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# Editorial

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This fifth issue of 2026 covers different articles from various disciplines of science and society, like economics, sociology, population, computer studies, management, etc. We hope this volume will contribute to generating new knowledge on management, technology, the economy, and the development processes of society, as well as the country. We would like to thank all the experts and reviewers, such as Mr. Ananda K.C, Mr. Arjun Saud, Dr. Ramesh Chandra Timilsena, Dr. Narayan Prasad Timilsena, Dr. Sudip Nakarmi, Dr. Shiva Ram Pandey, Dr. Karna Chonghang, Dr. Dil Nath Dangal, and Mr. Dadhi Ram Ghimire.

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# Income Tax Awareness and Tax Education Among College Faculty Members in Kathmandu Valley

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**Abstract**

The objectives of the study are to examine the level of income tax awareness and income tax education of the college faculty members. The faculty members are from the colleges in Kathmandu Valley, Nepal, comprising permanent and part-time faculty members. Nepal has adopted a self-assessment system in the Income Tax Act, 2058 (2002). The current tax system assumes that the taxpayer has a sufficient level of knowledge of the tax legislation to be able to perform this independently. Tax literacy is not an option. It's a fundamental duty of the law. The study used a descriptive quantitative research design. The data were obtained from 100 faculty members using a questionnaire consisting of 30 items on a Likert scale. There were five independent variables: taxpayer attitude and perception, socio-demographic influence, tax education, tax knowledge, and institutional context. Income tax awareness was the dependent variable. Frequency, percentage, mean, standard deviation, coefficient of variance, and Pearson correlation were used for the analysis of the data. The overall awareness was high with a composite mean of 4.15 out of 5. Tax knowledge, taxpayer attitude, and tax education were also highly rated. The five independent variables were found to have positive and significant relationships with income tax awareness. The strongest links were with taxpayer attitude (r = .52), tax education (r = .58), and tax knowledge (r = .64). The socio-demographic influence and institutional context were less strong but significant (r = .35 and .44, respectively). Based on the results, it can be concluded that tax education should be structured in order to increase the awareness of tax among academic staff and that the colleges do not make full use of their supporting role.

***Keywords:*** faculty member, income tax awareness, self-assessment system, tax education, tax knowledge, taxpayer attitude.

# 1. Introduction

## 1.1 Background of the study

Taxation is a primary tool for the government to collect revenue to provide public services and infrastructure development. A stable domestic tax revenue system in a developing country reduces dependence on external loans and aid. In Nepal, income tax is the major tax in the tax system, levied on the income of individuals and entities. Income tax is levied and administered in Nepal through the Income Tax Act 2058 (2002) of the Government of Nepal by the Inland Revenue Department (Government of Nepal, 2002). Nepal does not have any system for external assessment. The taxpayer, and not the tax office, is responsible for the calculation of taxable income, application of the correct tax rates, claiming of allowable deductions, and timely filing of the tax return. This design is based on assumptions that individual taxpayers have sufficient working knowledge of tax law to perform these duties.

College faculty members are a large group within Nepal's salaried, formally employed workforce. How well they understand and follow tax rules affects how much revenue the country collects. As teachers, they guide students who will soon become taxpayers themselves. But having a strong academic background does not automatically mean someone understands tax rules well. A physics professor with a PhD might know far less about rebate provisions or filing deadlines than a college accounts assistant without a high academic degree. This gap between general education and specific tax knowledge has not been studied closely in Nepal before. To fulfill this gap, the need to research this topic is raised.

## 1.2 Problem statement

Payment of income tax is a legal obligation of every employee of Nepal under the Income Tax Act, 2058 (2002). The Act is based on a system of self - assessment. This will require each taxpayer to determine, report, and pay their own taxes. Knowledge of tax slabs, deductions, rebate provisions, and filing procedures is required for the design. College faculty members are also expected to be able to teach students who will soon become taxpayers. However, the extent of income tax awareness, tax education received, and the institutional support provided at the workplace is yet to be tested in Nepal. In the empirical picture, most local tax studies have been limited to the business taxpayer and value added tax, excluding the academic community. This disconnection places both the Inland Revenue Department and college administrations in a position where they have no real evidence to design targeted outreach programmes that are targeted. In this context, the following are the main questions that the present study aims to answer.

i. What is the level of tax education, tax knowledge, and taxpayer attitude of the college faculty members in Kathmandu Valley?
ii. What is the relationship between socio-demographic and institutional factors and their awareness of income tax?

### 1.3 Objectives of the study

The major objective of the study is to determine the level of income tax awareness and tax education of college faculty members of Kathmandu Valley. The specific objectives are:

i. To find out the level of tax education, tax knowledge and tax attitude of the college faculty members.

ii. To find the correlation between socio-demographic and institutional factors with income tax awareness of college faculty members.

## 2. Literature review

### 2.1 Concept of income tax awareness

Income tax awareness is an awareness of the legal obligation to pay income tax, the process of filing an income tax return, current rates of income tax, and consequences for failure to file an income tax return. No one can be compelled to abide by an unknown rule. People vary in their existing knowledge and their capacity to acquire knowledge, as well as their knowledge of where to obtain assistance (Alm, 2019). This is also true in Nepal, where there is a disparity in awareness even among educated, paid groups like college faculty.

### 2.2 Tax education and tax knowledge

Tax education is any formal or informal learning which makes a person understand the workings of the tax system. Tax knowledge is the actual factual knowledge acquired in this learning, including the knowledge of tax slabs, deductions, and steps in filing tax. Tax education has been consistently correlated with tax compliance. Kwok and Yip (2018) examined taxpayers in Hong Kong and concluded that tax education increases tax compliance for three reasons: firstly, because it is easier to comply with the tax; secondly, because it makes the tax system fairer; and thirdly, because it makes people feel a greater moral obligation to pay the tax. In an emerging economy, Appiah et al (2024) discovered that an increase in tax knowledge coupled with trust in government leads to an increase in voluntary tax compliance. In 2019, Holik and Mulyeni conducted a study on financial awareness in Indonesia, in which the group of school teachers studied is quite similar to the group of faculty in this study, and the results showed that the level of financial awareness of the school teachers was relatively high, with a personal attitude toward financial awareness being the most determinant factor. All of these studies conclude one thing: Knowledge is not sufficient. It also takes attitude and a sense of duty.

### 2.3 Taxpayer attitude and perceptions

Taxpayer attitude is a person's overall view of the tax system. Perception is more specific: Perceived fairness of the system, how it is used, and the likelihood of non-compliance being detected. Jassem et al. (2022) examined the relationship between personality traits and the intent not to comply among Malaysian taxpayers, and they discovered that a tax sense of fairness accounts for some of the relationship between personality traits and the intent not to comply. Agbanyo et al. (2024) investigated tax morale and tax tolerance as factors influencing tax compliance in Ghana and concluded that tax morale and tax tolerance both positively influence tax compliance while political corruption negatively influences tax compliance in Ghana.

