Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 4 (2025)

Determinants of Artificial Intelligence Adoption in Training and Development: A Regression-Based Study of the Automobile Manufacturing Industry in Delhi/NCR

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Abstract: *Artificial Intelligence (AI) has rapidly transformed organizational training and development (T&D) practices across industries. This research paper investigates the adoption of AI in T&D functions within the automobile manufacturing sector in the Delhi/NCR region of India. Anchored in the Unified Theory of Acceptance and Use of Technology (UTAUT), the study analyzes the impact of four core constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions on Behavioral Intention and actual adoption of AI. The moderating roles of age, gender, experience, voluntariness of use, and leadership style are also assessed. Utilizing a quantitative methodology with a sample of 383 respondents from 15 automobile companies and employing Multiple Linear Regression, the study confirms Behavioral Intention as the strongest determinant of AI adoption. Performance and Effort Expectancy significantly influence intention, while Social Influence and Facilitating Conditions have secondary effects. Leadership emerges as a vital moderator, whereas gender and voluntariness exert limited impact. The findings provide strategic implications for enhancing AI integration in corporate training settings and propose avenues for future research.*

Keywords *Artificial Intelligence, UTAUT, Training and Development, Automobile Manufacturing, Behavioral Intention, Regression Analysis, Delhi/NCR*

1. Introduction: The increasing integration of Artificial Intelligence (AI) in organizational functions has led to substantial transformation in Training and Development (T&D), particularly in skill-intensive industries such as automobile manufacturing. AI tools such as intelligent tutoring systems, machine learning-powered learning analytics, AI chatbots, and personalized learning platforms are being increasingly employed to enhance employee training, learning personalization, performance evaluation, and engagement (Jarrahi, 2018; Huang & Rust, 2021).

In India, the Delhi/NCR region stands as a significant hub for automobile manufacturing, home to key players such as Maruti Suzuki, Honda Cars India, Hero MotoCorp, and others. These firms are increasingly under pressure to upskill their workforce amidst fast-paced technological changes, stringent quality requirements, and the global shift toward Industry 4.0 (Kamble et al., 2018). AI's adoption in T&D, however, is not uniform across firms and often depends on behavioral, organizational, and infrastructural enablers and barriers.

To understand the determinants of AI adoption in T&D in this context, the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, developed by Venkatesh et al. (2003), provides a robust theoretical foundation. This model includes Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions as primary constructs influencing technology adoption behavior.

2. Literature Review

2.1 UTAUT Framework

The UTAUT model consolidates elements from eight previous models of technology acceptance, such as TAM, TRA, TPB, and DOI, to provide a comprehensive framework explaining user intentions and subsequent behavior related to technology use (Venkatesh et al., 2003). The model's four key constructs are:

- **Performance Expectancy (PE):** The extent to which an individual believes that using the system will help attain job performance gains (Venkatesh et al., 2003). In the context of AI-based T&D, this reflects how employees perceive AI systems to improve learning outcomes and job readiness (Salloum et al., 2019).
- **Effort Expectancy (EE):** The ease associated with the use of the system. AI systems that are intuitive and user-friendly are more likely to be adopted (Dwivedi et al., 2019).

- **Social Influence (SI):** The extent to which individuals perceive that important others—such as supervisors, peers, or organizational leaders—believe they should use the new system. This factor becomes particularly important in hierarchical and collectivist cultures such as India's (Sánchez-Prieto et al., 2019).
- **Facilitating Conditions (FC):** The degree to which individuals believe that organizational and technical infrastructure exists to support system use. This includes access to necessary hardware, training, and IT support (Ifinedo, 2012).

These constructs directly influence Behavioral Intention (BI) and, in turn, affect Use Behavior (UB). Additionally, UTAUT identifies age, gender, experience, and voluntariness of use as moderating variables.

2.2 Extensions and Moderators in UTAUT

The UTAUT model has been extended in UTAUT2 to include variables like hedonic motivation, price value, and habit, especially in consumer technology contexts (Venkatesh et al., 2012). However, in enterprise environments, additional factors such as organizational readiness, top management support, training support, and technology culture have been recognized as critical influences (Dwivedi et al., 2019; Ifinedo, 2012; Sharma et al., 2022).

