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Adoption of Artificial Intelligence Technologies in SMEs: A Study of Kathmandu valley

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Abstract

Purpose: This study examines the adoption of Artificial Intelligence (AI) among Small and Medium Enterprises (SMEs) in the Kathmandu Valley.

Design/Methodology/Approach: The study employs an explanatory research design to investigate causal relationships among variables. The target population comprises owners, managers, and employees directly involved in decision-making or daily operations within SMEs in the Kathmandu Valley. A probability sampling technique was used to ensure representativeness, yielding a robust sample of 318 respondents. Data were analyzed using Structural Equation Modeling (SEM), a multi-factor statistical framework capable of examining relationships between latent (unobservable) and observed variables.

Findings: The research provides a comprehensive overview of AI adoption patterns among SMEs in the Kathmandu Valley, highlighting both the opportunities for digital transformation and the challenges impeding widespread implementation.

Originality/Value: This study contributes to the limited empirical literature on AI adoption in developing economies, particularly within Nepal's SME sector.

Keywords: artificial intelligence, attitude, AI adoption, SMEs, Kathmandu valley, structural equation modeling

Introduction

The rapid progress of Artificial Intelligence (AI) has transformed industries worldwide, reshaping how businesses operate and compete in the digital age. AI technologies ranging from machine learning and natural language processing to robotics and predictive analytics have demonstrated significant capacity to improve operational effectiveness, improve decision-making, and spark new ideas across various sectors (Kopka & Fornahl, 2024). From automating routine tasks to enabling data-driven interpretations, AI is increasingly becoming a cornerstone of modern business operations.

AI technologies have a lot of potential to boost operational efficiency, enhance customer satisfaction, and streamline supply chains in knowledge-intensive sectors like healthcare, finance, and manufacturing (Shahadat et al., 2023; Tominc et al., 2024). AI is allegedly used by SMEs in the financial sector to detect fraud, score credit, and provide exceptional customer service (Bag et al., 2023). Likewise, manufacturing SMEs use AI-driven automation to scale production and reduce costs. Still, a lesser percentage of companies adopt AI and several efforts should be made to further harness the support for SMEs that face challenges peculiar to their industries (Almashawreh et al., 2024).

For small and medium-sized enterprises (SMEs), which are the core of many economies, including Nepal, AI adoption offers considerable potential and formidable challenges. The business sector throughout the world has experienced the most significant adoption of AI through advanced economies which include the United States and European countries and East Asian regions. The regions receive benefits from their strong technological networks and forward-thinking government approaches and widespread technical knowledge and skilled workforce availability (Shahadat et al., 2023; Masudine al, 2021). The governments of these economies establish regulatory frameworks alongside subsidies and training programs which help developers innovate and make AI adoption simpler. AI technology integration proves difficult for emerging economies because they face unique challenges during the process.

AI implementation is gaining ground in the financial services and e-commerce sectors. Financial institutions are implementing AI to study customer behavior, identify fraudulent transactions, and perform various back-office operations (Bag et al., 2023). E-commerce platforms use AI chatbots and recommendation systems to increase customer engagement and sales. These developments are facilitated by government initiatives such as digital transformation policies and private sector investments promoting innovation. Nevertheless, Bangladeshi SMEs continue facing hurdles in inadequate IT infrastructure and a lack of skilled personnel that slow down broader AI adoption (Karim et al., 2026).

Rapid advancements in the field of AI provide an excellent set of opportunities for Small and Medium Enterprises to improve efficiency, innovativeness, and competition. In Nepal, AI adoption is still at an embryonic stage with very few companies actively looking at or implementing AI technologies. With the National AI Policy 2081, it has been set to create a welcoming environment for AI integration while taking into considerations ethics, data security, and legal frameworks (Subedi, 2024). But as far as implementation goes, especially at the smaller level of SMEs, very little is known. For example, the deployment of data-heavy AI applications like predictive analytics and machine learning modeling is hampered by the poor internet connectivity of many SMEs, particularly in rural areas (Lamsal et al., 2025). Many SMEs are discouraged from pursuing AI initiatives due to the high cost of purchasing and maintaining AI-related hardware and software, as well as the associated training. Adding to it is the small market size and the unavailability of funding opportunities (Devkota et al., 2024). Further impeding the introduction of AI tools into day-to-day activities is the lack of digital literacy among employees and management (Lutfi et al., 2020).

Lack of funding, inadequate infrastructure, digital illiteracy, and, lastly, ethical issues and cyber liabilities or job losses as a result of automation are major obstacles for SMEs in Nepal when it comes to implementing AI (Digital Media Foundation, 2024). In remote locations, these obstacles are exacerbated by inadequate Internet access and a lack of hardware required for AI adoption. Resistance to change is further fuelled by a leadership ill-informed and apathetic to the matter, thereby limiting the resources (Beliaeva et al., 2019). These factors limiting AI adoption, such as technology strategy, the knowledge of IT matters by employees, the degree of active managerial support, training programs, and reward systems, have been found through other global studies but mostly in developed countries or big organizations (Almashawreh et al., 2024). And the relevance of such conventional wisdom to resource-starved environments like Nepal has yet to be proven, creating a void in the existing literatures on how local factors-landscape governments, culture-specific attitudes toward technology, regional collaborations-weigh against AI adoption decision by Nepalese SMEs.