### 2.4 Socio-demographic influences

Several research studies have correlated age, gender, academic field, and income with tax awareness. Garg et al. (2024) found that demographic characteristics influence the relationship between attitude and tax compliance in the context of the Theory of Planned Behavior in India. Generally, the more experienced the person, and the older, the higher the level of awareness, as they have had more years of experience to find out. Women in Nepal receive an income tax rebate, and they have one more incentive to learn about income tax.

### 2.5 Institutional context

The workplace also influences tax awareness for salaried workers. The employer who withholds the tax at source, provides annual tax statements, and conducts training sessions on tax procedures can directly expose their employees to tax procedures as compared to the employee who has to look for this information on their own.

## 3. Theoretical Framework

**3.1 Theory of planned behavior:** One of the most popular models in the field of behavioural research is the Theory of Planned Behavior (Ajzen, 1991). As stated, actual behavior will result from a person's intention to behave, which in turn will depend on three factors: attitude toward the behavior, social norms surrounding the behavior, and level of perceived control over engaging in the behavior. A positive attitude towards tax filing, coupled with the confidence that other faculty members share this attitude and that the faculty filing system is user-friendly, is more likely to encourage a faculty member to file tax returns and comply with tax obligations. This is consistent with findings by Garg et al. (2024) who applied theory to the study of tax compliance intention. The theory in this study is used to support the taxpayer attitude variable.

### 3.2 Fischer's tax compliance model

This is more general model, known as Fischer's Tax Compliance Model (1992). It categorizes the factors affecting taxpayer behavior into four areas: demographics, opportunities to avoid paying taxes, attitudes and perceptions, and the characteristics of the tax system. The opportunity for non-compliance is mapped onto the variables of this study, as is tax knowledge, which can result in unintentional errors not knowing the rules. The attitude dimension is congruent with taxpayer attitude. Socio-demographic factors are grouped separately, like in the model. In the tax system structure category, items such as employer-side tax deduction and workplace support are similar to the definition of institutional context used in this study.

## 4. **Research methods**

### 4.1 Research design

The research design in this study is descriptive and correlational with quantitative approach and type of research is cross sectional survey. The descriptive part measures and describes the tax awareness, tax education, tax knowledge, taxpayer attitude and related variables. In the correlational part, Pearson correlation is used to test the relationship between the five independent variables and the level of awareness about income tax. The data was gathered at one time, suitable to the descriptive and exploratory nature of the study.

### 4.2 Population, sample and sampling method

Population represents the total number of all full-time and part-time faculty members of colleges in Kathmandu Valley (Kathmandu, Lalitpur and Bhaktapur districts). A purposive and convenience sampling technique was used to select a sample of 100 faculty members. The sample was purposive to ensure respondents comprised various academic disciplines, age groups and both part time and full time. The use of college contacts and the researcher's professional network facilitated convenience sampling.

### 4.3 Data collection procedure

Data were gathered by both face-to-face questionnaire distribution and an online form. The faculty members were approached one by one or in small groups and given information regarding the purpose of the study. Responses were anonymous and participation was voluntary. A total of 100 questionnaires were completely filled out, and were the only ones used in the final analysis.

### 4.4 Data analysis

MS Excel and IBM SPSS Statistics was used for data analysis. These techniques used were frequency and percentage distribution to describe the socio-demographic profile of respondents, mean and standard deviation to measure the central tendency and dispersion of each Likert scale item and variable, coefficient of variation (CV) to compare the relative consistency of responses across items and a five-interval scoring rule to interpret mean scores of the Likert scale items.

### 4.5 Score interpretation scale

The following scale was used to interpret the mean scores of the items on the Likert scale.

**Table 1**

*Interpretation scale for mean scroes*

| Mean score range | Interpretation |
|---|---|
| 1.00 to 1.80 | Very low |
| 1.81 to 2.60 | Low |
| 2.61 to 3.40 | Moderate |
| 3.41 to 4.20 | High |
| 4.21 to 5.00 | Very high |

### 4.6 Methodological summary

**Table 2**

*Summary of methodological approach*

| Element | Detail |
|---|---|
| Research design | Descriptive, correlational, quantitative, cross-sectional |
| Population | Permanent and part-time faculty of colleges, Kathmandu Valley |
| Sample size | 100 respondents |
| Sampling technique | Purposive and convenience sampling |
| Instrument | Structured questionnaire, 30 Likert items, five-point scale |
| Data type | Primary data; secondary sources used for background only |

## 5. Results and Discussion

This section was presented in two parts. The first part related with the socio-demographic profile of the respondents. The descriptive statistics of the six variables are presented as a second part and a discussion of these results is presented in the light of the literature reviewed.

### 5.1 Profile of respondents

In this section, the socio-demographic characteristics of the respondents were described. Table 3 shows the demographical characteristics of the 100 respondents. Frequencies and percentages are the same numbers if n = 100.

**Table 3**

*Demographic profile of respondents*

| Factor | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 60 | 60.0 |
| | Female | 39 | 39.0 |
| | Other | 1 | 1.0 |
| Age group | Below 30 | 30 | 30.0 |
| | 30 to 40 | 40 | 40.0 |
| | 41 to 50 | 23 | 23.0 |
| | Above 50 | 7 | 7.0 |
| Academic discipline | Management or Commerce | 39 | 39.0 |
| | Science or Technology | 26 | 26.0 |
| | Humanities or Social Science | 17 | 17.0 |
| | Law | 12 | 12.0 |
| | Other | 6 | 6.0 |
| Employment type | Permanent Faculty | 73 | 73.0 |
| | Part-time Faculty | 27 | 27.0 |
| Teaching experience | Less than 5 years | 25 | 25.0 |
| | 5 to 10 years | 30 | 30.0 |
| | 11 to 20 years | 23 | 23.0 |
| | Above 20 years | 22 | 22.0 |
| Highest qualification | Bachelor's Degree | 14 | 14.0 |
| | Master’s Degree | 45 | 45.0 |
| | M.Phil./Ph.D. | 41 | 41.0 |

***Note:*** Questionnaire survey, 2026

As seen in the profile, the sample consists mainly of males as there are 60 male and 39 female respondents. One person answered that they were of a different gender. The largest age group is 30 to 40 years (40%), followed by below 30 years (30%). 70% of the respondents are under 41 years of age, which is the general age profile of college faculty in Kathmandu valley. The largest group of faculty by discipline is 39% from management followed by science/technology at 26%. This is a helpful distribution, as it enables responses from both academic tax-trained and non-tax-trained environments to be captured within the study. 73% of the sample is from permanent faculty. The remaining 27% is made up of part-time faculty. The teaching experience profile is reasonably even. The majority of faculty members (30%) have 5 to 10 years of experience, followed closely by faculty members who have less than 5 years of experience (25%). The majority of the master's degree holders (45%) qualify, followed by a combined 41% in M.Phil. and Ph.D. degree holders. The sample, therefore, is representative of an academically well qualified group, and the issue of tax-specific knowledge is especially pertinent.

**5.2 Descriptive statistics by variable**

The mean, standard deviation and coefficient of variance for each item are given variable by variable. A mean score greater than 0 means that people agreed more. The smaller the coefficient of variation, the closer the responses of the sample are to each other.

