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Enhancing Workforce Skills: Employees' Intention toward Upskilling and Reskilling in Kathmandu Valley

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Abstract

Background: In today's fast-evolving work environment, employees must continuously upskill and reskill to remain competitive. Organizations in Kathmandu Valley are increasingly emphasizing learning initiatives. Understanding employees' behavioral intention toward these programs helps identify key drivers, such as knowledge acquisition and technical training, to design effective workforce development strategies.

Purpose: The purpose of this study is to determine employee's behavior intention towards upskilling and reskilling in Kathmandu Valley**.**

Design/methodology /approach: The study uses explanatory research design, TAM theory uses, Convenience sampling is used, Self-administered questionnaire is used and modified, Kobo toolbox is used for data collection, Kathmandu Valley is the study area, Smart PLS 4.0 is used for data analysis, Descriptive and Inferential data analysis techniques were used.

Findings: The findings show that most employees are aware of upskilling and reskilling and view them as essential for career growth. Knowledge acquisition ($\beta = 0.374$, $p < 0.05$) and technical training ($\beta = 0.452$, $p < 0.05$) significantly influenced employees' attitudes, while attitude strongly predicted behavioral intention to learn ($\beta = 0.378$, $p < 0.05$). Top management support ($\beta = 0.034$, $p = 0.432$) and subjective norms ($\beta = 0.039$, $p = 0.298$) were not significant predictors of attitude. Mediation results further confirmed attitude as a key intervening variable linking organizational and social factors with learning intention.

Conclusion: According to this study, Knowledge Acquisition and Technical Training has a significant relationship with attitude, Attitude and Behavior Intention to Learn has a significant relation and Attitude has mediating effect independent variable (Top Management Service, Technical Training and Subjective Norms) and Behavior Intention to Learn Upskilling and Reskilling.

Keywords: TAM, Employee Intention, Upskilling, Reskilling

1. Introduction

The rapid transformation of global labor markets following the COVID-19 pandemic has intensified the demand for continuous skill development among employees across sectors. Accelerated digitalization, automation, and the diffusion of advanced technologies such as artificial intelligence, machine learning, and blockchain have significantly reshaped how work is organized and performed (Chowdhury, 2024; George & George, 2024). As a result, traditional job roles are evolving, while entirely new occupations are emerging, requiring workers to continuously update or transform their skill sets (Jääskeläinen, 2015). International evidence suggests that employability and career sustainability increasingly depend on individuals' willingness and ability to engage in lifelong learning, particularly through upskilling and reskilling initiatives (Lang, 2023). Organizations, in turn, view a multiskilled and adaptable workforce as a strategic asset for maintaining competitiveness and resilience in volatile environments (Comyn, 2018). Consequently, employee development has shifted from a one-time training intervention to a continuous process embedded within organizational and national workforce strategies (Li, 2024; Ogbu, 2025). This global transition underscores the growing importance of understanding not only the availability of training opportunities but also employees' behavioral intentions to participate in upskilling and reskilling activities.

Within this global context, upskilling and reskilling have emerged as central concepts in human capital development and workforce transformation. Upskilling refers to the process of enhancing existing competencies to improve performance in current roles, whereas reskilling involves acquiring entirely new skill sets to transition into different job functions or occupations (Rosak-Szyrocka et al., 2025). Prior research highlights that employees' behavioral intention toward such learning initiatives is influenced by multiple factors, including attitudes toward learning, perceived usefulness of training, organizational support, availability of technical training, and top management commitment (Li, 2024; Farawowan, 2025). Drawing from behavioral theories such as the Theory of Planned Behavior and human capital theory, behavioral intention is widely recognized as a strong predictor of actual participation in learning and development activities (Mohammed et al., 2020). Understanding these intentions is therefore critical, as even well-designed training programs may fail if employees lack motivation or perceive limited value (Osaigbovo, 2022). Moreover, upskilling and reskilling are associated with several benefits, including enhanced productivity, improved employability, career advancement, and organizational performance, making them essential components of sustainable workforce development in rapidly changing economies.

The relevance of upskilling and reskilling is particularly pronounced in developing countries such as Nepal, where structural economic transitions coexist with skills mismatches and limited employment opportunities (Rahman & Akter, 2024). Nepal's labor market is characterized by a young workforce, high rates of early school dropout, and significant reliance on low-skilled and semi-skilled employment (Parikh & Shakya, 2020). Although the government has introduced vocational training, skill validation examinations, and soft-loan schemes, especially in response to COVID-19 and returnee migrant workers, these initiatives remain fragmented and often disconnected from evolving industry demands (Wickramasekara, 2022). The Technical and Vocational Education and Training (TVET) system and the National Qualifications Framework aim to create pathways between education and employment; however, challenges persist in terms of access, quality, relevance, and employee engagement (Renold et al., 2024). In urban economic hubs such as Kathmandu Valley, where service, finance, information technology, and manufacturing sectors are expanding, employees face increasing pressure to adapt to technological and organizational changes. Despite this, empirical research examining employees' perspectives, motivations, and intentions toward upskilling and reskilling within the Nepalese context remains extremely limited.