These challenges have no bearing on the fact that AI is becoming increasingly significant to Nepal's socioeconomic development. The National AI Policy 2081 stands as a historical achievement from the Nepalese government to establish digital transformation and AI adoption frameworks. The policy establishes ethical standards together with data protection protocols and cybersecurity measures and AI supervision agencies (Digital Media Foundation, 2024). The policy connects international benchmarks to national realities to drive innovation and controlled AI deployment. The policy demonstrates why ethical rules must govern AI use in critical domains, which include privacy protection and bias control and inclusivity implementation (Chuang et al., 2024). Public trust depends on these measures which also promote widespread adoption of AI technologies.

This study is based mainly on the theory of Diffusion of Innovation (DOI), which provides a very robust lens for understanding how AI technologies are considered and rejected or adopted depending upon the perceived attributes. Adoption decisions are occur by features such as social systems, IT knowledge, managerial support and the attitude itself. DOI address certain factors such as individual characteristics, internal characteristics of organizations and external characteristics of organization and it's effect on organizational innovativeness.

A growing body of literature on AI adoption in SMEs emphasizes that most studies have concentrated on the developed countries or the larger enterprises and have provided little insight into how SMEs in a resource-constrained environment face the challenges of AI integration (Almashawreh et al. 2024; Shahadat et al., 2023). Additionally, there is insufficient exploration of how Nepali SMEs can leverage their existing resources, such as human capital and partnerships, to overcome infrastructural and financial limitations (Shahadat et al., 2023).

Research Objective

The objective of this study is to develop context-specific strategies for AI adoption in Nepalese SMEs by exploring their understanding of AI, identifying the major factors that influence adoption, and examining the key challenges that hinder its implementation within Nepal's socio-economic and technological landscape.

Literature Review

AI adoption by SMEs has still not taken off, it holds a lot of promise for growth in Asian Countries, however, gaining ground in the financial services and e-commerce sectors. Financial institutions are implementing AI to study customer behavior, identify fraudulent transactions, and perform various back-office operations (Bag et al., 2023). E-commerce platforms use AI chatbots and recommendation systems to increase customer engagement and sales. India, Bangladesh, and Sri Lanka have made worthy strides toward integrating AI into industries like manufacturing, finance, healthcare, and agriculture. SMEs are using AI increasingly for improving operational efficiencies, customer experiences, and supply-chain management (Panda & Sharma, 2021).

AI adoption in developing economies, are greatly influenced by strong leadership and creativity undergird AI integration. Organizations always put effort into creating an environment that supports continuous development programs, managerial commitment, and reward mechanisms to promote employee willingness to embrace the new technologies. Lyver and Lu (2018) say that fostering a positive attitude toward AI would require a technical training as well as a mindset-altering change in the organization. Meanwhile, SMEs need to adopt cost-effective measures in emerging markets because of resource limitations. Partnerships among technology providers, government-led capacity-building exercises, and targeted incentives would help bridge that gap and foster AI adoption there.

In many of the developed nations, various incentives have been set up by the policymakers to create an environment conducive to AI adoption including the funding of R&D, creating innovation hubs, and providing regulatory clarity (Masa'deh et al., 2024). As an example, the AI Act of the European Union seeks to develop a harmonized framework for the ethical and responsible use of AI. Regional collaborations in emerging markets can accelerate AI adoption through shared resources, knowledge, and best practices on SMEs. South Asia and Africa could take inspiration from ASEAN's efforts to promote AI through regional frameworks (Lyver & Lu, 2018).

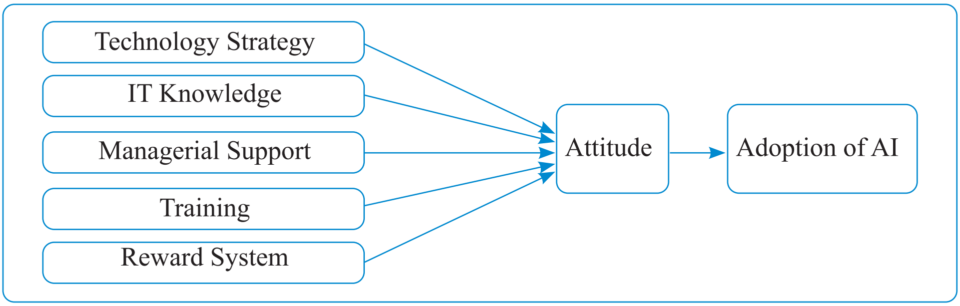
However, major challenges remain across the developing countries. Poor IT infrastructure is still the greatest hindrance, especially in rural vicinities where connectivity and access to newer technologies are limited (Alraja et al., 2022). Unstable internet access in rural areas have resulted in an inability of several SMEs to implement AI applications that require high data volumes for processing. The problem worsens with low digital literacy levels, and many employees and managers lack the technical know-how to use AI tools effectively (Lutfi et al., 2020). Gaps in widespread AI adoption due to inconsistent policies and frameworks that foster uncertainty for businesses attempting to incorporate AI-based solutions within their processes (Dadhich & Hiran, 2022). In agriculture, Sri Lankan SMEs are also making use of AI to predict weather conditions, assess crop health, and set irrigation parameters so that they can maximize production and minimize wastage of resources (Kurniawanti et al., 2023). These initiatives are complemented by various training programs sponsored by government bodies and facilitated by international organizations. AI offers significant potential to improve decision quality, operational efficiency, and financial forecasting—as demonstrated in global firms through AI-driven capital budgeting and managerial analytics (Celestin et al., 2026) and in corporate finance via enhanced forecast accuracy and risk management (Celestin & Mishra, 2025)—its implementation in Nepalese SMEs faces distinct socio-economic and technological constraints. Furthermore, the integration of AI requires not only technological readiness but also organizational and cultural adaptation, as highlighted in educational and employee-centric AI frameworks emphasizing the role of attitude, emotional intelligence, and institutional support in technology adoption (Ananda et al., 2025; Mishra et al., 2025; Mishra & Mishra, 2024).