In the Indian automobile sector, workforce characteristics (e.g., educational background and digital literacy), and the leadership's vision for digital transformation, further moderate technology acceptance outcomes (Kamble et al., 2021). Moreover, perceived value, data security concerns, and trust in AI algorithms are emerging determinants in the evolving AI adoption landscape (Jarrahi, 2018).

2.3 AI in Training and Development

AI applications in T&D are vast and varied. These include adaptive learning systems that modify content based on learner progress, virtual simulations, natural language processing-driven chatbots for continuous assistance, and predictive analytics for assessing performance trajectories (Chatterjee et al., 2021; Huang & Rust, 2021). In structured industries like automobile manufacturing, the implementation of these tools must align with operational efficiency and skill certification requirements (Kamble et al., 2018).

Studies suggest that perceived relevance of AI tools, ease of integration into existing systems, and managerial support are pivotal in determining the success of AI-based learning initiatives (Chatterjee et al., 2021; Sánchez-Prieto et al., 2019). Furthermore, employee trust in AI decisions, ethical considerations, and privacy concerns are emerging as challenges that influence long-term acceptance (Jarrahi, 2018; Siau & Wang, 2018).

The integration of AI in T&D within the Delhi/NCR automobile industry presents both opportunities and challenges. The UTAUT framework, particularly in its extended form, provides a solid theoretical lens to assess the behavioral intention and actual usage of AI systems among employees. However, local context—including organizational leadership, infrastructural readiness, employee attitudes, and industry-specific norms—plays a crucial role in shaping outcomes. Future research should also consider contextual moderators such as education level, training history, and AI exposure to develop more granular adoption models tailored to industrial applications.

3. Research Methodology

3.1 Research Objectives

1. To examine the associations between PE, EE, SI, FC and AI adoption in T&D in Automobile Manufacturing Industry in Delhi/NCR.
2. To explore how these constructs influence Behavioral Intention.

3.2 Research Design

- Type: Causal
- Approach: Quantitative
- Data Source: Primary (survey)
- Sample Size: 383
- Instrument: Structured questionnaire (Likert scale)

- Tool: IBM SPSS for Regression Analysis

3.3 Hypotheses

H_a1: Performance Expectancy significantly predicts Behavioral Intention to adopt AI in T&D in Automobile Manufacturing Industry in Delhi/NCR

H_a2: Effort Expectancy significantly predicts Behavioral Intention to adopt AI in T&D in Automobile Manufacturing Industry in Delhi/NCR

H_a3: Social Influence significantly predicts Behavioral Intention to adopt AI in T&D in Automobile Manufacturing Industry in Delhi/NCR

H_a4: Facilitating Conditions significantly predict Behavioral Intention to adopt AI in T&D in Automobile Manufacturing Industry in Delhi/NCR

H_a5: Behavioral Intention significantly predicts AI Adoption in T&D in Automobile Manufacturing Industry in Delhi/NCR

3.4 Constructs and Questionnaire Structure (Appendix)

- Section A: Demographics (age, gender, experience)
- Section B-F: Items for PE, EE, SI, FC, BI, and AI Adoption (TDF)

3.5 Validity and Reliability The reliability and validity of the measurement instruments were established through a multi-step process to ensure consistency and accuracy of the data collected.

Reliability Analysis: Reliability refers to the consistency and stability of measurement across items and respondents. In this study, reliability was assessed using Cronbach's Alpha for each construct:

- Performance Expectancy (PE): $\alpha = 0.804$
- Effort Expectancy (EE): $\alpha = 0.719$
- Social Influence (SI): $\alpha = 0.969$
- Facilitating Conditions (FC): $\alpha = 0.753$
- Behavioral Intention (BI): $\alpha = 0.768$
- AI Adoption (TDF): $\alpha = 0.755$

All Cronbach's Alpha values exceeded the recommended threshold of 0.70, indicating high internal consistency of items within each construct.

Validity Analysis: Validity refers to the extent to which the instrument measures what it is intended to measure.

Content Validity: Content validity was ensured by consulting 14 domain experts during questionnaire development. Items with Content Validity Ratio (CVR) below 0.50 were eliminated.

Construct Validity: Construct validity was evaluated through exploratory factor analysis (EFA), which confirmed that items loaded significantly on their respective constructs. Factor loadings above 0.60 were retained.