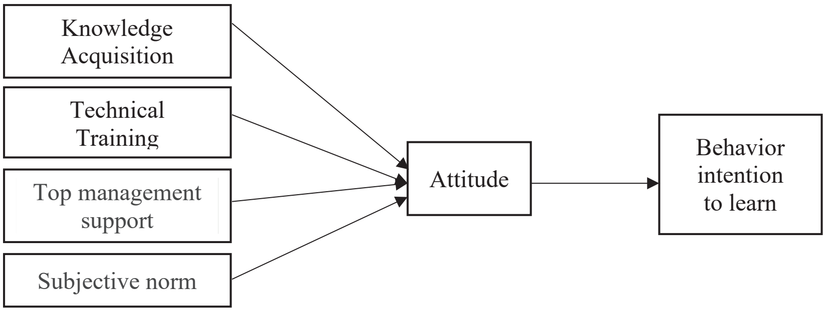
This lack of context-specific empirical evidence constitutes a significant research gap, particularly given Nepal's resource-constrained environment and ongoing digital transition. Existing studies on upskilling and reskilling are predominantly concentrated in developed economies, with limited applicability to developing countries where institutional support, organizational practices, and individual constraints differ substantially (Ehsan, 2023). Moreover, prior research often emphasizes program design and policy frameworks while paying insufficient attention to employees' behavioral intentions and perceptions, which ultimately determine participation and outcomes (Ekuma, 2023; Khan et al., 2025). Addressing this gap, the present study focuses on employees' behavioral intention toward upskilling and reskilling in Kathmandu Valley, examining the factors influencing these intentions and the perceived benefits from an employee perspective. The general objective of this study is to identify employees' perspectives on upskilling and reskilling across different sectors. Specifically, the study aims to examine behavioral intention toward upskilling and reskilling, assess the factors influencing such intentions, identify perceived benefits, and understand employees' overall intention to engage in skill development initiatives. By doing so, this research seeks to contribute to the literature on workforce development in developing economies and provide practical insights for organizations and policymakers in Nepal.

2. Theoretical Framework and Hypothesis

A theoretical framework provides a structured lens for explaining and organizing relationships among key study concepts (Kivunja, 2018; Devkota et al., 2021). This study reviews several established theories relevant to upskilling and reskilling, including Human Capital Theory, Learning Theory, the Organizational Upskilling Model, the Technology Acceptance Model (TAM), and the Integrated Skills–Technology Acceptance Model (ISSTAM). These theories collectively explain how skill acquisition, learning motivation, organizational systems, and technology-related perceptions shape employees' learning behaviors (Safira, 2025). Human Capital Theory emphasizes the economic and career value of investment in education and training; Learning Theory explains the psychological and motivational processes underlying learning behaviors; the Organizational Upskilling Model highlights structured organizational mechanisms for skill development, while TAM and ISSTAM focus on perceived usefulness and ease of use as determinants of technology-supported learning adoption (Shang et al., 2024). Reviewing these theories provides a comprehensive theoretical foundation for understanding employees' engagement with upskilling and reskilling initiatives.

Among the reviewed theories, Human Capital Theory and the TAM form the primary theoretical basis of this study. Human Capital Theory is central because upskilling and reskilling represent strategic investments in employees' knowledge and competencies that enhance productivity, employability, and long-term career outcomes (Safira, 2025). This theory is particularly relevant in developing economies like Nepal, where skill development is critical for workforce competitiveness and economic growth. TAM complements this perspective by explaining employees' behavioral intention to engage in technology-enabled training and learning systems, which are increasingly used for upskilling and reskilling (Khan et al., 2024). By integrating Human Capital Theory and TAM, the study effectively captures both the economic rationale for skill development and the behavioral mechanisms influencing employees' intention to participate, providing a robust framework for examining upskilling and reskilling intentions in the Kathmandu Valley context.

Figure 1: Conceptual Framework



Source: Adopted and modified from Kar et al. (2021)

Knowledge Acquisition and Attitude

Knowledge acquisition is a central element of employee learning and capability development (Agbim et al., 2014). When employees are provided with opportunities to acquire relevant knowledge, they are more likely to develop favorable perceptions toward learning initiatives (Papa et al., 2020). Prior studies suggest that access to knowledge reduces resistance to change and strengthens employees' confidence in skill development programs, thereby fostering a positive attitude toward learning (Abdekhoda et al., 2025). Knowledge acquisition also enhances employees perceived competence, which positively shapes their cognitive and emotional responses to organizational upskilling efforts (Kumar, 2024).

