

## AI-Driven Transformation in Finance: Assessing Technical Readiness and Skill Gaps among Commerce and Management Students and Graduates

Jerin Ninan Jose<sup>1\*</sup> | Subin K Sunny<sup>2</sup>

<sup>1</sup>2nd Year MBA Banking & Finance Student, Indira Gandhi Open University.

<sup>2</sup>Teacher, Infant Jesus ISC School, Mavelikkara.

\*Corresponding Author: jerinninanjose@zohomail.in

**Citation:** Jose, J. & Sunny, S. (2026). AI-Driven Transformation in Finance: Assessing Technical Readiness and Skill Gaps among Commerce and Management Students and Graduates. *International Journal of Advanced Research in Commerce, Management & Social Science*, 09(02(III)), 75–81.

### ABSTRACT

This study examines technical readiness and perceived skill gaps among commerce and management students and working graduates in Thiruvananthapuram, Kerala, concerning AI-driven financial environments. Using a quantitative descriptive design, primary data was collected via structured questionnaires from a sample of 200 B.Com, M.Com, BBA, and MBA students, alongside employed finance professionals. The research investigated how AI awareness, digital literacy, curriculum adequacy, and certification courses influence technical readiness. Data were analyzed using SPSS (correlation, chi-square, multiple regression) to offer evidence-based recommendations for aligning academic curricula with modern industry requirements. Key findings reveal a significant awareness–readiness gap, with students scoring 4.27/5 on perceived career impact of AI but only 3.18/5 on technical readiness. Curriculum adequacy, rated lowest at 2.58/5, emerged as the strongest predictor of technical readiness ( $\beta = 0.551$ ,  $R^2 = 30.4\%$ ). All six hypotheses were supported at  $p < 0.001$ , confirming that AI awareness, digital literacy, curriculum quality, workplace training, and certification courses are significant determinants of readiness and perceived skill gaps. Structured AI exposure—whether through employer training or short-term certification—was found to substantially improve both readiness and work efficiency.

**Keywords:** Artificial Intelligence, Technical Readiness, Skill Gap, Digital Literacy, Commerce Education, Financial Sector, FinTech.

### Introduction

Artificial Intelligence (AI) has emerged as a transformative force across many industries, significantly reshaping the way financial institutions operate. Technologies such as machine learning, predictive analytics, and automated decision systems are now widely used in risk assessment, fraud detection, investment analysis, and customer relationship management, enabling institutions to process large volumes of data with greater efficiency and accuracy (Davenport & Ronanki, 2018). As a result, the integration of AI into financial systems is creating new skill requirements for professionals entering the industry.

This shift has led to new competency expectations for finance professionals, who must now possess technological awareness and digital literacy alongside traditional financial knowledge (Brynjolfsson & McAfee, 2017). However, concerns have been raised regarding whether current academic curricula adequately equip students with these competencies, as many programmes continue to emphasise theoretical knowledge while providing limited exposure to AI tools and digital financial

platforms (Bughin et al., 2019). If skill gaps between academic training and industry expectations are not addressed, graduates may face significant challenges in adapting to AI-driven financial environments (World Economic Forum, 2020).

Against this background, this study aims to examine the level of technical readiness and identify perceived skill gaps among business and commerce students and working graduates in Thiruvananthapuram district, with respect to the growing influence of Artificial Intelligence in the financial sector.

### **Statement of the Problem**

The rapid integration of AI into the financial sector has transformed professional roles, increasing the demand for graduates with both financial knowledge and technological competence. However, many commerce and management programmes continue to focus primarily on traditional theories, providing limited exposure to AI tools and data analytics. This mismatch between academic preparation and industry expectations represents a critical problem that warrants empirical investigation. Therefore, this study examines the level of technical readiness and perceived skill gaps among business and commerce students and graduates in relation to AI-driven financial systems.

### **Research Gap**

While existing literature has extensively examined the impact of AI on financial institutions and employment patterns, relatively limited research has focused on the preparedness of students entering the finance workforce. A review of existing studies reveals three specific gaps that this study addresses. First, prior research on AI adoption in finance has predominantly focused on institutional adoption and organisational outcomes, with little attention given to the readiness of students and graduates who are entering these AI-driven environments. Second, there is a near-complete absence of empirical studies examining AI awareness, digital literacy, and skill gaps among commerce and management students in India, particularly in the state of Kerala, despite the rapid expansion of financial services and FinTech activity in the region. Third, no prior study has simultaneously examined both current students and working graduates within a single sample, nor has any study statistically tested the relationship between curriculum adequacy and technical readiness using regression analysis in this context. This study directly addresses all three gaps by conducting a hypothesis-driven, SPSS-based empirical investigation among 200 respondents in Thiruvananthapuram district, Kerala, combining student and graduate perspectives within a unified analytical framework grounded in the Technology Acceptance Model..

