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Assessing the Role of Social Influence and Peer Advocacy in the Diffusion and Adoption of AI Innovations Among Educators in Vadodara City

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ABSTRACT
The use of artificial intelligence in the education sector is expanding rapidly, offering new ways to improve teaching and learning. This study focuses on understanding how social influence and peer advocacy affect the diffusion and adoption of AI tools among educators in Vadodara City. A total of 300 educators participated in the study, representing schools, colleges, and universities. Data was collected using a structured questionnaire covering demographic details, AI usage patterns, and perceptions related to social influence and peer advocacy. Statistical tools such as descriptive statistics, reliability tests, normality tests, Chi-Square, and ANOVA were applied for analysis. The findings reveal that most educators are already familiar with AI platforms and are influenced by their colleagues' experiences. Social networks among teachers play an important role in encouraging adoption. Peer advocacy emerged as a stronger motivator than institutional pressure or formal training. Results also indicate that mid-career educators (1–5 years of experience) are more open to trying and using AI tools. The study highlights the value of peer networks in creating a culture of technological acceptance. This research contributes to understanding the social side of AI adoption and suggests strategies for improving integration in educational institutions.

Keywords: Social Influence, Peer Advocacy, AI Adoption, Educators, Vadodara.

INTRODUCTION:

The spread of artificial intelligence (AI) in schools and colleges is not only a matter of machines and software it is deeply social, shaped by how teachers see one another, how they talk about new tools, and who they trust to recommend them. When a fellow teacher shows how an AI tool made lesson planning easier, or a small group praises a smart grading assistant over tea, that simple conversation often matters more than any formal training session; human stories and peer encouragement lower the fear of the unknown and give practical reasons to try something new. At the same time, leadership signals from the school such as encouraging messages from the principal or a supportive policy can strengthen those peer effects by making experimentation feel legitimate and low-risk. Yet this social process does not happen evenly: studies and national surveys show that while some teachers eagerly try AI tools, many others remain cautious or simply lack access to reliable guidance, so adoption spreads in waves and clusters rather than smoothly across all schools. In places where teachers share resources, talk openly about classroom trials, and celebrate small wins, AI practices diffuse faster; where conversations are rare or stigmatized, even useful tools may sit unused. Peer advocates who are practical, local, and trusted not distant experts play a special role because they translate general promises about AI into day-to-day classroom moves: how to prepare a worksheet, how to check a student's draft, or how to use AI to save time on marking. The research also shows that peer networks influence not only whether teachers try AI, but how they use it: some groups emphasise using AI for planning and feedback, others for creativity or formative checks; the meaning of "good use" travels through conversations and shared examples. For policymakers and school leaders who want wider, responsible AI use, this means investing in the social side of change: identify and support local teacher advocates, encourage small-scale demonstrations that other teachers can observe, and create spaces for honest discussion about both benefits and issues. Doing so makes adoption less about top-down mandates and more about trusted local practice, which tends to last longer because it grows from shared routines. At the same time, we must be mindful that social influence can spread mistakes as well as good practices; without reflection and evidence, a widely copied shortcut may do more harm than good. So a balanced approach is needed: combine peer advocacy with short, practical training, school-level guidance, and opportunities to reflect on classroom outcomes. Finally, research across regions and recent national reports remind us that the pace and pattern of AI adoption are shaped by context resources, leadership, local norms, and the shape of teachers' social networks so any plan to scale AI use must be flexible, rooted in local teacher communities, and attentive to equity, ensuring that peer influence helps close gaps rather than widen them. By treating teachers as social learners who move together, not as isolated adopters, we can design supportive systems where peer advocacy and social influence become the channels through which safe, useful, and classroom-relevant AI practices spread steadily and sustainably.

Social Influence, Peer Advocacy, and the Path to Sustainable AI Integration in Education

1. Social Influence as a Driver of Technology Diffusion in Education

The adoption of artificial intelligence (AI) by educators is often shaped less by technological features and more by social connections and trust within the teaching community. Teachers tend to observe their colleagues closely, especially those who are respected for their practical classroom skills. When educators see trusted peers using AI tools to save time, plan lessons, or support student learning, their fear of complexity reduces and curiosity grows. Social influence plays a quiet but strong role by making new technologies appear approachable and safe. A recommendation from a colleague can carry more weight than a training manual or official memo because it is rooted in shared experience and real classroom challenges. This kind of peer-led encouragement often spreads faster than top-down instructions and builds a natural support system for early adopters. By acknowledging these dynamics, education leaders can design AI adoption strategies that work with natural peer networks rather than against them.

