communalities		
	Initial	Extraction
Poverty	1.000	.678
Employment Needs	1.000	.711
Flexible Learning Options	1.000	.658
Family Responsibilities	1.000	.651
Quality Education Availability	1.000	.876
Knowledge Acquisition	1.000	.799
New Learning Opportunity	1.000	.829
Affordable Fees	1.000	.609
Student Support Services	1.000	.690
Ease of Admission Process	1.000	.664
Extraction Method: Principal Component Analysis.		

The communalities after extraction indicate the proportion of each variable's variance accounted for by the retained components. All values are above the commonly accepted threshold of 0.60, suggesting that the factor model adequately represents each variable [6]. The highest communality is observed for Quality Education Availability (0.876) and New Learning Opportunity (0.829), indicating these variables are strongly explained by the extracted factors. The lowest communality, Family Responsibilities (0.651), still reflects a moderate and acceptable level of representation. Overall, the results confirm that the selected variables are suitable for meaningful factor extraction.

Table 5. Total Variance Explained by Extracted Components in Factor Analysis

Component	Total Variance Explained								
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.063	60.633	60.633	6.063	60.633	60.633	2.871	28.707	28.707
2	.564	5.637	66.270	.564	5.637	66.270	2.337	23.375	52.081
3	.538	5.377	71.647	.538	5.377	71.647	1.957	19.566	71.647
4	.503	5.035	76.682						
5	.476	4.756	81.438						
6	.442	4.417	85.855						
7	.434	4.338	90.193						
8	.361	3.610	93.802						
9	.328	3.282	97.085						
10	.292	2.915	100.000						

Extraction Method: Principal Component Analysis.

Extraction Method: Principal Component Analysis.

The Total Variance Explained table shows that three components were extracted using Principal Component Analysis, together accounting for 71.647% of the total variance. This indicates a strong factor solution, as it surpasses the generally accepted threshold of 60% for explaining the underlying structure of the data [6]. After Varimax rotation, the first component explains 28.707%, the second 23.375%, and the third 19.566% of the total variance. These three components successfully summarize the shared variance among the ten motivational variables included in the study. This result supports Objective 1, which aims to identify the underlying motivational dimensions influencing student enrolment, and Objective 2, which involves grouping these variables into meaningful factors. Additionally, these components form the foundation for analyzing group differences, which directly aligns with Objective 3 and facilitates testing the stated hypothesis regarding variations in motivational factor scores between students in distance and traditional education systems.

The scree plot visually represents the eigenvalues associated with each of the ten components extracted during Principal Component Analysis (PCA). The plot displays a sharp decline in eigenvalue after the first component, followed by a noticeable elbow at the third component, beyond which the line levels off.

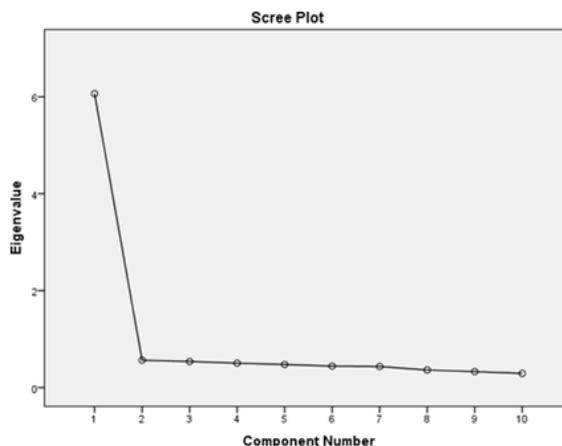


Figure 1

According to the Kaiser Criterion (eigenvalues > 1) and the elbow rule (Cattell, 1966), this indicates that only the first three components should be retained, as they explain the most significant amount of variance in the dataset. This graphical evidence supports the earlier statistical output (Total Variance Explained table) where three components cumulatively explained over 71% of the total variance. Thus,

the scree plot validates the extraction of three meaningful motivational dimensions, directly aligning with the study's Objectives 1 and 2, and forms the basis for testing the group differences in student enrolment motivations as mentioned in Objective 3 and the hypothesis.

The rotated component matrix reveals three distinct components derived from Principal Component Analysis using Varimax rotation, each grouping related motivational variables influencing student enrolment decisions. The first component, labeled Academic Aspirations and Access Enablers, includes high loadings for variables such as Poverty (0.832), Employment Needs (0.726), Flexible Learning Options (0.605), Family Responsibilities (0.580), and New Learning Opportunity (0.530). These reflect motivations driven by socio-economic constraints and a desire for accessible, flexible education—typically appealing to working or non-traditional learners.