### **Objectives of the Study**

- To examine the relationship between AI awareness, digital literacy, and technical readiness among commerce and management students.
- To assess the influence of digital literacy on the perceived skill gaps of students regarding AI-driven financial environments.
- To examine the relationship between technical readiness and perceived skill gaps in adapting to AI-driven financial environments.
- To evaluate the influence of curriculum adequacy on the technical readiness of students for AI-driven financial environments.
- To examine the impact of workplace AI training on the work efficiency of employed graduates.
- To assess whether completion of short-term AI certification courses significantly improves the technical readiness of students and graduates.

### **Review of Literature**

Davenport and Ronanki (2018) highlight that organisations across industries are increasingly adopting AI to automate routine processes and enhance decision-making, with applications in fraud detection, credit scoring, and investment analysis rapidly expanding. Brynjolfsson and McAfee (2017) similarly argue that digital technologies are transforming traditional business models and that professionals must develop technological competencies to remain relevant in an increasingly automated environment.

Bughin et al. (2019) emphasise that AI adoption is accelerating across financial institutions due to the growing availability of large datasets, with organisations investing heavily in AI-driven solutions to gain competitive advantages. The World Economic Forum (2020) further notes that this rapid

advancement is creating significant shifts in labour market requirements, with employers increasingly seeking graduates with digital literacy and analytical capabilities — competencies that many current graduates lack.

Schwab (2017) contextualises these developments within the Fourth Industrial Revolution, characterised by the fusion of digital and physical technologies, with AI at its core. Collectively, these studies underline the urgent need to examine how well commerce and management education prepares students for AI-driven financial environments — a gap this study directly addresses.

The theoretical foundation of this study draws on the Technology Acceptance Model (TAM) proposed by Venkatesh et al. (2003), which posits that perceived usefulness and ease of use are key determinants of technology adoption — constructs closely aligned with the technical readiness and digital literacy variables examined here. Additionally, Nunnally (1978) provides the methodological basis for the reliability thresholds applied in this study.

### Hypotheses of the Study

- H1: There is a significant positive relationship between AI awareness, digital literacy, and technical readiness among business and commerce students.
- H2: Students with higher digital literacy levels report significantly lower perceived skill gaps regarding AI-driven financial environments.
- H3: Students with lower technical readiness perceive significantly higher skill gaps in adapting to AI-driven financial environments.
- H4: Students who perceive their academic curriculum as adequate report significantly higher levels of technical readiness for AI-driven financial environments.
- H5: Working graduates who received workplace AI training report significantly higher work efficiency compared to those who did not receive such training.
- H6: Students and graduates who have completed short-term AI certification courses report significantly higher technical readiness compared to those who have not.

### Research Methodology

The present study adopts a **quantitative research approach** to examine the level of technical readiness and perceived skill gaps among business and commerce students in relation to the growing influence of Artificial Intelligence in the financial sector. A **descriptive and analytical design** is used in order to analyze students' awareness, technological preparedness, and perceptions regarding AI-driven financial environments.

The study is primarily based on **primary data** collected through a structured questionnaire. The questionnaire was designed to gather information regarding students' awareness of Artificial Intelligence, digital literacy, technical readiness, and perceived skill gaps in relation to the finance sector. The instrument also included demographic questions such as age, gender, educational level, and current status of respondents. Responses to attitudinal statements were measured using a **five-point Likert scale ranging from strongly disagree to strongly agree**.

The **population of the study** consists of two groups: (1) business and commerce students currently enrolled in higher education institutions in Thiruvananthapuram district, and (2) graduates from business and commerce programmes who are currently employed in the financial sector. The sample for this study comprises **200 respondents**, including students from B.Com, M.Com, BBA, and MBA programmes, as well as working graduates from the same fields. A **purposive sampling technique** was used to select respondents, ensuring that participants were specifically drawn from commerce and management backgrounds relevant to the study's objectives.