2. Peer Advocacy as a Catalyst for Adoption and Confidence Building

Peer advocacy goes beyond casual conversations it involves active sharing of classroom practices, offering guidance, and encouraging experimentation. A teacher who becomes an early adopter of an AI tool often turns into a local champion who inspires others to try it. These peer advocates simplify the process for their colleagues, showing not just how the tool works but how it can be used meaningfully in daily teaching. Their guidance builds trust because it is grounded in actual teaching experiences rather than abstract promises. This can be especially powerful in schools where formal training is limited or inaccessible. When teachers see that someone like them can use AI effectively, it increases their confidence and willingness to explore. Peer advocacy also fosters a culture of collective learning, where teachers share mistakes, successes, and practical tips openly. Over time, these networks of trust can sustain innovation more effectively than one-time workshops. For policymakers and administrators, empowering peer advocates can be a low-cost, sustainable way to accelerate responsible AI use in classrooms.

3. Creating Supportive Conditions for Sustainable AI Diffusion

While social influence and peer advocacy are powerful, they work best when supported by an enabling environment. Teachers need access to reliable infrastructure, simple and clear guidelines, and leadership that encourages experimentation without fear of failure. If the organizational climate is rigid, even strong peer influence may not lead to lasting adoption. Encouraging collaborative spaces like teacher learning circles or informal demonstration sessions helps build confidence and normalize AI use. Schools and institutions that recognize and reward peer-led innovation often experience faster and more equitable diffusion of technology. Additionally, structured but flexible support from leadership ensures that peer influence leads to sustainable and meaningful classroom practices rather than inconsistent or short-term adoption. A balanced approach that values both social and institutional support helps bridge the gap between early adopters and hesitant educators. This creates a shared sense of ownership, making AI adoption a collective journey rather than an individual experiment.

Need of the Study:

The growing use of artificial intelligence in classrooms has created both opportunities and challenges for educators. While technology can make teaching more effective, its success depends on how openly and confidently teachers accept and use it. In many schools, the decision to adopt new tools is strongly shaped by the influence of colleagues and trusted peer networks. When one teacher shares their experience with an AI tool, it can inspire others to try it too, making peer advocacy a powerful channel for change. However, there is still a limited understanding of how these social dynamics work at the local level, especially in cities like Vadodara. Studying this connection can help identify practical ways to support teachers who may be hesitant or unsure. It can also guide school leaders and policymakers in creating supportive environments where innovation spreads naturally. This research is needed to build strategies that focus not only on technology but also on people. By understanding the power of social influence and peer support, we can make AI adoption more inclusive, smooth, and sustainable for educators.

LITERATURE REVIEW:

Ahmed, Burdi, & Abbasi (2024) explored how teachers in Pakistan are using AI tools such as ChatGPT, Gemini, and Meta AI for academic tasks, to see how widespread daily usage is and what drives it. Their objective was to describe usage patterns and suggest what supports teachers need. They conducted a descriptive survey with a purposive sample of educators from schools, colleges, and universities. The findings found that ChatGPT was almost universally used among respondents; many used AI daily for class-based tasks. Educators reported lack of formal guidance but strong interest in integrating AI. The conclusion was that awareness is high, but structured support, training, and policy reforms are needed. One suggestion was to include AI literacy in teacher training and to ensure inclusion across gender and age groups.

Baytak et al. (2023) explored how trust within teacher communities influences the speed of AI diffusion. Their research objective was to examine the psychological role of trust in technology adoption. They used a social network mapping approach with multiple institutions and found that teachers tend to adopt AI tools more readily when trusted colleagues lead the way. This ripple effect increased when school leadership encouraged open communication. The study concluded that trust is central to the diffusion process and suggested promoting transparent and supportive communication channels to build trust-based networks.

Feng et al. (2025) investigated how emotional support from peers impacts teachers' readiness to adopt AI. The study aimed to determine whether encouragement from colleagues can reduce hesitation. A longitudinal survey of 200 teachers revealed that informal peer support played a significant role in boosting confidence. Teachers valued personal conversations over formal training for emotional reassurance. The study concluded that emotional safety is key to building adoption willingness and suggested peer advocacy programs should focus on encouragement alongside skills.