H1: Knowledge acquisition has a significant impact on employees' attitude toward upskilling and reskilling.

Top Management Support and Attitude

Top management support is a critical driver of organizational learning and employee motivation (Lee et al., 2018). Visible commitment from senior leadership through resource allocation, strategic endorsement, and active participation in learning initiatives signals the importance of upskilling and reskilling to employees (Niehoff, 1990). Such support cultivates trust, reduces uncertainty, and strengthens positive attitudes toward learning and development programs (Dong, 2009; Ssekiziyivu et al., 2025).

H2: Top management support has a significant impact on employees' attitude toward upskilling and reskilling.

Subjective Norm and Attitude

Subjective norms reflect perceived social pressure from peers, supervisors, and organizational leaders to engage in learning activities (Mousa et al., 2019). When learning is socially valued within the organization, employees are more likely to develop positive attitudes toward upskilling and reskilling (Alqasa et al., 2014). Social influence reinforces learning behaviors by creating shared expectations and collective motivation for skill development (Yang & Ahn, 2020).

H3: Subjective norms have a significant impact on employees' attitude toward upskilling and reskilling.

Technical Training and Attitude

Technical training equips employees with practical skills required to adapt to technological and job-related changes (Azodo, 2014). Effective and relevant training programs enhance employees' confidence and perceive usefulness of learning initiatives, which positively influence their attitudes (Ayub, 2015). Conversely, inadequate training may weaken attitudes toward upskilling efforts.

H4: Technical training has a significant impact on employees' attitude toward upskilling and reskilling.

Attitude and Behavioral Intention to Learn

Attitude is a key determinant of behavioral intention in behavioral and technology acceptance theories (Hameed et al., 2024). Employees with positive attitudes toward learning are more likely to participate in upskilling and reskilling programs (Songkaram et al., 2023). A favorable attitude enhances motivation, reduces perceived stress, and strengthens commitment to continuous learning (Lin et al., 2020).

H5: Employees' attitude has a significant impact on their behavioral intention toward upskilling and reskilling.

Table 1: Variable Definition Table

Constructs	Observed Variable	Indicator	Explanation
Knowledge Acquisition (Kar et al., 2021)	Ka1	Employee skills and knowledge	It has programs in place to improve employee skills and knowledge.
	Ka2	Tools and skills	Use various tools, knowledge and skills to meet their needs.
	Ka3	Workshops and seminars	Organization conducts different kinds of workshops and seminars.
	Ka4	Learning and rewards process	Encourage learning and rewards progress towards improvement.
	Ka5	Real-world training	Offers real-world training and job rotations
Technical Training (Azodo, 2014)	Tt1	Technical training	Offers employees technical training
	Tt2	Technical and soft skills	Values technical and soft skills
	Tt3	Sharing knowledge and skills	Promotes sharing knowledge and skills to better equipment
	Tt4	rewards	Rewards employees to develop skills and knowledge
	Tt5	Help team members	Manager help team members learn and grow.
Top Management Support (Ssekiziyivu et al., 2025)	Tms1	Quality improvement	Top managers in my department set clear goals for quality improvement
	Tms2	Suggestion for improvement	Top managers in this organization follow up on suggestions for improvement
	Tms3	Allocated resources to improve quality	Top managers in this organization allocate resources to improve quality
	Tms4	Improving the wat things are done	Top management is supportive of suggestions for improving the way things are done
Subjective Norm (Mousa et al., 2019)	Si1	Reskill	Encouraged by managers to reskill.
	Si2	Analysis and recommend	Managers do training need analysis and recommend.
	Si3	Influence	Influenced by friends and peers for upskilling
	Si4	Encourage reskill	Managers encourage teams to reskill based on skills in demand.
	Si5	Reskill	Encouraged by managers to reskill.
Attitude (Mousa et al., 2019)	A1	Satisfaction and well being	Prioritize employee satisfaction and well being
	A2	Diversity equity and inclusion	Promote diversity, equity and inclusion within the workplace
	A3	Values and culture	Communicate its values and culture
	A4	Employee feedback	Employee feedback is considered
	A5	Transparency	Transparent environment for employee
Behavior Intention to Learn (Hameed et al., 2024)	Bi1	Strategies	Utilize strategies to utilize employee
	Bi2	Stay up to work	Offers training and education
	Bi3	Adaptation	Managers are required to promote adaptation of technology
	Bi4	Explanation	Fosters creativity and innovation
	Bi5	Feedback	Employee feedback is necessary

3. Research Methodology

Study Area and Population

Employees from Kathmandu, Lalitpur, and Bhaktapur are the study's main target population. The primary audience for this study is employees from Kathmandu, Bhaktapur, and Lalitpur. The valley covers a total area of 721 km2 and runs from latitudes of 27°49′4″ to 27°31′42″ and 85°11′19″ to 85°33′57 a longitude (Rajbhandari et al., 2022). The possibility of more cost and convenience-effective data collecting is a key factor in choosing these locations (Bhatta et al., 2021). Another important reason for selecting Kathmandu, Bhaktapur, and Lalitpur is that data collection may be more convenient and cost-effective. The Kathmandu, Bhaktapur, Lalitpur is home to numerous professional and academic institutions, as well as media outlets. The Valley encloses the entire area of Bhaktapur district, 85% of Kathmandu district and 50% of Lalitpur district. This could provide access to relevant information and insights (Prajuli et al., 2019).