### 5.2.1 Tax education (TE)

**Table 4**

*Descriptive statistics for tax education*

| Item | Statement summary | Mean | SD | CV (%) |
|---|---|---|---|---|
| TE1 | Received formal education on income tax | 3.72 | 0.74 | 19.88 |
| TE2 | Attended tax-related workshops or training | 3.96 | 0.76 | 19.30 |
| TE3 | Actively seeks updated tax information | 3.80 | 0.77 | 20.14 |
| TE4 | Tax education helped understand obligations | 3.99 | 0.69 | 17.27 |
| TE5 | Tax education should be part of faculty orientation | 4.00 | 0.72 | 18.12 |
| Composite | Tax education (TE) | 3.89 | 0.74 | 18.94 |

***Note:*** Questionnaire survey, 2026

Tax Knowledge is in the High range with a composite mean of 4.02. The highest agreement is in the area of awareness of tax slabs and Permanent Account Number (PAN) process, with M = 4.09 for both items TK1 and TK5. Both are parts of the tax system that are readily seen in the day-to-day life of the working public. The lowest scoring items, TK3 (filing deadline) and TK4 (rebate provisions), remain near the high band scoring threshold, but indicate some procedural detail softness. This is similar to what Alm (2019) noted: that taxpayers tend to be more familiar with the general requirements than the finer details of the procedure.

### 5.2.2 Tax knowledge (TK)

**Table 5**

*Descriptive statistics for tax knowledge*

| Item | Statement summary | Mean | SD | CV (%) |
|---|---|---|---|---|
| TK1 | Aware of current income tax slabs and rates | 4.09 | 0.71 | 17.41 |
| TK2 | Can calculate taxable income with deductions | 4.04 | 0.76 | 18.92 |
| TK3 | Knows the filing deadline | 3.95 | 0.76 | 19.17 |
| TK4 | Aware of rebate provisions (e.g., for female taxpayers) | 3.95 | 0.73 | 18.48 |
| TK5 | Understands the PAN process | 4.09 | 0.73 | 17.75 |
| Composite | Tax knowledge (TK) | 4.02 | 0.74 | 18.34 |

***Note:*** Questionnaire survey, 2026

Taxpayer Attitude has an independent variable composite mean of 4.09, the second highest of all the independent variables. The average of all five items is above 4.00. The highest agreement is in item TA3 (effective use of tax revenues), and this is important because one of the issues that is typically discussed in public discussion in Nepal is inefficiency in public spending. This could be due to a relatively high level of satisfaction of the academic community with public services, as they are themselves provided by the publicly funded educational system. The civic responsibility item (TA1) has a high endorsement (M = 4.13). As indicated in the pattern, the positive and moral side of tax payment is still prevalent among faculty members, indicating the moral and attitudinal channel suggested by Kwok and Yip (2018).

### 5.2.3 Taxpayer attitude and perception (TA)

**Table 6**

*Descriptive statistics for taxpayer attitude and perception*

| Item | Statement summary | Mean | SD | CV (%) |
|---|---|---|---|---|
| TA1 | Paying income tax is a civic responsibility | 4.13 | 0.76 | 18.42 |
| TA2 | Current income tax system is fair and equitable | 4.05 | 0.76 | 18.69 |
| TA3 | Tax revenue is used effectively for public welfare | 4.14 | 0.74 | 17.85 |
| TA4 | Willing to pay tax voluntarily without enforcement | 4.03 | 0.69 | 17.08 |
| TA5 | Non-compliance is morally wrong regardless of audit | 4.08 | 0.72 | 17.65 |
| Composite | Taxpayer attitude (TA) | 4.09 | 0.73 | 17.94 |

***Note:*** Questionnaire survey, 2026

The composite mean for Socio-Demographic Influence is 3.69 which falls in the High range and is the lowest out of the 6 variables. All five items are grouped into a relatively small range (3.64 - 3.72). The relatively high CV values (20% to 22%) indicate that there was more variation across the sample than on the Tax Knowledge and Taxpayer Attitude items. Demographic factors seem to be recognised as influencing awareness, but opinions are not as consistent as to the strength of each factor.

### 5.2.4 Socio-demographic influence (SD)

**Table 7**

*Descriptive statistics for socio-demographic influence*

| Item | Statement summary | Mean | SD | CV (%) |
|---|---|---|---|---|
| SD1 | Academic discipline influences tax knowledge | 3.66 | 0.82 | 22.38 |
| SD2 | More experience leads to higher awareness | 3.71 | 0.73 | 19.65 |
| SD3 | Gender differences affect tax knowledge | 3.72 | 0.78 | 20.96 |
| SD4 | Higher salary leads to higher awareness | 3.70 | 0.72 | 19.40 |
| SD5 | Higher qualification linked to higher awareness | 3.64 | 0.76 | 20.85 |
| Composite | Socio-demographic influence (SD) | 3.69 | 0.76 | 20.65 |

***Note:*** Questionnaire survey, 2026

The composite mean for Institutional Context is 3.79. The employment type is most agreed by respondents as seen in item IC3 with a mean score of 3.89. A mean of 3.69 is found for Item IC4 which asks about difficulty in obtaining tax information. This item is designed to measure a negative experience and therefore should be interpreted with caution. Overall, the level of agreement is relatively high, suggesting that faculty members do not have an easy time getting clear tax-related information at the workplace even in an overall supportive institutional environment. Items IC1, IC2, and IC5 suggest that there is a general acceptance that colleges do provide some level of support, but there is potential to improve to offer more proactive guidance and communication.

### 5.2.5 Institutional context (IC)

**Table 8**

*Descriptive statistics for institutional context*

| Item | Statement summary | Mean | SD | CV (%) |
|---|---|---|---|---|
| IC1 | College provides tax-related guidance | 3.83 | 0.74 | 19.30 |
| IC2 | Employer deducts tax at source | 3.80 | 0.78 | 20.49 |
| IC3 | Employment type affects awareness | 3.89 | 0.75 | 19.30 |
| IC4 | Faces difficulties accessing tax information | 3.69 | 0.71 | 19.14 |
| IC5 | College admin encourages tax compliance | 3.72 | 0.82 | 21.98 |
| Composite | Institutional context (IC) | 3.79 | 0.76 | 20.04 |

***Note:*** Questionnaire survey, 2026

The composite mean for the variable Income Tax Awareness is 4.15, which is the highest among the six variables. The individual mean (M = 4.21) for Item ITA4 is in the Very High range. This reflects high levels of reported awareness of penalties for late and non-filing of income tax returns. Knowledge of the penalties can be a deterrent in themselves and can be a motivator to self-learning. 4.17 for both items ITA2 and ITA3 show good reporting of filing and a clear understanding of which income is subject to tax. The lowest of this section, ITA1 (M = 4.04), remains well in the High band. Combined, the section indicates that the sampled faculty consider that they are well positioned to fulfill their tax responsibilities.