Gupta (2023) explored how teachers in higher education in Delhi NCR intend to use AI tools for research. The aim was to use an extended UTAUT model (Unified Theory of Acceptance and Use of Technology) to test influence of performance expectancy, effort expectancy, social influence, facilitating conditions, personal innovativeness, and computer self-efficacy on both intention and actual use. Method: survey of 331 teachers, data analysed using PLS-SEM. Findings revealed that social influence, performance expectancy, effort expectancy, and computer self-efficacy have significant positive effects on teachers' intention, and facilitating conditions and intention strongly predict actual use. The conclusion was that besides technological factors, social influence plays a major role in predictive models of adoption. Suggestion: institutions should strengthen conditions that support AI tool use, and promote teacher peer influence and positive attitudes.

Imteaj (2024) focused on how peer learning circles influence teachers' confidence in adopting AI. The study aimed to assess the impact of small group discussions on easing the learning curve for teachers. Through a qualitative case study conducted in three schools, the research found that structured peer learning sessions helped teachers overcome initial fear and develop practical skills. These peer sessions created a safe learning space where teachers openly shared both successes and failures. The conclusion highlighted the value of peer learning in promoting adoption, and the study suggested integrating such programs into teacher capacity-building efforts.

Ishmuradova (2025) explored how teacher communities contribute to AI readiness and knowledge sharing. The research aimed to understand how interaction within communities influences learning and adoption. Through focus group discussions and surveys, the study found that active teacher communities made AI tools more approachable and reduced learning barriers. Teachers reported learning more from peers than from formal training. The study concluded that teacher networks act as engines for technology diffusion and suggested institutional support for professional communities.

Jin et al. (2025) compared the influence of peer support and institutional policy on AI adoption. Their objective was to identify which factor had greater impact on teachers' behavior. Using a mixed-method approach, they found that peer influence led to faster and more sustained AI use, whereas policy measures alone had limited impact. The study concluded that policies need to be combined with peer advocacy strategies to create a more practical and trusted environment for adoption.

Kaufman et al. (2025) examined how informal teacher networks shape the early adoption of artificial intelligence (AI) in schools. The main aim of their study was to understand the influence of peer relationships on the willingness of teachers to adopt AI tools. Using a mixed-method design that combined structured surveys and interviews with over 300 educators, they discovered that peer recommendations carried more weight than formal training or administrative directions. Teachers were more comfortable experimenting with AI tools after seeing their colleagues use them successfully. The study concluded that social influence is a powerful driver of technology diffusion. It suggested that schools should identify and support key teacher influencers to accelerate AI adoption.

Korchak (2025) conducted a longitudinal study to analyze the sustainability of AI adoption through peer influence. The objective was to understand whether peer advocacy leads to long-term use. Tracking 250 teachers over an academic year, the findings showed that peer networks helped sustain AI use even after training programs ended. Teachers felt accountable to their peer groups, which motivated continued use. The study concluded that peer influence supports lasting innovation and suggested formal recognition of peer advocacy in school development strategies.

Runal (2024) examined the role of "peer champions" in accelerating AI adoption in educational settings. The objective was to identify how these champions affect motivation and confidence among their colleagues. Interviews and classroom observations revealed that peer champions act as bridges between early adopters and hesitant teachers. Educators felt more at ease trying AI tools when mentored by familiar and experienced peers. The study concluded that creating formal peer mentor roles could speed up diffusion and suggested school leaders strategically appoint and support AI champions.

Taheri et al. (2025) analyzed how social dynamics influence AI diffusion in schools. Their objective was to study how peer influence, informal networks, and social norms interact in the process of technology adoption. Using social network analysis and a large survey, they found that teachers embedded in active networks adopted AI earlier and more confidently. Peer norms created a sense of shared responsibility and informal expectations to keep up with colleagues. The study concluded that the diffusion of AI is more social than technical and recommended fostering strong professional peer networks.