Sampling and Sample Technique

Since the population size of the study is unknown, a non-probability sampling technique was adopted, and convenience sampling was used to collect data from employees in Kathmandu Valley (Bhandari et al., 2021). To determine an adequate sample size, Cochran's (1977) formula for large or infinite populations was applied: $n = z^2pq / e^2$, where n represents the sample size, z is the standard value at 5% significance level (1.96), p is the estimated population proportion (0.5), $q = 1 - p$ (0.5), and e is the allowable error (0.05) (Naing, 2003). The calculated sample size was 384.16. After adding a 5% non-response rate, the final sample size was 403 respondents.

Research Instrument, Data Collection and Data Analysis

Data for this study were collected using a structured questionnaire developed through the KOBO Toolbox platform. Prior to the main survey, a pilot test was conducted with 15 respondents to assess the clarity, structure, and appropriateness of the questionnaire items. Feedback obtained from the pre-test was carefully reviewed, and necessary modifications were made to enhance the questionnaire's clarity and effectiveness. The data collected was analyzed using both descriptive and inferential statistical techniques. Descriptive analysis was performed to summarize respondent characteristics and key variables, while inferential analysis was used to test the proposed hypotheses and examine the strength and significance of relationships among the study constructs using SmartPLS 4.0. Microsoft Excel was utilized for data entry, coding, and preliminary descriptive analysis to ensure accuracy and consistency.

4. Results

Socio-economic Information

Table 2: Socio-Demographic Profile of Respondents

Title	Category	Number	Percentage (%)
Gender	Male	220	54.59
	Female	183	45.41
Marital Status	Married	197	48.88
	Unmarried	205	50.87
	Other	1	0.25
Age	18-27	156	38.71
	28-37	187	46.40
	38-47	43	10.67
	48-57	17	4.22

Education Level	Above Masters	21	5.21
	Masters	127	31.51
	Bachelors	200	49.63
	Intermediate / +2	50	12.41
	SLC	5	1.24
Income Level	Below 20000	35	8.68
	20000-40000	81	20.1
	40000-60000	91	22.58
	60000-80000	103	25.56
	80000-100000	52	12.90
	100000 and above	41	10.17
Location	Kathmandu	213	52.85
	Lalitpur	122	30.27
	Bhaktapur	68	16.87
Experience	Below 3 Years	103	25.56
	3-6 Years	187	46.40
	6-8 Years	77	19.11
	8-10 Years	21	5.10
	10 Years and above	15	3.72

The socio-demographic profile of the respondents indicates a diverse and representative sample of employees from Kathmandu Valley. Among the 403 respondents, 54.59% were male and 45.41% were female, reflecting relatively balanced gender participation. In terms of marital status, 50.87% were unmarried, 48.88% were married, and a small proportion (0.25%) identified as others. Most respondents were young to mid-career professionals, with 46.40% aged between 28–37 years and 38.71% between 18–27 years, while only 14.89% were above 37 years. Regarding educational attainment, nearly half of the respondents (49.63%) held a bachelor's degree, followed by 31.51% with a master's degree and 5.21% with qualifications above the master's level. Income distribution showed that most respondents earned between NPR 40,000 and 80,000 per month. Geographically, 52.85% were from Kathmandu, 30.27% from Lalitpur, and 16.87% from Bhaktapur. In terms of work experience, 46.40% had 3–6 years of experience, indicating a predominantly early- to mid-career workforce.