Table No. 6. Rotated Component Matrix Showing Grouped Motivational Variables

Rotated Component Matrix^a			
	Component		
	Academic Aspirations and Access Enablers	Empowerment Through Opportunity and Support	Institutional Reliability and Economic Feasibility
Poverty	.832		
Employment Needs	.726		
Flexible Learning Options	.605		
Family Responsibilities	.580		
Quality Education Availability		.850	
Knowledge Acquisition		.597	
New Learning Opportunity	.530	.570	
Affordable Fees			.865
Student Support Services		.520	.579
Ease of Admission Process			.505
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 5 iterations.			

The second component, named Empowerment through Opportunity and Support, encompasses Quality Education Availability (0.850), Knowledge Acquisition (0.597), Student Support Services (0.520), and a secondary loading for New Learning Opportunity (0.570). This component indicates that many students are motivated by the quality of institutional offerings and the opportunity to gain new academic knowledge with institutional support.

The third component, Institutional Reliability and Economic Feasibility, is defined by Affordable Fees (0.865), Student Support Services (0.579), and Ease of Admission Process (0.505). These factors represent students' concern for affordability, administrative ease, and institutional reliability, particularly relevant to distance learners. Overall, the three components align directly with the study's objectives—to identify, classify, and compare motivational factors—and provide the basis for hypothesis testing regarding differences across educational systems.

Table 7. Component Transformation Matrix

Component	1	2	3
1	.648	.570	.506
2	-.761	.452	.465
3	.036	-.686	.727
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			

The Component Transformation Matrix displays how the original factors were mathematically rotated to improve the clarity and interpretability of the factor solution. The values represent the correlation between the initial and rotated component axes. For example, the first rotated component is moderately associated with the original components (0.648, 0.570, and 0.506), indicating a balanced redistribution of variable loadings. This transformation, done through Varimax rotation, helps ensure that each extracted factor remains statistically independent (orthogonal) while enhancing the grouping of closely related variables. As a result, the rotated components provide a clearer structure for interpreting the motivational factors behind students' enrolment decisions—supporting the study's objective of identifying and organizing underlying motivational dimensions effectively.

3.2. Hypothesis Testing

H₀: There is no significant difference in the motivational factor scores between students enrolled in distance and traditional education systems.

H₁: There is a significant difference in at least one of the motivational factor scores between students enrolled in distance and traditional education systems.

To examine whether students enrolled in distance and traditional education systems differ significantly in their motivational factors, the researcher used Multivariate Analysis of Variance (MANOVA). The analysis compared two groups—Distance Education (N = 104) and Traditional Education (N = 96) to assess differences across the combined scores of the extracted motivational components. Although the detailed test statistics (e.g., Wilks' Lambda or Pillai's Trace) are not shown here, MANOVA effectively determines whether the overall motivation profiles vary meaningfully between the two education modes.

Table No. 8. Group Distribution in MANOVA by Education Mode

Between-Subjects Factors		
		N
Education Mode	Distance Education	104
	Traditional Education	96

This table shows the distribution of respondents across the two comparison groups used in the MANOVA test. A total of 104 students were enrolled in Distance Education, while 96 students were from the Traditional Education system. These two groups serve as the independent variable (Education Mode) in the analysis, allowing for the comparison of motivational factor scores between them. The fairly balanced sample sizes enhance the statistical validity and reliability of the MANOVA results.

Table 9. Multivariate Test Results for Differences in Motivational Factors by Education Mode

Effect	Value	F	Hypothesis df	Error df	Sig.	
Intercept	Pillai's Trace	.000	.001 ^b	3.000	196.000	1.000
	Wilks' Lambda	1.000	.001 ^b	3.000	196.000	1.000
	Hotelling's Trace	.000	.001 ^b	3.000	196.000	1.000
	Roy's Largest Root	.000	.001 ^b	3.000	196.000	1.000
Education Mode	Pillai's Trace	.009	.565 ^b	3.000	196.000	.639
	Wilks' Lambda	.991	.565 ^b	3.000	196.000	.639
	Hotelling's Trace	.009	.565 ^b	3.000	196.000	.639
	Roy's Largest Root	.009	.565 ^b	3.000	196.000	.639
a. Design: Intercept + EducationMode						
b. Exact statistic						

The multivariate test results using Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root all indicate no statistically significant difference in the combined motivational factor scores between students enrolled in distance and traditional education systems. Specifically, Wilks' Lambda was 0.991, with an F-value of 0.565, degrees of freedom (df) = 3, 196, and a p-value of 0.639, which is far above the 0.05 significance threshold. This means the three extracted motivational components—Academic Aspirations and Access Enablers, Empowerment through Support, and Institutional Feasibility—do not differ significantly across the two educational modes.