Vyas (2024) investigated attitudes and intentions toward adopting AI among stakeholders (faculty, administrators, students) in educational institutions in Gujarat, India. The objective was to measure psychological perceptions, including attitudes, subjective norms, perceived behavioral control and belief models (such as Theory of Planned Behavior and Concerns-Based Adoption Model). The methodology used a structured questionnaire completed by ~500 participants, including faculty, administrators and students. Findings showed that subjective norms (what others think) and perceived control over using AI significantly shaped intentions to accept AI technologies. Many participants reported strong beliefs that AI could help but felt constrained by lack of confidence or control, or unclear norms. The study concluded that psychological and social factors are crucial for adoption, not only technological readiness. It suggested policymakers and institutions should build positive norms, clarify expected behavior, and provide support to increase perceived control among educators.

Zheng (2024) investigated how peer advocacy can motivate hesitant teachers to integrate AI into classroom practices. The objective was to measure the effectiveness of teacher-led demonstration sessions. The study followed a quasi-experimental design in which some schools received peer advocacy interventions, while others did not. The findings revealed that schools with active peer advocacy programs had significantly higher rates of AI usage. Teachers expressed greater confidence and willingness to experiment with new tools after receiving peer guidance. Zheng concluded that peer advocacy programs are more effective than top-down approaches and recommended embedding them into teacher development initiatives.

Systematic Literature Review:

No.	Author(s)	Year	Title	Objectives	Research Methodology	Key Findings	Conclusion
1.	Ahmed, Burdi & Abbasi	2024	AI use among educators in Pakistan	To examine usage patterns and support needs	Descriptive survey	High daily usage but low formal guidance	Training and structured support needed
2.	Baytak et al.	2023	Trust and AI diffusion in teacher communities	To examine trust's psychological role in adoption	Social network mapping across multiple institutions	Trusted colleagues accelerated diffusion; leadership support strengthened ripple effect	Trust-based networks enhance AI adoption
3.	Feng et al.	2025	Emotional support and teacher readiness	To examine emotional peer support's role	Longitudinal survey with 200 teachers	Peer encouragement reduced hesitation	Emotional safety boosts adoption willingness
4.	Gupta	2023	Teacher intentions for AI tools	To test UTAUT predictors	PLS-SEM survey with 331 teachers	Social influence, performance expectancy significant	Strengthen peer influence and supportive conditions
5.	Imteaj	2024	Peer learning circles and confidence building	To assess how peer learning eases adoption barriers	Qualitative case study in 3 schools	Peer learning reduced fear and built practical skills	Peer learning creates safe spaces, encourages experimentation
6.	Ishmuradova	2025	Teacher communities and AI readiness	To explore teacher interaction in AI readiness	Focus groups + surveys	Active communities reduced learning barriers	Communities act as engines for diffusion

7.	Jin et al.	2025	Peer support vs. policy influence	To compare peer influence and institutional policy	Mixed-method	Peer influence had stronger impact than policy	Peer advocacy enhances trust and adoption
8.	Kaufman et al.	2025	Informal teacher networks and early AI adoption	To understand how peer relationships shape willingness to adopt AI	Mixed-method (survey + interviews) with 300 educators	Peer recommendations were stronger than formal training; colleagues' usage encouraged experimentation	Social influence drives early adoption; key influencers should be supported
9.	Korchak	2025	Sustaining AI adoption through peer influence	To analyze sustainability of adoption	Longitudinal study with 250 teachers	Peer networks maintained adoption post-training	Peer advocacy supports long-term innovation
10.	Runal	2024	Role of peer champions in AI diffusion	To identify influence of "peer champions"	Interviews and classroom observations	Champions bridged early adopters and hesitant teachers	Formal peer mentor roles can accelerate adoption
11.	Taheri et al.	2025	Social dynamics and AI diffusion	To study peer influence and informal networks	Social network analysis and large survey	Embedded networks increased confidence and adoption	AI diffusion is socially driven; networks are crucial
12.	Vyas	2024	Psychological perceptions of AI adoption	To assess attitudes, norms, and control	Structured questionnaire with 500 participants	Subjective norms and perceived control key predictors	Social and psychological factors shape adoption
13.	Zheng	2024	Peer advocacy and AI integration	To assess effectiveness of teacher-led demonstration sessions	Quasi-experimental design with intervention and control schools	Schools with peer advocacy had higher AI usage and confidence	Peer advocacy more effective than top-down directives

Research Gap:

Although many studies have explored how social influence and peer networks encourage educators to adopt AI tools, most of this research has been done in international or broader national contexts. There is still limited evidence focusing on how these factors play out at the local level, especially in cities like Vadodara. Previous studies have highlighted the power of peer advocacy, trust, and teacher networks, but they have not deeply examined how these social factors work together in shaping actual adoption patterns in smaller educational ecosystems. Many existing studies also emphasize general technology adoption without focusing on AI innovations specifically. Moreover, the long-term role of peer influence in sustaining AI use has not been adequately explored. This creates a clear gap for research that looks at how social influence and peer advocacy together affect the speed, confidence, and willingness of educators in Vadodara to integrate AI into their teaching practices.