Data collected through the questionnaire were organized and analyzed using **Microsoft Excel and Statistical Package for Social Sciences (SPSS)**. Various statistical techniques were employed to analyze the data. **Descriptive statistics**, including percentages and mean score analysis, were used to summarize the responses and understand general trends in AI awareness, technical readiness, and skill gap perceptions among students. In addition, **inferential statistical techniques** such as correlation analysis, chi-square tests, and **multiple regression analysis** were applied to examine the relationships between key variables in the study. Multiple regression was specifically employed to assess the combined influence of AI awareness and digital literacy on technical readiness, as hypothesised in H1.

The results obtained from these analyses help in understanding the level of preparedness of business and commerce students to adapt to AI-driven transformations in the finance sector and identify potential areas where additional training or educational improvements may be required.

### Data Analysis and Results

Data were collected from 200 respondents and analysed using SPSS. Table 8.1 presents the demographic profile and Table 8.2 presents construct reliability summary. Table 8.3 reports descriptive statistics for all key constructs. Tables 8.4a and 8.4b present hypothesis test results for regression/correlation and T-tests respectively. Tables 8.5 and 8.6 present the additional cross-tabulation and correlation analyses.

**Table 1: Demographic Profile of Respondents (n = 200)**

Variable	Category	n	%
<b>Gender</b>	Male	88	44.0
	Female	112	56.0
<b>Age</b>	18–25 years	168	84.0
	Above 25 years	32	16.0
<b>Status</b>	Student	128	64.0
	Graduate (Employed)	62	31.0
	Graduate (Unemployed)	10	5.0
<b>Education</b>	Undergraduate	108	54.0
	Postgraduate	92	46.0
<b>AI Cert.</b>	Completed Certification	68	34.0
	No Certification	132	66.0

**Table 2: Reliability Analysis — Cronbach's Alpha**

Construct	No of Items	$\alpha$	Verdict
<b>Technical Readiness</b>	5	0.83	Acceptable
<b>Digital Literacy</b>	5	0.79	Acceptable
<b>AI Usage in Work/Study</b>	4	0.77	Acceptable
<b>Curriculum Adequacy</b>	5	0.81	Acceptable
<b>Career Impact of AI</b>	4	0.76	Acceptable
<b>Perceived Skill Gap</b>	4	0.74	Acceptable
<b>Workplace AI Efficiency</b>	5	0.84	Acceptable

The sample is balanced across gender and education levels, with 64% current students and 36% graduates. All Cronbach's Alpha values range from 0.74 to 0.84, exceeding the accepted threshold of 0.70 (Nunnally, 1978), confirming internal consistency across all constructs and validating the measurement instrument for hypothesis testing.

**Table 3: Descriptive Statistics — Mean Score Analysis (1 = Strongly Disagree, 5 = Strongly Agree)**

Construct	Mean	SD	Level
Technical Readiness	3.18	0.76	Moderate
Digital Literacy	3.47	0.69	High
AI Usage in Work/Study	3.61	0.71	High
Curriculum Adequacy	2.58	0.83	Low–Moderate
Career Impact of AI	4.27	0.54	Very High
Perceived Skill Gap	3.94	0.62	High

The most critical contrast is between Career Impact of AI (4.27/5) and Technical Readiness (3.18/5). Students strongly believe AI will shape their careers but do not feel prepared for it. Curriculum Adequacy scored lowest at 2.58/5, indicating that students feel their academic programmes are inadequate. The Perceived Skill Gap score of 3.94/5 confirms this mismatch is strongly felt.

**Table 4a: Regression and Correlation Tests (H1–H4)**

Hyp.	Variables	Test	Key Statistic	p-value	H <sub>0</sub>
H1	AI Awareness + Digital Literacy → Technical Readiness	Multiple Reg.	R <sup>2</sup> =0.398; F=65.24; β(Digital Literacy)=0.394; β(AI Awareness)=0.308	0.000	Rejected
H2	Digital Literacy ↔ Perceived Skill Gap	Pearson Corr.	r = -0.493	0.000	Rejected
H3	Technical Readiness ↔ Perceived Skill Gap	Pearson Corr.	r = -0.538 (strongest in study)	0.000	Rejected
H4	Curriculum Adequacy → Technical Readiness	Simple Reg.	R <sup>2</sup> =0.304; β=0.551 (highest β in study)	0.000	Rejected

H1 confirms that AI awareness (β = 0.308) and digital literacy (β = 0.394) together explain 39.8% of the variance in technical readiness (R<sup>2</sup> = 0.398), consistent with the TAM framework (Venkatesh et al., 2003). H4 is the most policy-critical result: curriculum adequacy (β = 0.551) is the strongest single predictor of technical readiness yet recorded the lowest mean score (2.58/5), indicating an urgent need for curriculum reform.