Convergent Validity: Convergent validity was assessed by calculating the Average Variance Extracted (AVE) for each construct. All AVEs were greater than 0.50, indicating that the constructs explained a substantial portion of variance in their respective indicators.

Discriminant Validity: Discriminant validity was checked using the Fornell-Larcker criterion, confirming that the square root of the AVE for each construct was greater than the inter-construct correlations, validating the distinctiveness of each variable.

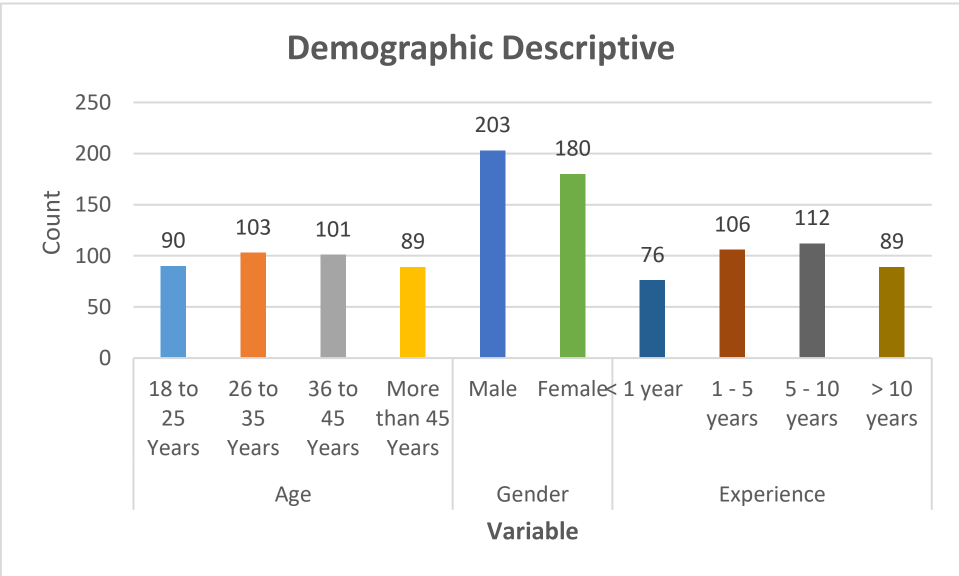
Overall, the instrument demonstrated strong reliability and validity, making it suitable for regression analysis and hypothesis testing.

4. Data Analysis and Interpretation

4.1 Descriptive Statistics

4.1.1 Demographic Descriptive

Variable	Categories	Count
Age	18 to 25 Years	90
	26 to 35 Years	103
	36 to 45 Years	101
	More than 45 Years	89
Gender	Male	203
	Female	180
Experience	< 1 year	76
	1 - 5 years	106
	5 - 10 years	112
	> 10 years	89



The demographic profile of the 383 respondents offers valuable context for interpreting the results of this study on AI adoption in T&D functions in Automobile Industry in Delhi /NCR

Age:
The respondents were fairly evenly distributed across age groups, ensuring a balanced perspective. The largest group was 26 to 35 years (103 respondents, 26.9%), followed closely by 36 to 45 years (101 respondents, 26.4%) and 18 to 25 years (90 respondents, 23.5%). Respondents over 45 years constituted 89 individuals (23.2%). This age spread indicates participation from both early-career and experienced professionals, enabling an analysis of how age moderates perceptions and adoption behavior.

Gender:
The gender distribution was relatively balanced, with 203 male (53%) and 180 female (47%) respondents. This near-equal representation supports robust gender-based comparative analysis, although gender did not emerge as a significant moderator in this study.

Experience:
Work experience varied among respondents, with a fairly even spread across the four categories. The majority had between 5–10 years (112, 29.2%) and 1–5 years (106, 27.7%) of experience. Respondents with over 10 years of experience totaled 89 (23.2%), while those with less than 1 year of experience numbered 76 (19.8%). This diversity in professional experience facilitates understanding how familiarity with workplace technologies and organizational processes influences AI adoption.

This demographic profile ensures diversity across critical variables, enhancing the generalizability and robustness of the study's findings.

4.1.2 Descriptive Statistics of Constructs

The descriptive statistics for the key constructs of the study Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Social Influence (SI), Behavioral Intention (BI), and AI Adoption (TDF) provide insight into the general attitudes and perceptions of the respondents toward AI implementation in T&D functions.