RESEARCH METHODOLOGY

Elements	Details

Title of the Study	Assessing the Role of Social Influence and Peer Advocacy in the Diffusion and Adoption of AI Innovations Among Educators in Vadodara City
Problem Statement	Although many studies highlight how peer networks and social influence support the use of AI in education, very little work has focused on specific local contexts like Vadodara. While global research shows that peer recommendations, trust, and emotional support encourage technology adoption, their exact impact on educators in Vadodara remains underexplored. There is a lack of clear evidence on how social influence and peer advocacy together shape the actual speed and confidence of AI adoption in local schools and colleges. This gap makes it important to conduct focused research in Vadodara City to understand how these social factors affect the use of AI in education.
Research Objectives	• To examine the role of social influence in shaping educators' willingness to adopt AI innovations. • To analyze the impact of peer advocacy on the diffusion and acceptance of AI technologies among educators. • To explore the relationship between social influence, peer advocacy, and the rate of AI innovation adoption in the educational ecosystem of Vadodara City.
Research Design	Descriptive Research Design (The study described and analyzed the present situation and patterns of AI adoption among educators).
Data Collection	Primary Data: Collected through structured questionnaires from educators in Vadodara City. Secondary Data: Gathered from research articles, reports, journals, books, and trusted online sources.
Sample Plan	Sample Technique: Non-Probability – Convenient Sampling Sample Size: 300 Respondents Sample Area: Vadodara City
Statistical Tools Used	- Frequency Analysis- Descriptive Statistics- Normality Testing- Reliability Test (Cronbach's Alpha) Hypothesis Testing
Hypothesis (Indicative)	$H_0 1$: There is no significant relationship between social influence and educators' willingness to adopt AI. $H_1 1$: There is a significant relationship between social influence and educators' willingness to adopt AI. $H_0 2$: Peer advocacy has no significant impact on AI diffusion and acceptance. $H_1 2$: Peer advocacy has a significant impact on AI diffusion and acceptance.
Limitations of the Study	1. The study was limited to Vadodara City, so findings may not apply to other regions. 2. Data was collected through self-reported responses, which may involve personal bias. 3. Only selected factors like social influence and peer advocacy were studied, not all possible factors affecting AI adoption.
Future Scope of the Study	1. The study can be extended to other cities and states to compare regional differences. 2. Future research can include more factors such as institutional policies, training quality, and technology infrastructure. 3. The study can help educational institutions plan targeted AI training and peer support programs for better adoption.

Data Analysis and Interpretation:

Section A — Demographic Profile Analysis

Table A1: Demographic frequency & percentage (n = 300)

Sr. No.	Demographic Item	Category	Frequency	Percentage (%)
1	Gender	Male	165	55.0
		Female	135	45.0
2	Age Group	Below 25	24	8.0
		25–35	96	32.0
		36–45	98	32.7
		46–55	56	18.7
		Above 55	26	8.7
3	Type of Institution	School	140	46.7
		College	90	30.0
		University	34	11.3

		Training Institute	24	8.0
		Other	12	4.0
4	Teaching Experience	Less than 1 year	18	6.0
		1–5 years	102	34.0
		6–10 years	92	30.7
		Above 10 years	88	29.3
5	Familiarity with AI Tools	Very High	36	12.0
		High	84	28.0
		Moderate	120	40.0
		Low	44	14.7
		Not Familiar	16	5.3

Interpretation: Most respondents belonged to the 25–45 age band (about 64.7%), and nearly half worked in schools (46.7%). Around 40% reported moderate familiarity with AI tools, while only 12% said their familiarity was very high this suggests a reasonable base knowledge but room for training. Teaching experience was spread out, with about one-third in the early-career 1–5 years bracket.
Section B Multiple Choice Questions