**Table 4b: Independent Samples T-Tests (H5–H6)**

Hyp.	Variables	Test	Group Means	t-value	p-value	H <sub>0</sub>
H5	Workplace AI Training → Work Efficiency (n=62 graduates)	Indep. T-Test	Trained: M=4.22 Untrained: M=3.11 Diff = 1.11	7.24	0.000	Rejected
H6	AI Certification → Technical Readiness (n=200)	Indep. T-Test	Certified: M=3.74 Non-cert: M=2.81 Diff = 0.93	9.51	0.000	Rejected

H5 demonstrates that workplace AI training improves efficiency by 1.11 points on a 5-point scale (t = 7.24, p < 0.01). H6 shows that self-driven AI certification raises technical readiness by 0.93 points (t = 9.51, p < 0.01). Both findings confirm that structured AI exposure — whether through employers or self-learning — meaningfully compensates for curriculum shortfalls.

**Table 5: Cross-Tabulation — AI Certification vs Education Level**

Education Level	Certified (n)	Not Certified (n)	Total	% Certified
Undergraduate (n=108)	26	82	108	24.1%
Postgraduate (n=92)	42	50	92	45.7%
Total (n=200)	68	132	200	34.0%

χ<sup>2</sup> = 10.84, df = 1, p = 0.001, Cramer’s V = 0.233 (moderate effect). PG students are significantly more likely to pursue AI certification (45.7%) compared to UG students (24.1%). UG students are more dependent on institutional curricula — the same curricula rated inadequate at 2.58/5.

**Table 6: Pearson Correlation Matrix (n = 200, \*\* p < 0.01)**

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) Tech. Readiness	1.00	0.394**	0.463**	0.551**	-0.538**	0.389**
(2) Digital Literacy	0.394**	1.00	0.511**	0.331**	-0.493**	0.422**
(3) AI Usage	0.463**	0.511**	1.00	0.318**	-0.341**	0.487**
(4) Curriculum Adequacy	0.551**	0.331**	0.318**	1.00	-0.447**	0.362**
(5) Skill Gap	-0.538**	-0.493**	-0.341**	-0.447**	1.00	-0.298**
(6) Career Impact	0.389**	0.422**	0.487**	0.362**	-0.298**	1.00

All construct pairs are significantly related (p < 0.01). Curriculum Adequacy → Technical Readiness is the strongest positive relationship (r = 0.551), while Technical Readiness → Perceived Skill Gap is the strongest negative relationship (r = -0.538). Together, these confirm that readiness and the skill gap are two sides of the same problem — rooted in curriculum inadequacy.

**Discussion of Findings**

The findings of this study collectively reveal a significant preparedness gap among commerce and management students in Thiruvananthapuram. The most critical and counterintuitive finding is that

curriculum adequacy — the factor students rated lowest (2.58/5) — simultaneously emerged as the strongest single predictor of technical readiness ( $\beta = 0.551$ ). This is consistent with Brynjolfsson and McAfee (2017), who argued that educational institutions play a pivotal role in equipping students with technological competencies. The current study demonstrates empirically that when this role is inadequately fulfilled, students enter the workforce with measurable readiness deficits. The awareness–readiness gap identified in this study — where students scored 4.27/5 on perceived career impact of AI but only 3.18/5 on technical readiness — further illustrates that belief in AI's importance does not automatically translate into preparedness. This gap of 1.09 points on a five-point scale represents a structural disconnect between student expectations and their actual competence, underscoring the urgency of institutional intervention.

The strong negative correlation between technical readiness and perceived skill gap ( $r = -0.538$ ) aligns with the World Economic Forum's (2020) observation that graduates increasingly lack the digital competencies demanded by employers. Importantly, the study found that students are independently compensating for this deficit: those who completed self-driven AI certification courses scored significantly higher in technical readiness (3.74 vs. 2.81), suggesting a proactive response to perceived curriculum inadequacy. This pattern is more pronounced among postgraduate students (45.7% certified) than undergraduates (24.1%), indicating that proximity to the job market increases motivation to upskill independently. Similarly, the significant efficiency gains observed among graduates who received workplace AI training (4.22 vs. 3.11) demonstrate that structured AI exposure — whether through self-learning or employer training meaningfully improves professional outcomes, corroborating the findings of Bughin et al. (2019) on the operational benefits of AI adoption. These findings collectively suggest that the skill gap is not a fixed condition but a closable one, provided that structured and purposeful AI exposure is made available through academic or professional channels.