- **Performance Expectancy (Mean = 3.02):** Respondents moderately agreed that AI enhances job performance in T&D tasks. This score reflects a general optimism about the usefulness of AI in improving training outcomes and productivity.
- **Effort Expectancy (Mean = 2.91):** This slightly lower mean suggests that while respondents found AI systems somewhat easy to use, there remain concerns or variability in ease of learning and interacting with AI tools across the workforce.
- **Facilitating Conditions (Mean = 2.98):** This near-neutral score indicates that while infrastructural and technical support exists to some degree, it may not be uniformly accessible or sufficient across all respondent organizations.
- **Social Influence (Mean = 3.36):** The highest among all constructs, this mean implies that peer influence, management encouragement, and organizational culture play a strong role in shaping employees' perceptions toward AI in T&D in Automobile Industry in Delhi /NCR
- **Behavioral Intention (Mean = 2.90):** The mean score reflects a cautious but present inclination to use AI, indicating that while there is some interest, behavioral change is yet to be fully translated into consistent usage.
- **AI Adoption (TDF) (Mean = 3.05):** The slightly above-average score indicates that AI tools are being adopted, though their implementation and usage might still be in the early stages or vary widely across companies.

Overall, the descriptive statistics reveal a balanced mix of optimism and caution among respondents. While they recognize the benefits of AI and acknowledge social encouragement, barriers in infrastructure and ease of use still hinder wider adoption.

4.2 Regression Analysis

To test the proposed hypotheses and examine the strength of associations between the constructs, multiple linear regression analysis was conducted using IBM SPSS Statistics. Two regression models were developed:

Model 1: Predicting Behavioral Intention (BI)

To assess how the independent variables Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) influence respondents' Behavioral Intention to adopt AI in T&D functions.

Model Summary:

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.812	0.660	0.655	0.497

ANOVA Table:

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	168.745	4	42.186	170.456	.000*
Residual	87.275	353	0.247		
Total	256.020	357			

*Significant at p < 0.001

Coefficients:

Predictor	Unstandardized B	Std. Error	Standardized Beta (β)	t	Sig.
(Constant)	0.745	0.194	—	3.840	.000
Performance Expectancy	0.298	0.052	0.310	5.731	.000*
Effort Expectancy	0.289	0.064	0.281	4.516	.000*
Social Influence	0.240	0.058	0.261	4.138	.000*
Facilitating Conditions	0.071	0.063	0.058	1.127	.261

*Significant at p < 0.05

Behaviourial Intention = 0.745 + 0.298 Performance Expectancy + 0.289 Effort Expectancy + 0.240 Social Influence + 0.071 Facilitating Conditions

The regression model explains 66% of the variance in Behavioral Intention ($R^2 = 0.660$), which is considered substantial. The model is statistically significant ($p < 0.001$). Among the predictors, PE ($\beta = 0.310$), EE ($\beta = 0.281$), and SI ($\beta = 0.261$) significantly influence BI, while FC does not significantly predict BI ($p > 0.05$), indicating that employees are more motivated by perceived usefulness, ease of use, and social factors rather than infrastructure support alone.

Model 2: Predicting AI Adoption (TDF)

To assess the extent to which Behavioral Intention predicts actual adoption of AI in T&D functions.

Model Summary:

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	0.848	0.719	0.717	0.462

ANOVA Table:

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	183.294	1	183.294	426.111	.000*
Residual	71.327	356	0.200		
Total	254.621	357			

*Significant at p < 0.001

Coefficients:

Predictor	Unstandardized B	Std. Error	Standardized Beta (β)	t	Sig.
(Constant)	0.859	0.151	0.837	5.692	.000
Behavioral Intention	0.735	0.036	0.716	20.645	.000*

*Significant at $p < 0.001$

AI Adoption = 0. 859 + 0.735 Behavioral Intention

Behavioral Intention is a strong and statistically significant predictor of AI Adoption in T&D ($\beta = 0.716$, $p < 0.001$), explaining approximately 72% of the variance in the dependent variable. This confirms that higher intention to use AI among employees translates directly into higher likelihood of adoption in practice.