### 5.2.6 Income tax awareness (ITA)

**Table 9** `

*Descriptive statistics for income tax awareness*

| Item | Statement summary | Mean | SD | CV (%) |
|---|---|---|---|---|
| ITA1 | Fully aware of tax obligations as salaried faculty | 4.04 | 0.78 | 19.24 |
| ITA2 | Filed individual tax return for recent fiscal year | 4.17 | 0.71 | 17.06 |
| ITA3 | Knows which income is taxable and which is exempt | 4.17 | 0.80 | 19.30 |
| ITA4 | Aware of penalties for late or non-filing | 4.21 | 0.77 | 18.27 |
| ITA5 | Has adequate awareness to fulfil obligations independently | 4.16 | 0.75 | 17.99 |
| Composite | Income tax awareness (ITA) | 4.15 | 0.76 | 18.37 |

***Note:*** Questionnaire survey, 2026

The composite mean for Income Tax Awareness is 4.15, the highest of all six variables. Item ITA4 records the highest individual mean (M = 4.21), which crosses into the Very High range. This shows strong reported awareness of penalties for late or non-filing of income tax returns. Awareness of penalties may itself act as a deterrent and as a driver of self-learning. Items ITA2 and ITA3, both at 4.17, indicate strong reported filing behaviour and a clear sense of which income is taxable. The lowest item in this section, ITA1 (M = 4.04), still sits firmly in the High band. Taken together, the section suggests that faculty members in the sample see themselves as well placed to meet their tax obligations.

### 5.3 Composite summary of variables

The summary of composite means across the six variables is presented below.

**Table 10**

*Composite means and interpretation of study variables*

| Variable | Code | Mean | SD | CV (%) | Interpretation |
|---|---|---|---|---|---|
| Tax education | TE | 3.89 | 0.74 | 18.94 | High |
| Tax knowledge | TK | 4.02 | 0.74 | 18.34 | High |
| Taxpayer attitude and perception | TA | 4.09 | 0.73 | 17.94 | High |
| Socio-demographic influence | SD | 3.69 | 0.76 | 20.65 | High |
| Institutional context | IC | 3.79 | 0.76 | 20.04 | High |
| Income tax awareness | ITA | 4.15 | 0.76 | 18.37 | High |

***Note:*** Questionnaire survey, 2026

The six variables are in the High range. The composite mean for income tax awareness is very high (M = 4.15) and is close to the upper limit of the High band. Taxpayer attitude (M = 4.09) and tax knowledge (M = 4.02) are second. Tax education is a step down from them (M = 3.89). Among the six, socio-demographic influence (M = 3.69) and institutional context (M = 3.79) have the lowest composite mean scores. This ordering is useful in that it brings forth some information. In the sample, faculty members report knowing about their tax obligations, a positive attitude towards paying taxes, and a reasonable understanding of the tax system. They also recognize the impact of demographic and institutional factors but not as consistently. The pattern indicates that the most salient reported factors for awareness in this group are personal attitude and self-rated knowledge, with institutional and demographic factors playing a secondary supporting role.

### 5.4 Correlation analysis

Pearson correlation on the six composite variables was conducted to explore the relationships between the study variables. The results are shown in Table 11.

**Table 11**

*Composite means and interpretation of study variables*

| Variable | TE | TK | TA | SD | IC | ITA |
|---|---|---|---|---|---|---|
| Tax education (TE) | 1.00 | | | | | |
| Tax knowledge (TK) | 0.62** | 1.00 | | | | |
| Taxpayer attitude (TA) | 0.41** | 0.48** | 1.00 | | | |
| Socio-demographic (SD) | 0.28** | 0.31** | 0.24* | 1.00 | | |
| Institutional context (IC) | 0.36** | 0.39** | 0.33** | 0.30** | 1.00 | |
| Income tax awareness (ITA) | 0.58** | 0.64** | 0.52** | 0.35** | 0.44** | 1.00 |

*Note.* * $p < 0.05$, ** $p < 0.01$ (2-tailed).

Income tax awareness is positively and statistically significantly related to all the five independent variables. Tax knowledge records the strongest association ($r = 0.64$, $p < 0.01$), followed by tax education ($r = 0.58$, $p < .01$) and taxpayer attitude ($r = 0.52$, $p < 0.01$). There are weaker, but significant associations with awareness for institutional context ($r = 0.44$, $p < 0.01$) and socio-demographic influence ($r = 0.35$, $p < 0.01$). Tax education and tax knowledge have the highest correlation among the independent variables ($r = 0.62$, $p < 0.01$). This is natural, because tax education is the basic of factual tax knowledge. Another significant correlation was between taxpayer attitude and tax knowledge ($r = 0.48$, $p < 0.01$), indicating that those faculty members with a higher level of tax knowledge have a more positive attitude toward the tax system.

The matrix thus provides the conceptual framework. The knowledge of tax, tax education and taxpayer attitude are the strongest correlates of income tax awareness while institutional and demographic variables play a supporting role.

## 6. Discussion

The overal findings of the study indicates that the awareness of income tax of faculty in colleges in Kathmandu Valley is positive. The scores on all six variables are consistently high, and do not seem to fit the typical picture of an uninformed salaried taxpayer. There are two reasons that are likely responsible for this. First, a high proportion of the faculty are from management/commerce (39%) and are more likely to encounter tax topics in their teaching. Second, there is a high proportion who are permanent employees (73%), who have regular contact with their employers who have a duty to withhold tax from their earnings, so they have direct experience of the tax system. These relationships are not random; the results of the correlation indicate this. They align to the conceptual framework. The highest positive correlation with income tax awareness is with tax knowledge ($r = 0.64$, $p < 0.01$), consistent with the literature that states factual knowledge is the most direct pathway to awareness. Tax education follows close behind ($r = 0.58$, $p < .01$), indicating that the relation between structured teaching and awareness is fairly direct. In line with the Theory of Planned Behavior (Ajzen, 1991), taxpayer attitude is also strongly linked to awareness ($r = 0.52$, $p < 0.01$). There is a moderate association between institutional and socio-demographic factors and awareness ($r = 0.44$, $p < 0.01$ and $r = 0.35$, $p < 0.01$). This is consistent with the concept of the Fischer et al. (1992) compliance model which proposes that when creating awareness, the role of the demographic and structural factors is not to create awareness per se, but to interact with attitude and knowledge in order to create awareness. The most useful result from a policy perspective is the strong relationship between tax education and tax knowledge ($r = 0.62$, $p < 0.01$). It demonstrates that the improvement of tax education at the college level is

likely to directly increase the tax knowledge of college teachers. This is supported by the respondents' preference for tax orientation that is structured as reflected in item TE5 (M = 4.00). By contrast, institutional context (M = 3.79) and socio-demographic influence (M = 3.69) had the lowest scores, and the least strong connections to awareness, meaning that respondents felt that these factors were present, but not central. The IC4 result (M = 3.69, 'some difficulty accessing tax information at work') indicates a genuine opportunity to be more proactive in distributing tax information at colleges. The levels of awareness reported here are closer to the levels reported from similar studies in relatively supportive environments, such as Hong Kong (Kwok & Yip, 2018), and the emerging economy sample studied by Appiah et al. (2024), than to the lower levels of awareness typically reported for the general taxpaying public in Nepal. The pattern also confirms the results of Holik and Mulyeni (2019), which found that the financial awareness of school teachers is fairly high, which is influenced primarily by attitude. Again, in this study, taxpayer attitude and tax knowledge are superior to institutional context and demographics in terms of inducing awareness. This is not reflective of the overall low tax awareness in Nepal. It argues, however, that a highly educated and formally salaried population, such as college professors, have a higher floor and that their task is not the personal knowledge and attitude, but institutional support, that explains that condition.