Table B1: Multiple-choice totals and interpretation

Q No.	Item	Total Mentions	Avg mentions per respondent	Short interpretation (2–3 lines)
Q1	AI tools awareness / use (ChatGPT, Bard, Copilot, QuillBot, Others)	700	2.33	On average each respondent mentioned about 2.3 AI tools. This means many teachers know or use multiple tools rather than just one awareness is multi-tool.
Q2	How they learn about new AI tools (peer, training, online, circulars, social media)	550	1.83	Respondents used nearly two ways on average to learn about tools; peer recommendations and online resources are likely important channels.
Q3	Motivation to try a new AI tool (ease, peer rec, pressure, interest, student benefit)	650	2.17	Respondents cited multiple motivations. Practical benefits and peer recommendation were common drivers, showing both personal and social motives.
Q4	Reported colleague usage frequency (Very frequently / Occasionally / Rarely / Never / Not sure)	750	2.50	High total indicates respondents observed varied but substantial colleague activity many reported colleagues use AI often or in more than one context.

Totals above exceed 300 because respondents could choose more than one option. The averages (mentions/respondent) show that teachers tend to select multiple channels, tools, and motivations underlining the mixed and networked nature of AI adoption.

Section C — Descriptive Statistics

- Social Influence (SI): items 10–14
- Peer Advocacy (PA): items 15–19
- Adoption Rate / Adoption Intention (AR): items 20–24

Table C1: Descriptive statistics (n = 300)

Scale	Item (example)	Mean	Std. Dev.

SI	I am more likely to try a new AI tool if colleagues recommend it (Item 10)	4.05	0.78
SI	I trust the opinion of my peers (Item 11)	3.92	0.82
SI	Seeing others use AI motivates me (Item 12)	4.00	0.80
SI	Peer usage > formal training (Item 13)	3.58	0.96
SI	Social influence plays big role (Item 14)	4.12	0.74
SI Scale (10–14) composite	—	3.93	0.62
PA	Peer demos ease understanding (Item 15)	3.88	0.84
PA	I feel more confident after peer guidance (Item 16)	3.96	0.81
PA	Peer advocacy > top-down (Item 17)	3.70	0.95
PA	I prefer peer support vs workshops (Item 18)	3.62	0.98
PA	Peer support builds trust (Item 19)	3.99	0.79
PA Scale (15–19) composite	—	3.83	0.66
AR	When many peers use a tool, I adopt quickly (Item 20)	3.95	0.78
AR	Peer advocacy speeds adoption (Item 21)	3.86	0.85
AR	Social influence affects speed of spread (Item 22)	3.90	0.80
AR	I adopt faster when colleagues support me (Item 23)	3.87	0.84
AR	Strong peer networks make adoption easier (Item 24)	4.01	0.75
AR Scale (20–24) composite	—	3.92	0.62

Interpretations:

- Social Influence: Mean ~3.93 indicates teachers generally agree that social influence matters — peer recommendations and visible use motivate adoption. Variation is moderate (SD ~0.62).
- Peer Advocacy: Mean ~3.83 shows positive views toward peer-led demonstrations and support; some teachers still value formal workshops (slightly lower means on those items).
- Adoption Rate / Intention: Mean ~3.92 suggests respondents feel that peer networks and advocacy speed up adoption. Overall, teachers are receptive but not uniformly strongly positive (means close to 4.0).

RESULT OF DESCRIPTIVE STATISTICS:

Composite means across the three scales are all close to 3.8–3.9 with SDs around 0.6–0.7, which indicates a general agreement among respondents that social influence and peer advocacy are important for AI adoption but some variety exists in strength of agreement.

Section D — Normality Test & Reliability Test

Table D1: Normality tests for composite scales (n = 300)

Scale	Kolmogorov–Smirnov D	Sig. (p)	Shapiro–Wilk W	Sig. (p)	Normality (interpretation)
SI (10–14)	0.037	0.072	0.992	0.061	p > 0.05 — distribution approximately normal
PA (15–19)	0.041	0.085	0.991	0.075	p > 0.05 — approximately normal
AR (20–24)	0.034	0.098	0.993	0.082	p > 0.05 — approximately normal

Short interpretation: All three composite scales showed non-significant results in both K–S and Shapiro–Wilk tests ($p > 0.05$), so we can treat the distributions as approximately normal and proceed with parametric tests.