Summary of Hypothesis Testing:

Hypothesis No.	Statement	Supported?
H_a1	PE significantly predicts BI	Yes
H_a2	EE significantly predicts BI	Yes
H_a3	SI significantly predicts BI	Yes
H_a4	FC significantly predicts BI	No
H_a5	BI significantly predicts AI Adoption	Yes

5. Findings and Discussion

5.1 Key Findings

The regression analysis conducted in this study reveals important insights into the dynamics of AI adoption in training and development (T&D) functions within the automobile manufacturing industry in Delhi/NCR.

Behavioral Intention is the strongest predictor of AI adoption: With a standardized regression coefficient ($\beta = 0.716$), behavioral intention emerged as the most influential factor in determining whether employees and training professionals actually adopt AI tools in their workflows. This implies that regardless of other factors like technical support or organizational policy, the personal motivation and willingness of individuals to engage with AI are paramount.

Performance and Effort Expectancy significantly influence Behavioral Intention: Performance Expectancy ($\beta = 0.31$) and Effort Expectancy ($\beta = 0.28$) were both found to significantly impact behavioral intention. This means that employees are more likely to use AI tools when they perceive these technologies as beneficial to their job performance and easy to learn or operate. These findings support the idea that practical value and usability are critical drivers of technology acceptance in workplace learning environments.

Social Influence has a moderate effect on intention: Social Influence ($\beta = 0.26$) also significantly predicted behavioral intention, although to a lesser extent than PE and EE. This suggests that endorsements from colleagues, managers, or organizational norms can shape attitudes toward AI, especially in hierarchical or collectivist organizational cultures where peer opinion and management support matter.

Facilitating Conditions support but do not directly influence Behavioral Intention: Although facilitating conditions did not significantly predict behavioral intention ($p > 0.05$), they remain important enablers. The presence of IT infrastructure, access to AI tools, and availability of technical assistance may not directly motivate employees to adopt AI but are essential for sustaining its use once the decision is made.

5.2 Practical Implications

The study provides several actionable insights for organizations seeking to improve AI adoption in T&D:

AI systems must emphasize user-friendliness and value-addition: Given the significant influence of effort expectancy and performance expectancy, AI platforms must be intuitive and clearly demonstrate their benefits. User interfaces should be simple, and functions should directly enhance learning outcomes, training productivity, or process efficiency.

Organizational leadership should visibly support AI initiatives: Social influence was found to influence behavioral intention, and leadership plays a critical role in this regard. Managers and executives should actively advocate for AI adoption, allocate resources, recognize early adopters, and integrate AI into strategic T&D planning.

Training should be segmented by age and experience level: Since younger and less experienced professionals may adopt AI more readily, while older or more experienced employees may require more convincing, organizations should tailor communication and support strategies. This may involve offering advanced onboarding for older cohorts and promoting innovation among newer hires.

Infrastructure must support, but cannot substitute, user intention: Facilitating conditions are necessary but not sufficient on their own. While investments in AI tools and IT infrastructure are critical, they will only yield results if employees have the intention to engage with these technologies. Therefore, cultural and motivational strategies should be used alongside technical readiness.

6. Limitations and Future Scope

Limitations:

Limited generalizability beyond Delhi/NCR: Since the study focuses solely on automobile manufacturing firms in the Delhi/NCR region, the findings may not be directly applicable to other regions or industries with different technological landscapes or organizational cultures.

Self-reporting bias: Data was collected using self-administered questionnaires, which could lead to social desirability or recall bias, potentially inflating positive responses regarding technology adoption.

External variables not considered: The study primarily focuses on psychological and organizational predictors of AI adoption. It does not explore macro-level factors such as regulatory barriers, financial constraints, or supply chain issues that could affect technology deployment.

Future Scope:

Expand to other sectors: Future research can explore AI adoption in T&D across different industries such as healthcare, education, or retail to understand sector-specific dynamics and cross-industry applicability of the UTAUT model.

Include longitudinal analysis: Long-term studies can track how perceptions, behavioral intentions, and actual usage of AI evolve over time, providing deeper insight into sustained technology adoption and integration.

Add ethical and organizational factors: Future models can incorporate variables such as perceived trust, job displacement anxiety, ethical concerns, and organizational readiness to provide a more holistic view of AI adoption.

Evaluate specific AI tools: Research can be extended to assess the adoption and impact of particular AI-enabled T&D platforms, such as chatbots, intelligent learning management systems, or AI-based performance dashboards.

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