This result leads us to fail to reject the null hypothesis, confirming that students in both systems are influenced by similar motivations when choosing their educational pathway. Given the absence of

significant differences, it can be concluded that the distance education system is now performing effectively and on par with traditional education. It reflects growing confidence, accessibility, and perceived value of distance learning among students in the current educational landscape.

The Tests of Between-Subjects Effects table evaluates whether students enrolled in distance and traditional education differ significantly in their scores on key motivational components.

Table 10. Tests of Between-Subjects Effects for Motivational Factors by Education Mode

Tests of Between-Subjects Effects						
Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	Academic Aspirations and Access Enablers	.227 ^a	1	.227	.226	.635
	Empowerment Through Opportunity and Support	.010 ^b	1	.010	.010	.920
	Institutional Reliability and Economic Feasibility	1.468 ^c	1	1.468	1.472	.227
Intercept	Academic Aspirations and Access Enablers	.000	1	.000	.000	.985
	Empowerment Through Opportunity and Support	1.610E-005	1	1.610E-005	.000	.997
	Institutional Reliability and Economic Feasibility	.002	1	.002	.002	.961
EducationMode	Academic Aspirations and Access Enablers	.227	1	.227	.226	.635
	Empowerment Through Opportunity and Support	.010	1	.010	.010	.920
	Institutional Reliability and Economic Feasibility	1.468	1	1.468	1.472	.227
Error	Academic Aspirations and Access Enablers	198.773	198	1.004		
	Empowerment Through Opportunity and Support	198.990	198	1.005		
	Institutional Reliability and Economic Feasibility	197.532	198	.998		
Total	Academic Aspirations and Access Enablers	199.000	200			
	Empowerment Through Opportunity and Support	199.000	200			
	Institutional Reliability and Economic Feasibility	199.000	200			
Corrected Total	Academic Aspirations and Access Enablers	199.000	199			
	Empowerment Through Opportunity and Support	199.000	199			
	Institutional Reliability and Economic Feasibility	199.000	199			
a. R Squared = .001 (Adjusted R Squared = -.004)						
b. R Squared = .000 (Adjusted R Squared = -.005)						
c. R Squared = .007 (Adjusted R Squared = .002)						

The analysis shows no statistically significant differences in any of the three extracted factors: Academic Aspirations and Access Enablers (F = 0.226, p = 0.635), Empowerment through Opportunity and Support (F = 0.010, p = 0.920), and Institutional Reliability and Economic Feasibility (F = 1.472, p = 0.227). The high p-values (all > 0.05) confirm that the mode of education has no significant impact on students' underlying motivations for enrolment. Additionally, the low R-squared values (ranging from 0.000 to 0.007) indicate that the type of education mode explains very little variance in the motivational factor scores. These results align with the multivariate findings and lead us to fail to reject the null hypothesis.

Importantly, these findings suggest that the motivational factors influencing educational choice are

largely similar across both systems, highlighting the growing maturity, credibility, and effectiveness of distance education. As a result, a noticeable transformation is taking place in India, where many students are shifting from traditional to distance education due to influential factors like flexibility, affordability, and access to quality education. This trend marks a significant shift in the higher education landscape, validating the role of distance learning as a viable and competitive academic pathway.

Table No. 11. *Estimated Marginal Means*

Dependent Variable	Education Mode				
	Education Mode	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
Academic Aspirations and Access Enablers	Distance Education	.032	.098	-.161	.226
	Traditional Education	-.035	.102	-.237	.167
Empowerment Through Opportunity and Support	Distance Education	.007	.098	-.187	.201
	Traditional Education	-.007	.102	-.209	.194
Institutional Reliability and Economic Feasibility	Distance Education	-.082	.098	-.275	.111
	Traditional Education	.089	.102	-.112	.290

Table No. 11 presents the estimated marginal means of the three motivational components for students enrolled in distance and traditional education systems. The results indicate that students across both groups hold very similar motivational perceptions. For Academic Aspirations and Access Enablers, distance education students reported a slightly higher mean score (0.032) compared to traditional education students (-0.035). However, the overlapping 95% confidence intervals confirm that this difference is not statistically significant. Likewise, for Empowerment through Opportunity and Support, both groups exhibited nearly identical means (0.007 and -0.007, respectively), suggesting shared attitudes toward educational empowerment and institutional support. Regarding Institutional Reliability and Economic Feasibility, traditional students had a slightly higher mean (0.089) than distance learners (-0.082), but the overlapping confidence intervals again indicate that the difference lacks statistical significance.