## 7. **Conclusion**

The main objective of this study was to measure the level of income tax awareness among the permanent faculty and part-time faculty of colleges of Kathmandu Valley and to find out the relationship between tax education, tax knowledge, attitude of taxpayers, socio-demographic factors and income tax awareness. As per the first objective, the overall income tax awareness of faculty members was found to be high with a composite mean

of 4.15 out of 5 with n = 100, and a positive attitude of faculty members towards paying tax with a composite mean of 3.85 out of 5 with n = 100 was also reported. To achieve the second objective, Pearson correlation revealed that all the five independent variables positively and significantly correlate with income tax awareness. The strongest links are taxpayer attitude (r = 0.52), tax education (r = 0.58) and tax knowledge (r = 0.64). The other factors are socio-demographic influence (r = 0.35) and institutional context (r = 0.44) but these are weaker and still significant. The Income Tax Act, 2058 (2002) presumes that the salaried taxpayers can do self-assessment of their income. The results of this study indicate that the assumption is largely true for the academic community sampled in Kathmandu Valley, but the low scores and weak correlations for institutional context suggest that there is definitely one area that requires attention, not a general rejection of the self-assessment approach. There is a strong relationship between the tax education points and tax knowledge, tax awareness also points in the same direction, structured and accessible tax education is the best medium to spread the income tax awareness among the college faculty in Nepal.

## Implications

The Inland Revenue Department may consider higher education institutions to be a specific tax paying entity and provide a few reminders through emails and social media, or even short notice periods or awareness programs in Nepali, conducted a few days to weeks prior to the tax compliance deadlines. Colleges may implement the appointment of a tax liaison officer or tax committee and include a brief tax training during staff induction. This can be especially relevant to part-time staff. Regarding curriculum, tax educators may include a brief lesson on personal taxation and financial literacy. Faculty development plans may be modified to include new teaching approaches. Subsequent

studies may include a regional sample from the rest of Nepal, and employ more advanced study protocols. There may be a comparative study of tax awareness across the various private and community campuses of Tribhuvan University.

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# Topic Modeling for Nepali Text

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**Abstract**

Topic Modeling identifies latent themes or topics within individual documents or collections of documents. By analyzing text, Topic Modeling detects patterns and relationships that reveal these underlying themes, offering valuable insights for decision-making in large datasets. Because most research has focused on Topic Modeling based on traditional techniques, and limited studies have explored its application in Nepali text, this research explores an innovative approach to topic modeling for Nepali text using BERTopic. The coherence score and Topic Diversity have been used as the evaluation criteria to explore the quality and interpretability of topics generated by BERTopic with the embedding model paraphrase-multilingual-MiniLM-L12-v2. The coherence Score and topic diversity were recorded as 0.58 and 0.85, respectively, using paraphrase-multilingual-MiniLM-L12-v2. This study concludes that BERTopic can effectively model Nepali text and extract coherent topics despite the unique challenges posed by the Nepali language.

**Keywords**: Topic Modeling, Nepali Text Analysis, Sentence Embedding, Multilingual Topic Extraction, Embedding-Based Clustering, BERTopic Modeling.

## 1. Introduction

The ability to make important inferences from vast amounts of unstructured text data has grown in significance in the era of information overload. The modeling of topics is a natural language processing (NLP) technique to identify obscure themes or subjects within a group of documents. There are many uses for this technique, including studying social media trends, comprehending customer inputs, and even conducting academic research (Kumar, 2024). Topic models have been demonstrated to be an efficient unsupervised method for identifying recurring topics and the underlying story in text. Conventional techniques like LDA (Latent Dirichlet Allocation) and Non-Negative Matrix Factorization (NMF) consider each text as a mixture of latent topics and describe it as a bag of words. A limitation of these models is that they neglect the semantic connections among words by employing bag-of-words representations. Due to the lack of consideration for sentence context, the bag-of-words input may not provide an accurate depiction (Grootendorst, 2022).

Topic models have been demonstrated to be an efficient unsupervised technique to recognize the underlying story in text. Many researchers working in the subject of topic modeling have conducted research to identify the abstract topics of the document utilizing a variety of statistical and probabilistic topic models as well as classical and traditional topic modeling techniques including LDA (Latent Dirichlet Allocation), LSA (Latent Semantic Analysis), NFA (Non-negative Matrix Factorization), and PLSA (Probabilistic Latent Semantic Analysis).

This research aims to apply topic modeling to Nepali text using BERTopic. Nepali, as a low-resource language in the NLP field, poses distinct challenges due to its intricate morphology, varied dialects, and limited annotated data. Despite these difficulties, advanced models like BERTopic offer the ability to capture the language's contextual subtleties more effectively. The main objective is to identify underlying themes within

Nepali news articles, offering insights into Nepal's socio-political, economic, and cultural contexts. By employing BERTopic, the research highlights how modern NLP methods can be effectively used for low-resource languages, contributing to the broader areas of language technology and computational linguistics. In addition to enhancing the understanding of topic modeling for Nepali news, this study seeks to expand the growing body of work on NLP applications for under-resourced languages.

NLP uses mapping sentences or short paragraphs to a dense vector space, where related sentences are near each other, are numerous. However, due to a lack of useful training data for other languages, the majority of sentence embedding models now in use are monolingual and typically only work with English. Few sentence embedding models are available for multilingual and cross-lingual contexts (Reimers & Gurevych, 2020). Although topic modeling techniques have advanced, there is still limited application of these methods to low-resource languages such as Nepali. Applying traditional methods to Nepali presents considerable challenges because they were created and tested mostly on high resource languages like English. These challenges are exacerbated by the language's complicated morphology, variety of dialects, and paucity of annotated datasets. This study aims to address the existing gap by exploring how BERTopic, a modern topic modeling technique, can effectively capture and analyze the latent themes within Nepali Text.

## 2. Literature Review

Authors in (Mutsaddi et al., 2025) explored the use of BERTopic for Hindi, a language closely related to Nepali linguistically. Their research evaluates BERTopic's performance in modeling short Hindi texts and compares it with other topic modeling methods. This study provides valuable methodological insights for adapting BERTopic to Nepali text. While topic modeling techniques have been extensively studied for global languages like English, Nepali, as a low-resource language, remains largely underexplored. This

research aims to enhance and refine topic modeling for Nepali text, addressing its unique linguistic and semantic complexities. By leveraging pre-trained models such as paraphrase-multilingual-MiniLM-L12-v2, the study contributes to NLP advancements for low-resource languages, showcasing the application and effectiveness of the model in a Nepali context.