Employee Understanding Upskilling and Reskilling

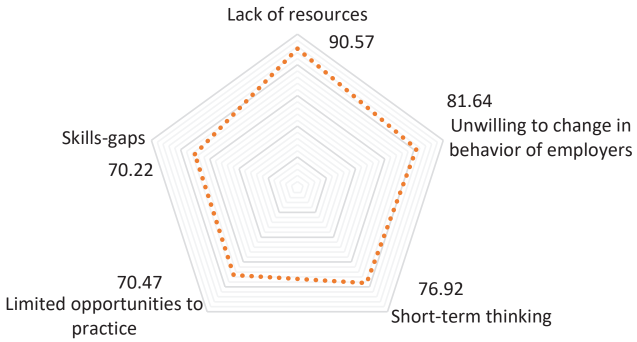
Employee understanding of upskilling and reskilling is increasingly critical in the context of rapid technological change and evolving workforce demands. Globally, it is estimated that 30–40 percent of workers will need to significantly upgrade their skills over the next decade to remain employable. In response, multinational corporations such as Amazon, IBM, Infosys, and Walmart are actively investing in both technical and soft skill development to prepare their human capital for AI-driven and digital work environments (Jaiswal et al., 2022). In the present study, employees from diverse job positions and sectors in Kathmandu Valley demonstrated a high level of awareness regarding upskilling and reskilling. Out of 403 respondents, 96 percent reported that they were familiar with the concepts, indicating strong conceptual recognition of skill development as a future workforce requirement.

Further analysis reveals that employees' understanding is not limited to terminology but extends to practical interpretations and organizational practices. A large majority (90.32%) perceived upskilling and reskilling as the acquisition of new skills and capabilities, while 86.1 percent associated it with vocational training, and 72.46 percent viewed it as regaining or updating existing knowledge. Organizational commitment to skill development was also evident, with most organizations offering training three to four times a year. Employees reported high familiarity with technical, digital, and soft skills, followed by analytical, leadership, and industry-specific skills. Technical training, such as Excel, programming languages, data analysis, and digital tools, emerged as the most commonly provided, highlighting organizations' focus on enhancing job-relevant competencies and employees' practical understanding of upskilling and reskilling initiatives.

Challenges and Solutions of Upskilling and Reskilling

The findings indicate that employees face multiple challenges in adopting upskilling and reskilling practices. As illustrated in Figure 2, the most significant barriers are the scarcity of organizational resources and employees' unwillingness to change. A substantial majority of respondents (90.57%) identified lack of resources, such as limited budgets, training infrastructure, and learning support, as a major constraint, while 81.64 percent reported resistance to behavioral change. Additionally, more than half of the employees highlighted short-term organizational thinking, limited opportunities to practice newly acquired skills, and persistent skill gaps as critical challenges. These barriers reflect systemic issues rather than individual shortcomings, as respondents equally attributed responsibility to government bodies, organizations, educational institutions, and employees themselves. This indicates that the challenges of upskilling and reskilling are multidimensional and require coordinated efforts across all key stakeholders.

Figure 2: Challenges and Problems While Adopting Upskilling and Reskilling



In addressing these challenges, respondents emphasized several strategic solutions. The radar analysis shows that resource allocation strategies were the most frequently suggested, with more than 350 employees highlighting the need for adequate financial, technological, and human resources to support continuous learning. Effective communication strategies were also emphasized by 311 respondents, underscoring the importance of clearly conveying the value and long-term benefits of upskilling and reskilling initiatives. Furthermore, skills-gap analysis, lifelong learning strategies, and change management approaches were equally recognized as essential mechanisms for successful implementation. Collectively, these strategies suggest that management reforms focusing on structured planning, inclusive communication, and sustained learning cultures are critical for overcoming barriers and strengthening the adoption of upskilling and reskilling practices.

Inferential Analysis

Common Method Bias: Common method bias refers to systematic measurement error arising from the data collection method rather than the constructs being measured (Kock, 2017). It was assessed using a full collinearity test, where variance inflation factor (VIF) values below the threshold of 3.3 indicate the absence of bias (Kock, 2017). In this study, all VIF values were below 3.3, confirming that common method bias was not a concern (Table 3).

Table 3: Full Collinearity Test

	bi	ka	si	tms	tt
vif	2.382	2.182	1.09	1.091	2.331

Measurement Model Assessment

The measurement model analysis was conducted to assess the reliability and validity of the latent constructs and their observed indicators in accordance with established PLS-SEM procedures (Henseler et al., 2015). Internal consistency reliability was evaluated using Cronbach's alpha (CA) and composite reliability (CR). As per Hair et al. (2015) reliability values above 0.70 indicate acceptable to strong reliability, while values above 0.60 represent the minimum threshold for exploratory research. The results indicate that all constructs achieved CA and CR values exceeding 0.70 (Table 4), demonstrating strong internal consistency and confirming that the measurement items consistently represent their respective constructs.

Convergent validity was examined through factor loadings and average variance extracted (AVE). Recommended guidelines suggest that AVE values should be at least 0.50 (Maharjan et al., 2025), indicating that a construct explains more than half of the variance of its indicators, while factor loadings should exceed 0.70 to ensure indicator reliability (Ab Hamid et al., 2017; Lawaju et al., 2023). The findings reveal that all constructs met these criteria, with AVE values above 0.50 and factor loadings surpassing the recommended threshold (Table 4). These results confirm that the indicators converge adequately to measure their intended constructs, establishing satisfactory convergent validity.