Measuring Adoption of AI in SEMs

The adoption of innovations are highly dependent on numerous characteristics, may it be individual, internal or external characteristics. The adoption of AI is influenced by technology strategy, IT knowledge, Managerial support, training, reward system and attitude.

Figure 1

Conceptual Framework



Technology Strategy

A well-articulated technology strategy determines attitudes toward AI usage. When a firm defines how to use AI for efficiency or decision-making, positive perceptions of AI will be built on the employees' side, which leads to higher levels of AI usage by those employees (Almashawreh et al., 2024). Again, technology strategy limits the risk related to AI adoption, including issues of disruption to operations and for unfulfilled business goals, which would in turn generate positive attitudes supporting AI usage over time (Lyver & Lu, 2018).

H1 Technology strategy has a significant positive effect on attitudes toward AI usage in

IT Knowledge

Employees must have good IT knowledge to understand, implement, and utilize AI-related tools properly. A lack of IT awareness makes it difficult for organizations to cultivate a positive attitude toward the integration of AI Almashawreh et al. (2024). An employee's IT knowledge weighs on attitude toward the use of AI by creating the environment whereby they can interact and use AI tools confidently in a learning environment (Zaman et al., 2021).

H2 Employees' IT knowledge has a significant positive effect on attitude toward AI usage in SMEs.

Managerial Support

Managerial support, against the backdrop, is integral to the formation of attitudes regarding AI usage. It allows an environment conducive to innovation to grow, where employees are encouraged to embrace new technologies (Park & Kim, 2021). Leadership becomes vital in driving change; this includes prioritizing AI adoption, balancing resource allocation for implementation activities, and communicating the need and benefits of AI to counter resistance to change (Talukder, 2014). Leadership commitment has been said to impact organizational attitudes toward the acceptance of AI (Almashawreh et al., 2024).

H3 Managerial support has a significant positive effect on attitudes toward AI usage in SMEs.

Training

Training encourage digital literacy and an innovative culture among employee (Kurniawanti et al., 2023). Training makes the employees of an organization accept tools aided by AI because they have the skills and confidence to operate these challenges (Zaman et al., 2021). According to Almashawreh et al. (2024), training programs strongly influence attitudes toward the adoption of AI, hence necessitating continuous learning and skill development. Companies investing in rigorous programs see a greater level of engagement of employees with AI technologies and tangible productivity gains (Chau & Deng, 2018).

H4 Training has a significant positive effect on attitudes toward AI usage in SMEs.

Reward System

Reward systems drive employees to accept AI technologies because they make persons feel that their value and appreciation compensate them for what they do (Zighan & Dwaikat, 2023). Rewards like recognition and job growth opportunities might therefore yet be very helpful in fostering AI-related solutions (Aoujil et al., 2023). Reward systems drive employees to accept AI technologies because they make persons feel that their value and appreciation compensate them for what they do (Zighan & Dwaikat, 2023). Good performance management strategies influence the attitude of employees toward the use of AI through employee motivation.

H5 Reward System has a significant positive effect on attitudes toward AI usage in SMEs.

Attitude to AI Applications

Attitude toward AI usage plays a central role in the adoption of artificial intelligence within organizations; especially so in the realm of SMEs. This reflects the way these understanding, beliefs, or feelings held by the workers or managers about AI technologies affect their willingness to accept them and use them (Almashawreh et al., 2024).

It increases openness to change and encourages proactive engagement with an AI tool. Thus, attitude constitutes a major psychological link between external enablers (such as training, strategy, and support) and the final behavioral enactment of AI adoption.

H6 Attitude toward AI usage has a significant positive effect on adoption of AI usage in SMEs.