The majority of this research has focused on classical and traditional topic modeling techniques such as LDA, NMF, and LSA (Egger & Yu, 2022). However, limited research has been conducted using BERTopic, developed in late 2020. To increase diversity between datasets, BERTopic was validated using three datasets: 20 Newsgroups, BBC News, and Trump's tweets. Two commonly used metrics, topic coherence and topic diversity, show how well the topic models in this study performed (Grootendorst, 2022). Authors in (Axelborn & Berggren, 2023) investigated how topic modeling techniques could be used to extract insights from social media data, especially Twitter tweets, about human behavior and societal events. They assessed the effectiveness of Top2Vec, BERTopic, Latent Dirichlet Allocation (LDA), and Non-Negative Matrix Factorization (NMF) as topic modeling methods. The results of (Egger & Yu, 2022) demonstrated the usefulness of BERTopic and NMF for social media data analysis, especially in the context of social research, and provided fresh insights into the interpretation of social phenomena using computational techniques.

The approach in (Bulut et al., 2022) offers a feasible mechanism for identifying overlapping topics and maintaining test quality, which can enhance human rater training and monitoring in such assessments. Through the use of coherence scores, the authors demonstrated that BERTopic consistently excelled in generating coherent topics, even from short and diverse Hindi Text (Mutsaddi et al., 2025). The main objective of this research is to generate a set of coherent and meaningful topics by using BERTopic from Nepali text and to evaluate the performance of the BERTopic model in addressing the unique linguistic challenges posed by the Nepali text.

## 3. Materials and Methods

### Data Collection

The dataset for this research was collected from ekantipur.com through web scraping, targeting a diverse range of Nepali text. This process involved extracting content from multiple categories, including politics, education, agriculture, sports, and others, to ensure a well-rounded representation of topics. The web scraping process generated approximately 3 GB of data, comprising around 50,000 articles, which serve as the foundation for the topic modeling analysis. The collected sentences were then stored in comma-separated values (CSV) format for efficient processing and analysis. The text was fragmented into individual tokens based on spaces and punctuation, ensuring that Nepali language syntax was handled correctly. Along with tokenization, other pre–processing steps such as removing digits, extra spaces were performed in this step. Nepali stop words such as 'को', 'छ', 'र', which don't contribute significantly to topic discovery.

**Table 1: Sample Nepali Text Dataset**

| S. N | Story |
|---|---|
| 1 | सुरुङ्गा) झापा — (सुनसरीको पकलीबाट इलामको कन्यामतर्फ वनभोजका लागि जाँदै गरेको बस आज बिहान पूर्वपश्चिम राजमार्गअन्तर्गत झापाको शिव सताक्षी नगरपालिका–७ मा दुर्घटना हुँदा १६ जना घाइते भएका छन् । |
| 2 | टेपरी) बाँके — (कटान नियन्त्रणका लागि हालै निर्माण गरिएको अधुरो पक्की तटबन्ध भत्काउँदै राप्ती नदीको धार गाउँतिर पसेपछि यहाँका १ सयभन्दा बढी घरपरिवार जोखिममा परेका छन्। |
| 3 | किभ) रोयटर्स — (युक्रेनका नयाँ राष्ट्रपति पेट्रो पोरोसेन्कोले क्रिमिया आफ्नै देशको अंग भएको, सधैं युक्रेनी भूभाग नै रहने बताएका छन् । उनले यति सजिलै क्रिमियालाई रुसमा गाभिएको नमान्ने सन्देश रुसलाई दिएका छन् । |
| 4 | काठमाडौं — गायिका जानुका राईको पहिलो गीति एलबम तथा भिडियो 'थिबिया 'सार्वजनिक भएको छ ।सभामुख ओनसरी घर्ती मगरले शनिबार राजधानीमा सुम्निमा कल्चर एकेडेमीद्वारा आयोजित समारोहमा सार्वजनिक गरेकी हुन् । |
| 5 | काठमाडौं — गीतकार तथा गायिका गायत्री थापाले तीजको मुखमा माइतीघरको झल्को एल्बम ल्याएकी छन् ।थापाको शब्द रहेको एल्बमको शीर्ष गीतको म्यूजिक भिडियो सार्वजनिक गरिएको छ । |

### Embedding

For this study, SBERT was used to generate contextual embeddings for each Nepali text corpus. SBERT enhanced the process of generating efficient sentence embeddings by modifying the original BERT model to handle sentence-pair tasks.

**Dimensionality Reduction**

UMAP was applied to the SBERT embedding generated by BERTopic (which supports UMAP by default) to reduce its dimensionality from 384 to a more manageable space. This step supported the improvement of clustering performance and was key for visualizing the topic structure. It helped condense that high-dimensional embedding from BERTopic into a lower-dimensional space for better clustering performance.

**Clustering**

The dimensionality-reduced embedding were essential to be clustered using a clustering algorithm. HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) was applied to the UMAP (Uniform Manifold Approximation and Projection) - reduced embedding to identify dense clusters.

**Topic Representation**

Every cluster created represented a topic. BERTopic then utilized the words from the text corpus within each cluster to identify representative keywords for each topic. These keywords aided in the interpretation and labeling of the topics.

**Evaluation**

To assess the quality and effectiveness of the BERTopic model in generating meaningful topics from Nepali text data, two primary evaluation metrics were used: topic coherence and topic diversity.

Topic coherence measures the semantic consistency of words within a topic. A well-coherent topic consists of words that frequently co-occur in the dataset and share similar meanings.

$C_v = \frac{1}{|W|} \sum_{w_i \in W} \sum_{w_j \in W, j \neq i} f(V(w_i), V(w_j)).NPMI(w_i, w_j)$

Where,

W = Set of top-N words in a topic

$w_i$, $w_j$ = Words in the topic

$(V(w_i), V(w_j)$ = Vector embedding of words $w_i$, $w_j$

f (V ($w_i$), V($w_j$)) = cosine similarity between word embeddings

The NPMI score is given by

$$\text{NPMI } (w_i, w_j) = \frac{\log \frac{P(w_i, w_j)}{P(w_i), P(w_j)}}{-\log P(w_i, w_j)}$$

Where,

P ($w_i$, $w_j$) is the probability of seeing both words in the same document.

P($w_i$) and $P(w_j)$ are the probabilities of each word appearing in the corpus.

Topic diversity assesses the degree of topic diversity as well as the presence of topic duplication. The fraction of unique terms across all themes is known as topic diversity.

$$\text{Topic Diversity} = \frac{Unique\ words}{Total\ Words}$$

Total words = N * Number of Topics.

Unique words = the count of distinct words in the top-N words across all topics.

**Implementation Environment**

The implementation was carried out using Python with the Hugging Face Transformers library. Experiments were executed on Google Colab, leveraging GPU acceleration for efficient model training and evaluation.

## 4. Results and Discussion

The implementation of BERTopic on Nepali Text data successfully identified meaningful topics using SBERT embedding, UMAP for dimensionality reduction, and HDBSCAN for clustering. The topics generated were both coherent and diverse, as shown in the following Table 2.