Discriminant validity was assessed using multiple criteria, including the Fornell–Larcker criterion, heterotrait–monotrait ratio (HTMT), and cross-loadings. As shown in table 4, all HTMT values were below the recommended thresholds of 0.85 (see Table 5) for distinct constructs and 0.90 for related constructs, supporting discriminant validity (Ab Hamid et al., 2017). Additionally, the square root of each construct's AVE exceeded its correlations with other constructs (Table 6), satisfying the Fornell–Larcker criterion (Hair et al., 2020). In table 7, cross-loading analysis further demonstrated that each indicator loaded highest on its respective construct (Hair et al., 2020). Overall, these results confirm the robustness, reliability, and validity of the measurement model, providing a sound basis for subsequent structural model analysis.

Further, to assess the overall model fit, the Goodness-of-Fit (GoF) was evaluated using the Standardized Root Mean Square Residual (SRMR) (Kock, 2017). As per Hair et al. (2020), SRMR values below the acceptable threshold of 0.10 indicate adequate model fit. In this study, the SRMR value of 0.0781 demonstrates that the proposed model fits the empirical data well and is considered acceptable.

Table 4: Factor Loading, AVE, CA, CR and VIF

Construct	Items	Factor Loading	AVE	CA	CR
Attitude	a1	0.763	0.53	0.776	0.849
	a2	0.629			
	a3	0.753			
	a4	0.754			
	a5	0.731			
Behavior Intention to learn	bi1	0.915	0.769	0.85	0.909
	bi2	0.889			
	bi3	0.823			
Knowledge Acquisition	ka1	0.694	0.512	0.761	0.84
	ka2	0.716			
	ka3	0.657			
	ka4	0.76			
	ka5	0.746			

Subjective Norm	si1	0.821	0.56	0.74	0.835
	si2	0.708			
	si3	0.693			
	si4	0.766			
Top Management Support	tms1	0.714	0.554	0.741	0.83
	tms2	0.798			
	tms3	0.855			
	tms4	0.583			
Technical Training	tt1	0.755	0.538	0.786	0.853
	tt2	0.673			
	tt3	0.735			
	tt4	0.774			
	tt5	0.727			

Table 5: Heterotrait-Monotrait ratio (HTMT) Results

	a	bi	ka	si	tms	tt
a						
bi	0.07					
ka	0.882	0.079				
si	0.072	0.242	0.111			
tms	0.089	0.063	0.081	0.389		
tt	0.792	0.079	0.866	0.081	0.09	

Table 6: Fornell- Larcker Criterion Results

	a	bi	ka	si	tms	tt
a	0.728					
bi	-0.013	0.877				
ka	0.683	0.027	0.716			
si	-0.054	0.202	-0.039	0.749		
tms	0.045	0.05	0.03	0.277	0.744	
tt	0.707	-0.008	0.676	-0.029	-0.001	0.734

Table 7: Cross Loading

	a	bi	ka	si	tms	tt
a1	**0.763**	-0.018	0.566	-0.061	-0.031	0.588
a2	**0.629**	0.006	0.438	-0.031	0.052	0.442
a3	**0.753**	0.028	0.511	-0.048	0.011	0.468
a4	**0.754**	-0.034	0.453	-0.023	0.07	0.538
a5	**0.731**	-0.024	0.508	-0.031	0.071	0.521
bi1	0.045	**0.915**	0.077	0.194	0.039	0.028
bi2	-0.041	**0.889**	0.005	0.13	0.01	-0.026
bi3	-0.051	**0.823**	-0.021	0.193	0.072	-0.03
ka1	0.528	0.056	**0.694**	0.024	0.043	0.512
ka2	0.465	0.025	**0.716**	-0.076	-0.018	0.431
ka3	0.433	0.068	**0.657**	-0.021	0.063	0.443
ka4	0.526	-0.023	**0.76**	-0.081	-0.017	0.509
ka5	0.482	-0.027	**0.746**	0.013	0.042	0.514
si1	-0.023	0.184	-0.006	**0.821**	0.218	-0.011

si2	-0.042	0.124	-0.012	**0.708**	0.161	-0.009
si3	-0.079	0.155	-0.092	**0.693**	0.206	-0.054
si4	-0.013	0.129	0.004	**0.766**	0.245	-0.008
tms1	0.008	0.053	-0.031	0.199	**0.714**	-0.076
tms2	0.038	0.042	0.039	0.219	**0.798**	0.008
tms3	0.05	0.039	0.054	0.216	**0.855**	0.03
tms4	0.036	-0.007	0.004	0.235	**0.583**	0.046
tt1	0.569	0.04	0.592	0.013	0.042	**0.755**
tt2	0.425	0.045	0.414	-0.023	0	**0.673**
tt3	0.47	0.002	0.488	0.038	-0.02	**0.735**
tt4	0.529	-0.01	0.494	-0.008	-0.058	**0.774**
tt5	0.573	-0.09	0.475	-0.117	0.025	**0.727**

Structure Model Assessment

In PLS-SEM, the structural model is used to estimate path coefficients, test the proposed hypotheses, and assess the model's explanatory power (Hair et al., 2020). The key criteria for evaluating the structural model include path coefficients and the coefficient of determination (R^2). According to Ab Hamid et al. (2017), R^2 values of 0.25, 0.50, and 0.75 indicate weak, moderate, and substantial explanatory power, respectively. As illustrated in Figure 3, the adventure construct reports an R^2 value of 0.378, demonstrating moderate predictive relevance and indicating that the model explains a meaningful proportion of variance in the constructs.