Methodology

This study uses an explanatory research design, which has special applications in studying cause and effect of the relationships among variables and testing hypotheses. The focus of the study is Kathmandu Valley. Small and Medium Enterprises (SMEs) in Nepal are highly concentrated in the Bagmati Province (approx. 33%), primarily in the Kathmandu Valley. The target population for the study comprises middle and higher-level managers and technical people, all those that were employed in implementing projects or supervising them. The Probability sampling method was implemented. This study incorporates three measures to capture the AI adoption in SMEs i.e general understanding of employer regarding understanding of AI adoption, key factors influencing AI adoption and challenges faced by employer regarding AI sdoption in SMEs. 5-point scale is was used (1= Strongly Disagree and 5= Strongly Agree) and data was collected form 318 sample points. A powerful multi-factor statistical framework, Structural Equation Modeling (SEM) effectively analyzes relationships between unobservable (latent) and observed variables. Microsoft Excel was used for data preparation and cleaning. Further analysis was done through Smart PLS 4 software, which is suitable for Partial Least Squares Structural Equation Modeling (PLS-SEM). The SmartPLS software was preferred because it allows for both reflective and formative measurement models, is most appropriate for smaller sample sizes, and is capable of modeling more complex relationships among latent variables.

Results and Discussion

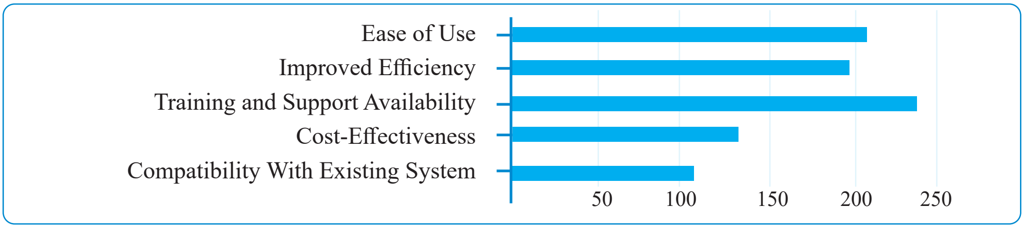
General Understanding on Adoption of AI in SMEs

The exploration of understanding of respondents with AI technologies in the Small and Medium Enterprise (SME) sector in Kathmandu Valley, revealed automated customer service was the most commonly used AI application, with 61.8% of users Process automation tools are fairly popular, with 40.9% of respondents claiming to be applying the tools to repetitive tasks to increase productivity. Support systems are embraced by 37.3% of respondents, thus showing that AI is very much used nowadays in aiding managerial decision-making. And lastly, 28.9% worked with predictive analytics tools, confirming the hype for prediction and planning based on the available data.

AI technologies more attractive for adoption due to it's improved efficiency indicated 74.8% of respondents, suggesting that AI is largely seen as a tool for productivity gains. Ease of use was mentioned by 65.7% of respondents, 62.6% of instances, cost-effectiveness. All the other factors were mentioned but remain at a lower precedence: compatibility with existing systems, availability of training, and support.

Figure 2

Factors Leads to Adoption of AI in SMEs



The results suggest that AI technologies play an important role in helping organizations perform well through various means. A large number of respondents (82.4%) agreed that AI technology aids the overall performance of organizations by boosting productivity and effective business management. Another significant 63.2% indicated that savings on costs was another notable contribution of AI. In addition, 66.4% of the respondents claimed that AI technology facilitates efficient decision-making because of its ability to provide reliable data analysis and real-time information needed for making informed decisions. Besides, another substantial group of 44.3% said that AI helped boost customer satisfaction.

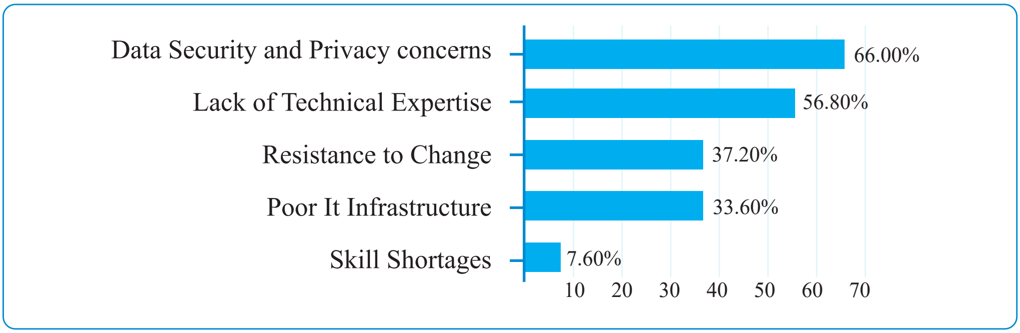
The potential application of AI in in several organizational areas, respondents felt particularly in operations and logistics (59.7%), marketing and sales (58.8%), and customer service (56%) are the main fields where AI could make a greater impact. These findings reflect the growing recognition of AI's ability to enhance organizational effectiveness and are consistent with global trends emphasizing AI-driven operational optimization, marketing personalization, and customer relationship management.

Challenges of Adoption of AI in SMEs

Out of 318 responders, 218 (about 69%) stated they had problems implementing and carrying out AI-related operations. Among the respondents, several major barriers were recorded. Over 66% felt data security and privacy concerns were an issue, with fears over data breaches and scant regulatory protections while the digital infrastructure is still developing. Meanwhile, 56.8% felt that lack of technical expertise in their workforce was a major concern, as most SMEs do not have the required technical know-how to establish and manage AI systems properly. Resistance to change was exerted by 37.2% of respondents, thus accounting for organizational inertia or concerns regarding job displacement or workload. Thirty-eight point-eight percent cited budget constraints as a deterrent because of the initial costs of the AI technology. In addition, 33.6% pointed to poor IT infrastructure, which included inconsistent internet access and poor availability of digital tools. Another 7.6% pointed out skills shortages, thereby calling for continuous capacity-building activities. Other obstacles included lack of government support and an unclear regulatory framework.