These findings align with recommendations by Hair et al. (2019), who emphasize that non-significant differences with overlapping confidence intervals suggest uniformity in group responses. The results further support the assertion by Allen and Seaman (2017) that distance education is gaining parity with traditional education, especially in terms of perceived quality and learner satisfaction. In the Indian context, this suggests a growing trend where students are transitioning toward distance learning formats due to their flexibility, affordability, and enhanced access to academic opportunities (IGNOU, 2021; UGC, 2022).

4. CONCLUSION AND POLICY SUGGESTIONS

This study investigated the underlying motivational factors influencing student enrolment in distance and traditional education systems in India using factor analysis and MANOVA techniques. The analysis revealed three distinct components: Academic aspirations and Access Enablers, Empowerment through Opportunity and Support, and Institutional Reliability and Economic Feasibility. These components encapsulated key factors such as poverty, employment needs, flexible learning options, perceived quality of education, student support services, and affordability.

The MANOVA and Between-Subjects Effects tests found no statistically significant differences between students from distance and traditional education modes across the extracted motivational factors. This suggests that students in both systems are influenced by similar motivations, confirming the increasing credibility and performance of distance education in line with traditional formats. As access, affordability, and flexibility remain crucial for today’s learners, the findings highlight a broader shift in student preferences toward distance learning in India’s evolving educational landscape. In light of these findings, the following policy suggestions are proposed:

- Strengthen digital infrastructure to support accessible and high-quality distance education, especially in rural and underserved areas.
- Enhance student support services such as academic counseling, helplines, and mentorship programs to boost learner confidence and retention.

- Subsidize fees and expand financial aid to maintain the economic feasibility of both education modes, especially for economically disadvantaged groups.
- Promote flexible curriculum designs and modular learning to support students with employment or family responsibilities.
- Increase awareness campaigns to highlight the parity of quality between distance and traditional education, reducing stigma and improving enrolment.
- Encourage collaboration between traditional and open universities to foster hybrid learning models that cater to diverse learner needs.

Overall, the study reinforces that distance education is not only a comparable alternative but increasingly a preferred pathway for a wide segment of Indian learners seeking quality, affordability, and flexibility in higher education.

REFERENCES

- Moore, M. G., & Kearsley, G. (2012). *Distance education: A systems view of online learning* (3rd Ed.). Wadsworth Cengage Learning.
- Xu D, Jaggars SS. The impact of online learning on students' course outcomes: Evidence from a large community and technical college system. *Economics of Education Review*. 2013; 37:46–57.
- Allen, I. E., & Seaman, J. (2017). *Digital Learning Compass: Distance Education Enrollment Report 2017*. Babson Survey Research Group.
- Raza SA, Qazi W, Umer B. Examining the impact of social media on students' academic performance through collaborative learning in virtual environments. *Interactive Learning Environments*. 2021; 29(4):496–512.
- Jaggars SS, Bailey T. Effectiveness of fully online courses for college students: Evidence from a large community and technical college system. *Community College Research Center Working Paper*. 2010;(22).
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). Sage Publications.
- Singh, Y. K. (2006). *Fundamental of Research Methodology and Statistics*. New Age International Publishers.
- Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). Likert scale: Explored and explained. *British Journal of Applied Science & Technology*, 7(4), 396.
- Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). Sage Publications.
- Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (7th ed.). Pearson Education.
- Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, 39(1), 31–36. <https://doi.org/10.1007/BF02291575>
- Allen, I. E., & Seaman, J. (2017). *Digital Learning Compass: Distance Education Enrollment Report 2017*. Babson Survey Research Group.

AUTHOR'S BIOGRAPHY



Dr. Vishal V. Ambedkar is an Academic Coordinator in Economics (Assistant Professor level) at the School of Humanities and Social Sciences, Yashwantrao Chavan Maharashtra Open University (YCMOU), Nashik, India. He holds dual PhDs in Environmental Economics and Public Finance and has over seven years of teaching and research experience. His academic work focuses on socio-economic development, public policy, inclusive growth, and rural development. He has authored several reference books, contributed twelve book chapters, and published more than thirty six research papers in peer-reviewed journals. He has also completed funded research projects on govt. policy analysis, religious tourism and education systems in India and has presented his work at global level.

Citation: Vishal V Ambedkar. " Exploring Determinants of Student Enrolment in Distance and Traditional Education: A Factor Analysis Approach" *International Journal of Humanities Social Sciences and Education (IJHSSE)*, vol 13, no. 3, 2026, pp. 26-35. DOI: <https://doi.org/10.20431/2349-0381.1303003>

Copyright: © 2026 Author. This is an open-access article distributed under the terms of the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.