The results of H1 provide important theoretical validation. Grounded in the Technology Acceptance Model (Venkatesh et al., 2003), H1 tested whether AI awareness and digital literacy together predict technical readiness. The significant regression model ( $R^2 = 0.398$ ,  $p = 0.000$ ) confirms that these two TAM-aligned constructs collectively explain nearly 40% of the variance in readiness. Notably, digital literacy ( $\beta = 0.394$ ) emerged as a stronger predictor than AI awareness ( $\beta = 0.308$ ), consistent with TAM's proposition that perceived ease of use outweighs perceived usefulness as a driver of technology adoption. This finding has direct pedagogical implications: building practical digital skills — through hands-on tools, labs, and applied exercises — is more impactful than simply increasing students' theoretical awareness of AI. The moderate-to-strong negative correlation between digital literacy and perceived skill gap ( $r = -0.493$ , H2) further reinforces this conclusion, demonstrating that digitally capable students not only perform better but also feel more confident and less disadvantaged in an AI-driven environment.

### Conclusion and Recommendations

This study examined the technical readiness and perceived skill gaps of 200 business and commerce students and graduates in Thiruvananthapuram district in relation to AI-driven financial environments. All six hypotheses were supported, with all null hypotheses rejected at the 1% significance level. The findings confirm that AI awareness, digital literacy, curriculum adequacy, workplace AI training, and self-directed certification courses are all significant determinants of technical readiness and perceived skill gaps. The central finding — that curriculum adequacy is the strongest predictor of technical readiness ( $\beta = 0.551$ ) yet is rated the lowest by students (2.58/5) — points to an urgent and actionable gap in commerce and management education. The study also confirms the relevance of the Technology Acceptance Model in a finance education context, validating that ease of use (digital literacy) outpredicts perceived usefulness (AI awareness) as a driver of readiness. Together, these findings indicate that the awareness–readiness gap is not an attitude problem but a systemic preparation failure — one that can be addressed through deliberate institutional action.

Based on these findings, three evidence-based recommendations are proposed. First, universities offering B.Com, BBA, M.Com, and MBA programmes should integrate dedicated AI and digital tools modules into their core curriculum, covering applications directly relevant to financial services such as data analytics, automated reporting, and AI-driven risk assessment. Given that curriculum adequacy ( $\beta = 0.551$ ) is the strongest predictor of readiness, this intervention has the highest potential impact of any single reform. Second, institutions and regulatory bodies such as UGC should establish formal partnerships with platforms such as NPTEL and Coursera to embed structured short-term AI

certification pathways into degree programmes, particularly at the undergraduate level where self-certification rates are lowest (24.1%). H6 demonstrates that such certifications raise readiness by 0.93 points on a five-point scale, making them a cost-effective and immediately implementable intervention. Third, financial sector employers in Kerala should formalise AI onboarding programmes for fresh graduates rather than relying on informal or self-directed learning. H5 confirms that structured workplace AI training raises work efficiency by 1.11 points ( $t = 7.24, p < 0.01$ ), providing compelling justification for investment in formal onboarding. Collectively, these recommendations require coordinated action from academic institutions, regulatory bodies, and industry — without which the awareness–readiness gap documented in this study is likely to widen.

### Limitations of the Study

This study has several limitations that should be considered when interpreting the findings. First, the sample is geographically restricted to Thiruvananthapuram district, which limits the generalisability of findings to other regions of Kerala or India. Second, the use of purposive sampling, while appropriate for the study's objectives, restricts statistical generalisation to the broader population. Third, as data were collected through self-reported questionnaires, responses may be subject to social desirability bias, particularly regarding self-assessed readiness and skill levels. Fourth, the cross-sectional design of the study captures respondents' perceptions at a single point in time and cannot establish causal relationships between variables. Future studies could address these limitations by adopting longitudinal designs to track changes in readiness over time, expanding the sample geographically across multiple districts or states, incorporating employer perspectives to triangulate student self-assessments, and developing fully validated multi-item Likert scales for AI awareness to enable more rigorous construct measurement.

### References

1. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review*, 7(1–20), 3–11.
2. Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2019). Notes from the AI frontier: Modeling the impact of AI on the world economy. McKinsey Global Institute.
3. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
4. Schwab, K. (2017). *The fourth industrial revolution*. Crown Business.
5. Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.
6. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
7. World Economic Forum. (2020). *The future of jobs report 2020*. World Economic Forum.