**Table 2: Topics identified by BERTopic**

| S. N | Topic | Count | Name | Representation | Representative_Docs |
|---|---|---|---|---|---|
| 0 | -1 | 203 | 1_तिनले_किनकि_रोगको_सहरी | तिनले, किनकि, रोगको, सहरी, प्रकाशित चैत्र, वि... | काठमाडौँ मेरो मूल चिनारी भूतपूर्व कर्मचारी र.. |
| 1 | 0 | 231 | 0_भनिन्छ_सम्पदा_भाषामा_समुदायमा | भनिन्छ, सम्पदा, भाषामा, समुदायमा, बनाएका, परम | काठमाडौँ ङवाङ छिरिङ शेर्पा ट्रेकिङ गाइड बन्न... |
| 2 | 1 | 109 | लकडाउनको_सडकमा_गाउँमा_थाल्यो | लकडाउनको, सडकमा, गाउँमा, थाल्यो, लकडाउन, लेख्. | काठमाडौँ तब राजाले ठूलो निञा निसाप हेर्नु अन्... |
| 3 | 2 | 95 | प्रकाशित आश्विन_भारतका_शैलीमा_पुस्तकमा | प्रकाशित आश्विन, भारतका, शैलीमा, पुस्तकमा, सं. | काठमाडौँ तीन दशकदेखि नेपाली संगीतमा फरकपनसहित.. |
| 4 | 3 | 46 | भारतका_मानवीय_चीनले_प्राथमिकतामा | भारतका, मानवीय, चीनले, प्राथमिकतामा, घटनाको, | काठमाडौँ सदा झैं कार्यालय समयमा फुर्सद निकाले.. |
| 5 | 4 | 45 | लकडाउनको_भाइरसको_कोरोना भाइरसको_महामारीको | लकडाउनको, भाइरसको, कोरोना भाइरसको, महामारीको | काठमाडौँ मान्छेलाई रोग र भोकको समस्या एकैचोटि.. |
| 6 | 5 | 44 | भौगोलिक_पृथ्वीको_फोहोर_मात्रामा | भौगोलिक, पृथ्वीको, फोहोर, मात्रामा, मानवीय, व.. | केही दशकअघि काठमाडौंमा अहिलेको तुलानामा धेरै |
| 7 | 6 | 44 | भनिन्छ_जीवनको_आमाको_मृत्युको | भनिन्छ, जीवनको, आमाको, मृत्युको, सम्पदा, महिल | काठमाडौँ जोन काठ भन्छन् एक आदर्श पात्र हुनु श |
| 8 | 7 | 38 | सोझै_सालको_अर्थमा_वैकल्पिक | सोझै, सालको, अर्थमा, वैकल्पिक, इतिहासको, तिनल | काठमाडौँ फागुन सात म सात सालमा लिम्बुवानको एउ |
| 9 | 8 | 29 | व्यावहारिक_देखिँदैन_गैरकानुनी_सिक्ने | व्यावहारिक, देखिँदैन, गैरकानुनी, सिक्ने, सीप,... | काठमाडौँ घरको काममा सिन्कोसमेत भाँच्न लगाएको... |

Table 2 summarizes the outcomes of topic modeling conducted on a Nepali text dataset using BERTopic. Each topic is identified by a unique label (e.g. -1,0,1, etc.), along with the document count (Count) , topic titles derived from key terms, representative keywords(Representation), and sample extracted from the text (Representative_Docs). Topic -1 represents outlier or unclustered data, while topics 0 through 8 highlight distinct

themes, such as health and urban issues (“रोगको”, "सहरी") and cultural or societal matters (“सम्पदा”, “भाषामा”).

**Evaluation:**
The coherence score and topic diversity for the model were calculated and expressed in Table 3.

**Table 3:**
*Topic coherence score and topic Diversity From BERTopic*

| Method | Coherence Score(C_V) | Topic Diversity (TD) |
|---|---|---|
| With KeyBERT-Inspired | 0.58 | 0.85 |
| Without KeyBERT | 0.44 | 0.72 |

The results show that when KeyBERT was applied, the Coherence Score improved to 0.58, indicating better semantic alignment and interpretability of topic keywords. Similarly, Topic Diversity increased to 0.85, demonstrating a reduction in overlapping terms across topics and improved uniqueness. Without KeyBERT, the Coherence Score dropped to 0.44, reflecting weaker relationships among topic terms, and Topic Diversity decreased to 0.72, indicating higher redundancy. These results confirm that incorporating KeyBERT– inspired methods significantly enhances the quality of topic modeling for Nepali text by generating more contextually accurate and diverse topics.

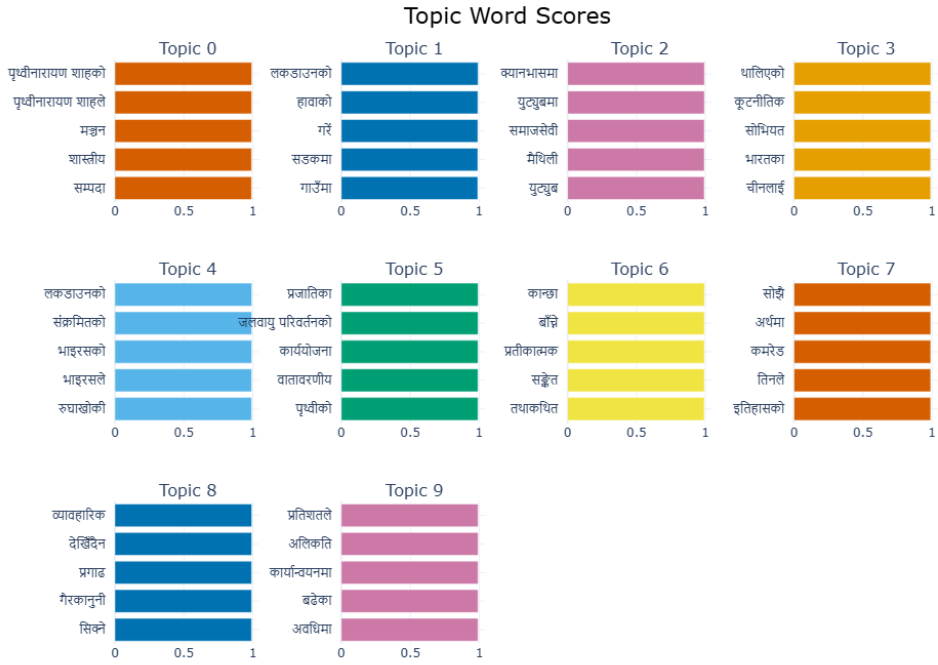


**Figure 1: Bar chart of Top 10 Topics**

As shown in the bar chart in Figure 1, there are still some repeated words and stop words present in the representative topics. Therefore, effective tokenization and lemmatization techniques for Nepali could improve topic quality.

## 5. Conclusion

In this study, the BERTopic topic modeling technique was applied to analyze Nepali text data. The model's performance was evaluated using coherence scores and topic diversity, which indicated that the topics generated were meaningful and distinguishable.

Although the calculated scores are satisfactory, they could be improved further according to the findings of other researchers. To enhance performance, additional preprocessing steps, such as the inclusion of stemming, could be applied in the analysis. Additionally, exploring alternative embedding models may improve the model's ability to generate

more contextually relevant topics. Furthermore, expanding the dataset and incorporating other machine learning techniques for the clustering process and dimensionality reduction techniques could enhance the model's performance and adaptability, allowing it to better handle a broader range of Nepali text data using the BERTopic model.