Figure 3: Path Analysis

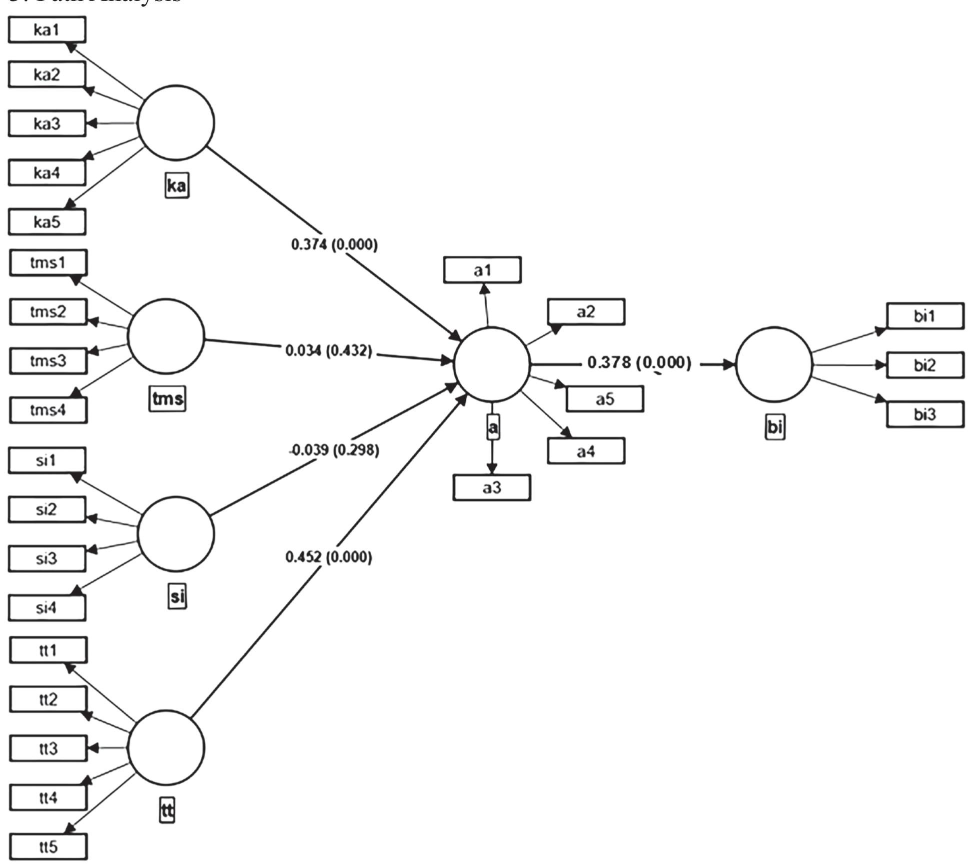


Table 8: Hypothesis Testing

Hypotheses	Beta	SD	t Values	P values	LL2.5%	UL97.5%	Result
H1: ka -> a	0.374	0.055	6.749	0.000	0.263	0.48	Supported
H2: tms -> a	0.034	0.043	0.786	0.432	-0.069	0.105	Not supported
H3: si -> a	-0.039	0.037	1.042	0.298	-0.095	0.055	Not Supported
H4: tt -> a	0.452	0.05	9.091	0.000	0.354	0.551	Supported
H5: a -> bi	0.378	0.124	0.927	0.000	0.105	0.427	Supported

Table 8 presents the results of hypothesis testing. The findings indicate that Knowledge Acquisition has a significant positive relationship with Attitude ($\beta = 0.374$, $p < 0.05$), with the β coefficient lying within the confidence interval; therefore, H1 is accepted. In contrast, Top Management Support does not show a significant relationship with Attitude ($\beta = 0.034$, $p = 0.432$), leading to the rejection of H2. Technical Training is found to have a significant positive effect on Attitude ($\beta = 0.452$, $p < 0.05$), supporting the acceptance of H3. However, Subjective Norm does not significantly influence Attitude ($\beta = 0.039$, $p = 0.298$), resulting in the rejection of H4. Finally, Attitude demonstrates a significant positive relationship with Behavioral Intention to Learn ($\beta = 0.378$, $p < 0.05$), confirming the acceptance of H5.