Figure 3

Challenges of AI Adoption



The results reveal that some strategic steps may enable organizations to overcome obstacles related to AI adoption. Specifically, most of the participants 76.8% felt that it was important for an organization to have adequate IT infrastructure for successful adoption of AI solutions. At the same time, 59.4% of the respondents pointed out that providing access to affordable AI technology. Another strategy which should be employed is the participation of management, cited by 55%

of respondents. Furthermore, 47.8% stressed the importance of regular training programs to enhance employee skills and AI literacy.

Measurement Model Assessment

The measurement model was aimed toward probing the precision, reliability, and relevance of the assumed relationships between the latent construct and its observable indicator in this research. For measurement models' sturdiness, three important criteria should be met: convergent validity, discriminant validity, and internal consistency reliability (Almashawreh et al., 2024). These criteria were investigated through different metrics: factor loading, Cronbach's alpha, average variance extracted, and composite reliability.

Internal Consistency Reliability

Internal consistency reliability assesses whether the items within each construct consistently measure the same concept. It is commonly evaluated using Cronbach's alpha and composite reliability. Cronbach's alpha measures the consistency among items, while composite reliability provides a more robust estimate by considering individual factor loadings. Values above 0.70 generally indicate acceptable reliability (Hair et al., 2020), although values around 0.60 may be acceptable in exploratory research (Bujang et al., 2018). As shown in Table 1, all constructs meet the recommended thresholds, confirming satisfactory internal consistency reliability.

Table 1

Cronbach's Alpha and Composite Reliability

Construct	Cronbach's Alpha	Composite Reliability
ATT	0.839	0.892
EIT	0.909	0.932
MS	0.769	0.852
RS	0.877	0.91
TR	0.92	0.943
TS	0.723	0.827
US	0.779	0.847

Convergent Validity

Convergent validity guarantees that the items measuring each construct truly reflect the concept intended. It was assessed by examining factor loadings and Average Variance Extracted (AVE) values. Following the criteria prescribed by Hair et al., (2019), factor loadings should be greater than 0.7, while AVE values should exceed 0.5.

Table 2

Employees' IT Knowledge

Construct	Indicators	Outer Loading	AVE
Attitude	ATT1	0.868	0.675
	ATT2	0.786	
	ATT3	0.776	
	ATT4	0.851	
IT Knowledge	EIT1	0.903	0.732
	EIT2	0.874	

Construct	Indicators	Outer Loading	AVE
	EIT3	0.844	
	EIT4	0.824	
	EIT5	0.831	
Managerial Support	MS1	0.755	0.592
	MS2	0.752	
	MS3	0.659	
	MS5	0.894	
Reward System	RS1	0.863	0.67
	RS2	0.856	
	RS3	0.824	
	RS4	0.726	
	RS5	0.817	
Training	TR1	0.912	0.807
	TR2	0.929	
	TR3	0.931	
	TR4	0.815	
Technology Strategy	TS1	0.586	0.553
	TS3	0.597	
	TS4	0.842	
	TS5	0.897	
Adoption of AI	US1	0.811	0.53
	US2	0.617	
	US3	0.611	
	US4	0.806	
	US5	0.767	

The results indicate strong convergent validity for most constructs. Factor loadings for all constructs, except some indicators of Technology Strategy (TS) are below 0.7 , and AVE values were above 0.5 for all constructs. Indicators with loadings below 0.7 (e.g., TS1 = 0.586, US2 = 0.617) were retained as their removal did not significantly affect the overall AVE. This confirms that the constructs are well-measured.

Discriminant Validity

Discriminant validity guarantees that the constructs in the model are different and measure disparate underlying concepts. Three criteria were considered in making this judgment: cross-loading, the Heterotrait-Monotrait Ratios (HTMT), and the Fornell-Larcker criterion. Cross-loadings found that every indicator was generally loaded more on their intended construct than on any other construct. All HTMT values were below the recommended threshold, indicating that the constructs are sufficiently distinct and do not excessively correlate with each other. The Fornell-Larcker criterion also demonstrated discriminant validity, as the square root of the Average Variance Extracted (AVE) for each construct exceeded its correlations with other constructs.