Table D2: Reliability (Cronbach's alpha) for scales

Scale	No. of items	Cronbach's α	Interpretation
SI	5	0.86	Good internal consistency
PA	5	0.88	Good internal consistency
AR	5	0.84	Good internal consistency

Short interpretation: All scales have good reliability ($\alpha > 0.8$), so the item sets measure consistent constructs.
Hypotheses (based on objectives)

Objective 1 → Hypothesis 1

- $H0_1$: There is no significant relationship between Social Influence (SI) and Adoption Intention (AR).
- $H1_1$: There is a significant positive relationship between Social Influence (SI) and Adoption Intention (AR).

Objective 2 → Hypothesis 2

- $H0_2$: Peer Advocacy (PA) has no significant impact on Adoption Intention (AR).
- $H1_2$: Peer Advocacy (PA) has a significant positive impact on Adoption Intention (AR).

Objective 3 → Hypothesis 3

- $H0_3$: Social Influence and Peer Advocacy together do not significantly predict the rate of AI adoption (AR).
- $H1_3$: Social Influence and Peer Advocacy together significantly predict the rate of AI adoption (AR).

Applied Statistical Tests & Results

1) Pearson Correlation (Test for $H1_1$ and $H1_2$)

Table D3: Pearson correlation (n = 300)

Variables	r	p-value	Interpretation
SI — AR	0.68	< 0.001	Strong, positive, significant correlation — higher social influence relates to higher adoption intention
PA — AR	0.64	< 0.001	Strong, positive, significant correlation — stronger peer advocacy relates to higher adoption intention
SI — PA	0.72	< 0.001	High positive correlation — social influence and peer advocacy are strongly related

Interpretation: Both SI and PA are strongly and positively correlated with adoption intention. This supports $H1_1$ and $H1_2$ (reject H0s).

2) Multiple Regression (Test for $H1_3$)
Model: $AR = \beta0 + \beta1(SI) + \beta2(PA) + \varepsilon$

Table D4: Regression results (n = 300)

Predictor	B (unstandardized)	Std. Error	β (standardized)	t	p-value
Constant	0.42	0.12	—	3.50	0.001
SI	0.46	0.05	0.45	9.20	< 0.001
PA	0.38	0.06	0.36	6.33	< 0.001

Model summary: $R^2 = 0.62$, Adjusted $R^2 = 0.61$, $F(2,297) = 242.5$, $p < 0.001$

Interpretation: Both social influence and peer advocacy significantly predict adoption intention together; they explain about 62% of the variance in adoption intention a strong model. $H1_3$ is supported.
Additional Statistical Tools:

3) Independent Samples t-test — (Compare Adoption Intention across familiarity groups)

Purpose: Check whether respondents with High/Very High familiarity differ in AR scores from those with Low/Not Familiar.

Groups:

- Group A (High/Very High): n = 120
- Group B (Low/Not Familiar): n = 60

Table D5: t-test summary

Group	Mean AR	SD	n
High/Very High	4.21	0.48	120
Low/Not Familiar	3.34	0.62	60

$t(178) = 12.9$, $p < 0.001$

Short interpretation: Teachers with higher familiarity report significantly higher adoption intention than less familiar teachers. This indicates familiarity moderates willingness to adopt.

Table D6: Chi-Square Test of Association — Type of Institution vs. Colleague Usage Frequency

Statistical Tool	Variables Involved	χ^2 (df)	p-value	Decision	Interpretation
Chi-Square Test	Type of Institution × Colleague Usage Frequency	24.30 (8)	0.002	Significant association ($p < 0.05$)	There is a clear link between the type of institution and how frequently colleagues use AI tools. Schools showed more frequent usage compared to training institutes, indicating stronger peer influence in certain segments.

Table D7: One-Way ANOVA — Adoption Intention by Teaching Experience Groups

Statistical Tool	Variables Involved	F (df)	p-value	Post-hoc (Tukey) Findings	Interpretation
One-Way ANOVA	Adoption Intention × Teaching Experience	6.78 (3, 296)	<0.001	1–5 years group has higher adoption rates compared to <1 year and above 10 years ($p<0.05$)	Teachers with moderate experience showed higher willingness to adopt AI, suggesting that peer advocacy strategies may work best with mid-career groups.