Table 9: Mediation Analysis

	Beta	SD	t Values	P values	LL2.5%	UL97.5%	Result
H6: tms -> a -> bi	0.144	0.007	0.548	0.003	0.101	0.219	Supported
H7: ka -> a -> bi	-0.043	0.048	0.902	0.367	-0.105	0.044	Not Supported
H8: tt -> a -> bi	0.052	0.056	0.923	0.006	0.111	0.056	Supported
H9: si -> a -> bi	0.204	0.006	0.69	0.039	0.019	0.298	Supported

Table 9 presents the mediation analysis results examining the indirect effects of the antecedent variables on behavioral intention through attitude. The findings show that attitude significantly mediates the relationships between top management support and behavioral intention ($\beta = 0.144$, $p = 0.03$), technical training and behavioral intention ($\beta = 0.052$, $p = 0.06$), and subjective norms and behavioral intention ($\beta = 0.204$, $p = 0.039$); therefore, H6, H8, and H9 are supported. However, the mediating effect of attitude between knowledge acquisition and behavioral intention is not significant ($\beta = –0.043$, $p = 0.367$), leading to the rejection of H7. Overall, the results highlight attitude as a key mechanism through which organizational and social factors influence employees' behavioral intention to engage in upskilling and reskilling.

5. Discussion

This study examined employees' behavior and behavioral intention toward upskilling and reskilling in Kathmandu Valley by empirically testing direct and mediating relationships among key organizational and individual factors. A total of nine hypotheses were proposed, of which H1, H3, and H5 demonstrated significant direct effects, along with the mediating hypotheses H6, H8, and H9. Reliability and validity analyses confirmed the robustness of the measurement model, while hypothesis testing was conducted using a significance threshold of $p < 0.05$, consistent with established statistical guidelines (Hair et al., 2017). The results indicate that Hypotheses H1, H3, H5, H6, H8, and H9 were supported, highlighting the central role of attitude in shaping employees' learning intentions.

Specifically, the acceptance of H1 confirms a significant relationship between knowledge acquisition and attitude, suggesting that employees who perceive greater opportunities to acquire relevant knowledge tend to develop more favorable attitudes toward upskilling and reskilling (Papa et al., 2020; Chowdhury, 2024). In contrast, H2 was rejected, indicating that top management support did not directly influence attitude, despite its recognized importance in organizational contexts (Khan et al., 2025). Technical training showed a significant positive relationship with attitude (H3), emphasizing that practical and job-relevant training enhances employees' learning orientation (Ayub, 2015). However, subjective norms were found to have no direct impact on attitude (H4), implying that social pressure alone may be insufficient to shape employees' learning attitudes in this context (Mousa et al., 2019). The strong support for H5 confirms that attitude is a key predictor of behavioral intention to learn, reinforcing its pivotal role in employees' engagement with upskilling and reskilling initiatives (Hameed et al., 2024).

The mediation analysis further strengthens these findings by revealing that attitude serves as an important explanatory mechanism. Attitude significantly mediated the relationships between top management support and behavioral intention (H6), technical training and behavioral intention (H8), and subjective norms and behavioral intention (H9). These results suggest that while some factors may not directly influence learning intentions, they exert meaningful indirect effects by shaping employees' attitudes. Overall, the findings underscore attitude as a critical level through which organizational support, training practices, and social influences translate into employees' intentions to engage in upskilling and reskilling (Lin et al., 2020).

6. Conclusion

This study examined employees' behavioral intentions toward upskilling and reskilling in Kathmandu Valley, with a particular focus on the role of attitude and its mediating effects. The findings reveal that knowledge acquisition and technical training significantly influence employees' attitudes, which in turn strongly predict their intention to engage in upskilling and reskilling activities. Although top management support and subjective norms did not exhibit direct effects on attitude, their indirect influence through attitude was found to be significant, highlighting the central role of employees' internal evaluations in learning-related decision-making. Overall, the results emphasize that employees are more likely to participate in upskilling and reskilling initiatives when they perceive learning as valuable, relevant, and supportive of their career development. The study contributes empirical evidence from a developing economic context, demonstrating that fostering positive learning attitudes is essential for building a future-ready workforce in Kathmandu Valley.

The findings offer important implications for organizations, policymakers, and training institutions. Organizations should prioritize knowledge-sharing mechanisms and relevant technical training while actively cultivating positive learning attitudes among employees. Policymakers and educational institutions can support this by aligning skill development programs with industry needs and promoting lifelong learning cultures. Future research may adopt longitudinal designs to examine changes in learning intentions over time, including sector-specific comparisons, or integrate additional variables such as job insecurity, digital readiness, or organizational culture to further enrich understanding of upskilling and reskilling behavior.

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