Table 3

Cross Loading

Indicators	ATT	EIT	MS	RS	TR	TS	US
ATT1	0.868	0.282	0.486	0.583	0.357	0.373	0.712
ATT2	0.786	0.559	0.492	0.637	0.597	0.23	0.7
ATT3	0.776	0.027	0.448	0.73	0.292	0.657	0.656
ATT4	0.851	0.331	0.531	0.447	0.447	0.411	0.637
EIT1	0.248	0.903	0.566	0.164	0.476	0.049	0.244
EIT2	0.366	0.874	0.438	0.274	0.559	0.01	0.318
EIT3	0.365	0.844	0.497	0.192	0.519	0.085	0.325
EIT4	0.257	0.824	0.322	0.167	0.408	0.2	0.301
EIT5	0.275	0.831	0.239	0.229	0.516	0.09	0.212
MS1	0.485	0.035	0.755	0.46	0.029	0.491	0.505
MS2	0.367	0.54	0.752	0.423	0.455	0.047	0.456
MS3	0.379	0.691	0.659	0.266	0.744	0.235	0.3
MS5	0.564	0.361	0.894	0.414	0.527	0.525	0.54
RS1	0.641	0.126	0.586	0.863	0.42	0.43	0.61
RS2	0.603	0.226	0.43	0.856	0.391	0.35	0.552
RS3	0.469	0.247	0.416	0.824	0.41	0.376	0.487
RS4	0.492	0.215	0.169	0.726	0.229	0.312	0.453
RS5	0.742	0.209	0.434	0.817	0.302	0.253	0.595
TR1	0.411	0.547	0.444	0.418	0.912	0.145	0.312
TR2	0.472	0.489	0.448	0.313	0.929	0.036	0.223
TR3	0.552	0.474	0.554	0.459	0.931	0.201	0.345
TR4	0.393	0.639	0.504	0.334	0.815	0.219	0.346
TS1	0.192	0.144	0.456	0.272	0.001	0.586	0.085
TS3	0.305	0.033	0.167	0.197	0.262	0.597	0.202
TS4	0.393	0.125	0.232	0.33	0.118	0.842	0.452

	ATT	EIT	MS	RS	TR	TS	US
TS5	0.527	0.033	0.52	0.406	0.107	0.897	0.611
US1	0.587	0.306	0.371	0.247	0.056	0.303	0.811
US2	0.485	0.046	0.308	0.177	-0.074	0.245	0.617
US3	0.44	0.25	0.401	0.183	0.069	0.394	0.611
US4	0.741	0.177	0.591	0.844	0.456	0.577	0.806
US5	0.682	0.409	0.448	0.747	0.542	0.353	0.767

Table 4

Heterotrait-Monotrait Ratio (HTMT) Results

Construct	ATT	EIT	MS	RS	TR	TS	US
ATT							
EIT	0.422						
MS	0.728	0.651					
RS	0.829	0.276	0.605				
TR	0.579	0.646	0.713	0.474			
TS	0.616	0.2	0.638	0.52	0.24		
US	0.996	0.423	0.739	0.745	0.404	0.618	

Table 5

Fronell and Larker Criterion

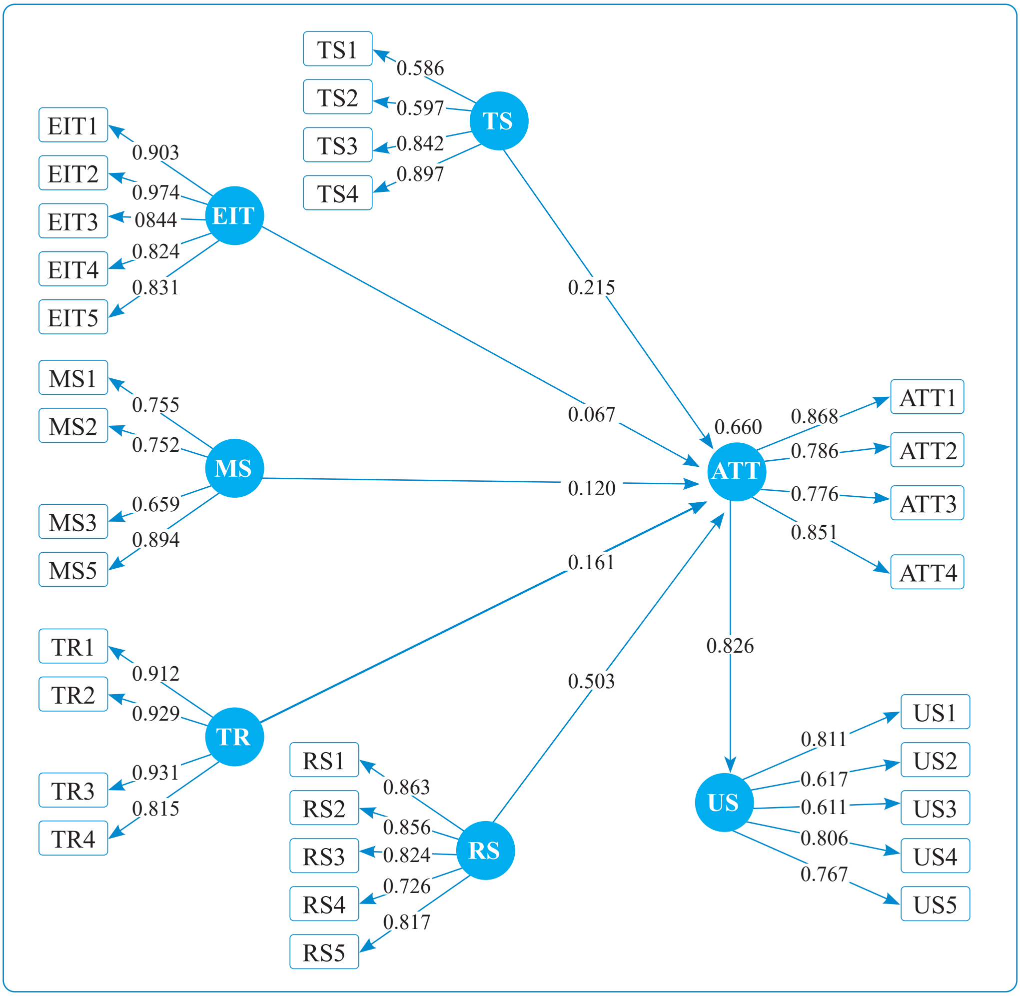
Construct	ATT	EIT	MS	RS	TR	TS	US
ATT	0.822						
EIT	0.364	0.856					
MS	0.596	0.488	0.77				
RS	0.739	0.245	0.51	0.819			
TR	0.516	0.587	0.545	0.427	0.898		
TS	0.512	0.095	0.459	0.415	0.166	0.744	
US	0.826	0.334	0.595	0.668	0.339	0.526	0.728