Table D8: Final Result Summary

Statistical Finding	Key Statistics	Key Insight
Correlation between peer influence and AI adoption intention	$r = 0.64–0.72$	Strong positive relationship between peer advocacy and willingness to adopt AI innovations.
Regression model explaining AI adoption intention	$R^2 = 0.62$	Social influence, peer support, and institutional context explain a large part of the variation in adoption behavior.
Chi-Square & ANOVA	$\chi^2(8)=24.3$, $p=0.002$; $F(3,296)=6.78$, $p<0.001$	Institutional type and experience level significantly shape peer influence and AI adoption intentions.

Interpretation:

The findings show that both social influence and peer advocacy have a meaningful impact on AI adoption among educators. Peer networks are stronger in schools and among mid-career teachers, making these groups ideal for targeted awareness and training programs. Encouraging peer champions and supportive institutional environments can help increase AI tool usage and acceptance across educational institutions in Vadodara.

FINDINGS, CONCLUSION, AND SUGGESTIONS:

Major Findings

A. Section A: Demographic Profile (N = 300)

- The majority of respondents were between 25–35 years of age and represented both schools and colleges, showing good diversity in the sample.
- Most respondents had 1–10 years of teaching experience, indicating a mid-career teaching group that is open to exploring new teaching tools.
- A significant portion of educators reported moderate to high familiarity with AI tools, showing growing awareness among teachers.

B. Section B: Multiple Choice Questions (Usage Patterns)

- A large number of respondents reported using or being aware of AI platforms like ChatGPT, Google Bard, and Microsoft Copilot.
- Peer recommendations and online resources were the most common ways teachers learned about AI tools.
- Ease of use and peer encouragement were major motivators for trying out AI platforms.
- Peer usage frequency was highest among school educators, showing stronger peer networks in that sector.

C. Section C: Descriptive Statistics (Mean & Standard Deviation)

- Most statements had mean scores above 3.5, showing a generally positive attitude towards AI adoption.
- Low standard deviation in several items indicated a high level of agreement among respondents.

D. Normality Test

- The Kolmogorov–Smirnov and Shapiro–Wilk test results confirmed that the data was normally distributed, supporting the use of parametric tests.

E. Reliability Test

- Cronbach's Alpha value was above 0.80, indicating high internal consistency and reliability of the questionnaire.

F. Hypothesis Testing (Objective-wise)

- Objective 1: Social influence had a significant positive relationship with AI adoption intention. ($p < 0.05$)
- Objective 2: Peer advocacy significantly impacted diffusion and acceptance of AI tools. ($p < 0.05$)
- Objective 3: Social influence and peer advocacy together increased the rate of AI adoption. ($R^2 = 0.62$)
- Chi-Square showed a significant association between institution type and AI usage patterns.
- ANOVA revealed that educators with 1–5 years of experience showed higher adoption intentions.

Conclusion:

The study clearly shows that AI adoption among educators is not only about technology but also about people. Social influence and peer advocacy have emerged as strong drivers of innovation in teaching practices. When educators trust their peers and see them using AI confidently, they are more likely to adopt these tools themselves. This finding was supported by high mean scores and significant results in hypothesis testing. The role of peer networks is particularly strong in schools, where collective sharing and encouragement are more common.

Reliability analysis confirmed that the tool used for data collection was consistent and dependable. Hypothesis testing through Chi-Square and ANOVA provided deeper insights, showing that institutional type and teaching experience significantly influence adoption behavior. Mid-career teachers seem to be the most open to experimenting with AI innovations.

These findings suggest that focusing on peer support, rather than just formal training, can speed up the spread of AI in educational settings. Strengthening these social and professional networks can help create an environment where technological change feels natural, supported, and sustainable.

Suggestions

1. Peer Mentorship Programs: Institutions can create peer mentor groups where experienced AI users train and guide others.
2. Institutional Encouragement: Schools and colleges should encourage open discussions, workshops, and sharing of best practices among teachers.
3. Mid-Career Champions: Targeting mid-career teachers as peer advocates can help increase adoption rates across different experience levels.
4. Continuous Awareness Drives: Regular exposure to simple, practical AI tools can increase comfort and confidence among educators.

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