Structural Model

A structural equation analysis was used to assess the study's hypothesis. A path diagram was used to visualize both the findings of the path analysis. In structural modeling bootstrapping analysis was conducted with 10,000 subsamples to determine the path coefficient and associated t-value for both direct and mediating relationship. The observed variables were connected on the SmartPLS interface to illustrate the relationships proposed in the conceptual model. This study includes 6 direct hypotheses.

Figure 4

Path Analysis



Hypothesis Testing

Hypothesis testing for examines the link between two variables. If P value is ≤ 0.05 the hypothesis is accepted, otherwise it is rejected. Confidence interval test the lower and upper limits of the confidence interval at 95%. If the value 0 does not fall within this interval the hypothesis is accepted, otherwise it is rejected (Kock, 2016).

Table 6

Hypothesis Testing

H	Relationship	Beta (ß)	SD	T-Value	P Values	CI		Decision
						2.50%	97.50%	
H1	TS → ATT	0.215	0.026	4.129	0.001	0.167	0.268	Supported
H2	EIT → ATT	0.067	0.033	0.923	0.213	0.007	0.137	Not supported
H3	MS → ATT	0.120	0.039	1.397	0.162	0.037	0.168	Not supported

H	Relationship	Beta (ß)	SD	T-Value	P Values	CI		Decision
						2.50%	97.50%	
H4	TR → ATT	0.161	0.032	2.531	0.011	0.098	0.226	Supported
H5	RS → ATT	0.503	0.027	7.138	0.0012	0.449	0.557	Supported
H6	ATT → US	0.826	0.019	6.788	0.001	0.788	0.862	Supported

Table 6 illustrate that P-value is less than 0.1 and CI lies in between lower limit (LL) and upper limit (UL) of confidence interval for hypotheses H1, H4, H5 and H6, which means that there is significant positive relationship between Attitude toward Technology (ATT) and Adoption of AI (US), Technology Strategy (TS) and Attitude toward Technology (ATT), Training (TR) and Attitude toward Technology (ATT), and Reward System (RS) and Attitude toward Technology (ATT). On the other hand, there is no significant relationship between Employees' IT Knowledge (EIT) and Attitude toward Technology (ATT), and Managerial Support (MS) and Attitude toward Technology (ATT).

Mediation Analysis

The mediation analysis reveals that Attitude toward Technology (ATT) significantly mediates the relationship of each of the independent variables studied, i.e., Employees' IT Knowledge (EIT), Managerial Support (MS), Reward System (RS), Training (TR), and Technology Strategy (TS), with the Adoption of AI (US). The findings suggest that positive attitudes toward technology should be fostered as a means through which various technological factors affect the behavior of users. Overall, the findings indicate that changing users' perceptions and experiences with technology can greatly enhance the use and acceptance of AI-related tools in SMEs.

Table 7

Mediation Analysis

Mediation Path	Beta (β)	SD	t-Value	p-Value	LL	UL	Decision
EIT → ATT → US	0.056	0.028	2.012	0.044	0.006	0.116	supported
MS → ATT → US	0.099	0.032	3.142	0.002	0.031	0.154	supported
RS → ATT → US	0.416	0.026	15.731	0.0001	0.365	0.469	supported
TR → ATT → US	0.133	0.026	5.105	0.0001	0.083	0.185	supported
TS → ATT→ US	0.178	0.022	8.054	0.0001	0.137	0.223	supported

This study examines the factors influencing AI adoption among SMEs in the Kathmandu Valley, Nepal, grounded in the Technology–Organization–Environment (TOE) framework and Diffusion of Innovation (DOI) theory. These theoretical lenses provide a robust foundation for understanding technology adoption behavior at both individual and organizational levels. Structural Equation Modeling (SEM) was employed to test the hypothesized relationships among constructs, yielding six hypotheses derived from the conceptual framework. The findings offer nuanced insights into the drivers and barriers of AI adoption within Nepal's resource-constrained SME sector.

Attitude and AI Usage

Attitude toward AI Usage (ATT) exhibits a significant positive effect on actual AI Usage (US), corroborating established literature on the pivotal role of attitude in shaping behavioral intentions toward innovative technologies. Davis (1989) posits that individuals with favorable attitudes toward a technology are more likely to adopt it when opportunities arise. Similarly, Almashawreh et al. (2024) found that SMEs with positive perceptions of AI are more inclined to integrate it into their operations. This suggests that interventions aimed at enhancing awareness and cultivating positive attitudes toward AI could substantially increase its practical adoption among Nepalese SMEs.

Technological Strategy and Attitude

Technological Strategy (TS) demonstrates a significant positive influence on Attitude toward AI Usage (ATT). Alignment between technological advancement and strategic planning plays a critical role in shaping perceptions. A well-articulated technology strategy communicates long-term commitment and vision, thereby enhancing managerial and employee willingness to implement AI. These results align with Shahadat et al. (2023), who identified strategic planning and leadership engagement as key drivers of technology adoption in SMEs. In Nepal's resource-constrained context, an explicit technology roadmap enables SMEs to prioritize investments and mitigate resistance to change.

Employees' IT Knowledge and Attitude

Contrary to prior expectations, Employees' IT Knowledge (EIT) shows no significant relationship with Attitude toward AI Usage. This finding diverges from Dadhich and Hiran (2022), who emphasized that digital literacy and technical competence shape attitudes toward new technologies. A plausible explanation is that while employees may possess baseline IT knowledge, they lack exposure or training that connects theoretical understanding to practical AI applications within SMEs. Additionally, skepticism or fear of job displacement associated with AI may attenuate the influence of IT knowledge on attitudes.

Managerial Support and Attitude

Managerial Support (MS) was hypothesized to positively influence Attitude toward AI Usage but was not supported in this study. This contrasts with Chuang et al. (2009), who reported that managerial backing facilitates technology adoption decisions in SMEs. In the present study, although many respondents indicated some degree of managerial support, it did not translate into a significant impact on employee attitudes. This suggests that while managerial appreciation may exist, it is either insufficiently articulated or poorly integrated into organizational practices to meaningfully influence employee perspectives.

Training and Attitude

Training (TR) exhibits a positive and significant effect on Attitude toward AI Usage (ATT), supporting Almashawreh et al. (2024), who identified training as a key enabler of AI adoption. Investment in training interventions equips employees with technical skills and confidence in using AI tools, reduces anxiety about new technologies, and fosters an innovation-oriented culture. In Nepal, where formal education in emerging technologies remains scarce, workplace training is particularly critical for advancing AI readiness among SMEs.

Reward System and Attitude

The Reward System demonstrates a significant positive relationship with Attitude toward AI Usage. This indicates that when employees perceive incentives—whether monetary or non-monetary—linked to AI adoption, their attitudes toward AI become more favorable. This aligns with motivation theory, which affirms that rewards and recognition reinforce intrinsic behaviors and intentions. Emami and Khajeheian (2019) similarly demonstrated that incentive mechanisms strengthen entrepreneurial behaviors. Consequently, Nepalese SMEs should develop performance-linked reward systems to encourage AI usage.

These findings offer actionable considerations for policymakers, business leaders, and educators. Encouraging SMEs to develop clear technology strategies, invest in continuous training, and establish reward mechanisms can improve attitudes toward AI and facilitate its practical application. Further research could explore how Employees' IT Knowledge and Managerial Support might be better integrated into organizational objectives to exert a stronger positive influence on AI adoption. Additionally, longitudinal studies could examine the sustainability of AI implementation and its impact on SME performance in Nepal's evolving digital economy.

Conclusion

The awareness of artificial intelligence among SMEs in Kathmandu Valley is gradually increasing, actual adoption remains limited. Most firms recognize AI's potential to improve efficiency, reduce costs, and strengthen competitiveness, yet their knowledge often lacks depth and is more conceptual than practical. Adoption is concentrated in basic areas such as automation, customer interaction, and decision support rather than advanced applications.

The findings laid out Nepali SMEs are highly aware and interested in AI yet they are hardly engaged in practical AI application because of various existing internal and external barriers. Key enablers such as technology strategy, training programs, and reward systems significantly affected the attitude of employees toward AI use. Perhaps other factors indicating IT knowledge of the employees and support from the management that were not shown to have direct statistically significant effects would need to be structured jointly with strategic and training efforts time-wise to produce the desired results.

SMEs encounter several barriers in adopting AI. The most significant challenges include poor digital infrastructure, unstable internet connectivity, high implementation costs, and a shortage of skilled human resources. Many firms also face digital illiteracy, lack of technical expertise, and cultural resistance to change. These obstacles are more pronounced in rural and semi-urban areas, where access to technology and training opportunities is limited.

To foster AI adoption, stakeholders stressed the importance of government support in the form of favorable policies, subsidies, and infrastructure development. SMEs also emphasized the need for affordable AI solutions, leadership commitment, targeted training programs, and awareness campaigns. Public-private partnerships were recommended to reduce financial burdens and strengthen capacity-building efforts, ensuring SMEs can adopt AI in a sustainable and competitive manner.

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