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The authors confirm that they have no competing interests to declare.

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# Performance Evaluation of Machine Learning Techniques for Ransomware Detection: A Comparative Analysis

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**Abstract**

In today's fast-paced digital world, application security has become an essential aspect for protecting organizations from increasing cyber-attacks and data breaches. Among these threats, ransomware is one of the most destructive malwares that attacks vulnerabilities of applications and systems through phishing, outdated software, and other insecure system configurations. As ransomware attacks are constantly evolving and traditional detection methods are not always capable of detecting attacks quickly and accurately, this study comparatively evaluate different machine learning (ML) algorithms for ransomware detection in terms of precision, recall, accuracy, F1-score, ROC-AUC, and logarithmic loss. The experimental results show that the Support Vector Machine (SVM) model shows better results than other classifiers. It has 97.73% precision, 96.00% recall, 98.00% accuracy, 97.00% F1-score, and the lowest logarithmic loss of 0.082, demonstrating superior effectiveness. The findings aim to strengthen application security, increase public trust in the digital ecosystem, and safeguard sensitive personal and institutional data.

**Keywords:** Ransomware Detection, Machine Learning, Malware Detection, Data Protection, Risk Assessment, Cybersecurity, Comparative Analysis.

# 1. Introduction

## 1.1 Background of the research

Safeguarding information and identifying vulnerabilities have remained critical concerns for organizations across industries for many years. However, managing cyber risks and maintaining comprehensive information technology (IT) infrastructures have become increasingly complex. According to IBM, the average global cost of a data breach reached $4.45 million in 2023, which is a 15% increase over the past three years. In response to data breaches, over half of organizations are planning to boost their security expenditures, focusing on areas such as incident response planning, staff training programs, and advanced tools for identifying and mitigating threats. It is noteworthy that companies employing artificial intelligence (AI) and automation for security purposes save an average of $1.76 million more than those that do not incorporate these technologies (IBM, 2023).

In the field of cybersecurity, ransomware has seen remarkable growth and transformation over the past decade, outpacing many other threats. Ransomware is a type of malicious software (malware) that restricts access to a victim's system or data. It is usually delivered through phishing emails or drive-by downloads, where users unintentionally visit compromised websites, leading to automatic installation of the malware. The rise in ransomware can be partly linked to the COVID-19 pandemic, which accelerated remote work and merged personal and professional digital environments, creating new opportunities for cybercriminals. As employees began accessing networks beyond cybersecurity (CS) measures, ransomware attackers were able to exploit additional vulnerabilities (Norman, 23 Jul 2024).

In Nepal, as in many other countries, ransomware attacks have surged over the past few years. Notably, in June 2017, Turkish hackers breached the official website of the Department of Passport, delivering a stark warning to reveal confidential government information (Ghimire, July 24, 2017). Similarly, in September 2025, a ransomware group

known as TheGentlemen targeted the Instituto Socio-Económico Comunitario (INSEC), a prominent NGO in Nepal. Attackers claimed responsibility for encrypting and threatening to leak sensitive organizational data unless negotiations were initiated with them. This incident reflects how ransomware groups are not just targeting corporations globally but also civil society and nonprofit organizations within Nepal (DeXpose, September 18, 2025).

The detection of ransomware is particularly difficult compared to general malware, as the number of ransomware variants with unique signatures continues to rise. Although ransomware may initially appear to be a simple form of cyberattack, it employs complex and continuously evolving techniques that significantly delay detection and prolong recovery processes.

However, despite the growing adoption of ML-based solutions, existing studies often focus on individual algorithms or limited performance comparisons, in terms of detection accuracy, computational efficiency, and adaptability to emerging ransomware variants. This study aims to address limitations by conducting an in-depth comparative analysis of four widely used classification algorithms: Decision Tree (DT), Logistic Regression (LR), Naïve Bayes (NB), and Support Vector Machine (SVM).

### 1.2 Significance of the Research

This research is significant for guiding organizations toward the selection of the most effective ML models for ransomware detection by providing a comprehensive performance evaluation. It aims to enhance understanding of the strengths, weaknesses, and trade-offs associated with various ML techniques, thereby supporting informed decision-making in cybersecurity strategy.

Moreover, the study provides valuable insights into relevant security standards and frameworks. By highlighting potential gaps in existing detection methods, this research contributes to the development of improved practices and guidelines for mitigating ransomware threats. Ultimately, the findings serve as a foundational reference for both

practitioners and researchers, supporting the advancement of academic work and the evolution of technologies in the field of ransomware detection.

## 2. Review of The Literature

### 2.1 Previous Work

In 2021, Omar Shamil Ahmed and Omar Abdulmunem Ibrahim Al-Dabbagh presented the paper “Ransomware Detection System Based on Machine Learning” that aimed at improving the detection of ransomware on Android smartphones by monitoring the network traffic. With the CICAndMal2017 dataset, the authors tested six machine learning (ML) algorithms, such as Decision Tree (DT), Random Forest (RF), and eXtreme Gradient Boosting (XGBoost). The classifiers that showed best results in distinguishing ransomware from benign applications were Decision Tree (DT) and eXtreme Gradient Boosting (XGBoost) with detection accuracy of 99.30% and 99.20% respectively. This study highlighted the significance of data preprocessing, feature selection and dynamic analysis in improving the ransomware detection performance. Additionally, the authors recommended for future research that they extend the detection framework to other malware families and include other characteristics such as memory dumps and API calls information to increase the robustness and generalizability of ransomware detection systems (Ahmed & Ibrahim Al-Dabbagh, 2021).

Indra Chaudhary and Suyash Adhikari presented the paper on "Ransomware Detection Using Machine Learning Techniques" in 2024, dealing with the increasing menace of ransomware attacks. The UG Ransom dataset was used to compare the performance of three classifiers: Decision Tree (DT), Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP). Evaluations of the models were performed using the accuracy, precision, recall and F1-score. The experimental results indicated that DT performed better than SVM and MLP with accuracy 98.83% and precision, recall and F1 score 99.41%. The study showed the effectiveness of the Decision Tree (DT) approach to the extraction of complex non-linear relationships in ransomware data. Additionally, the

authors suggested future studies use wider data sets, apply ensemble learning methods, consider adversarial machine learning methods, and create real-time detection of ransomware systems to enhance detection accuracy and robustness (Chaudhary & Adhikari, 2024).

Herrera-Silva and Hernández-Álvarez suggested a dynamic feature-based dataset for ransomware detection in 2023, which utilizes machine learning techniques. The authors processed JSON files created by ransomware and goodware (non-ransomware) artifacts from a sandbox environment and extracted 326 dynamic features from the artifacts. Later they chose 50 relevant and non-redundant features to create a 2000-sample dataset. Random Forest (RF), Gradient Boosted Regression Trees (GBRT), and Artificial Neural Networks (ANNs) were used to analyze the dataset. The detection accuracy for the experimental results was obtained to be more than 99% by performing 10-fold cross validation. The study proved that dynamic analysis could effectively detect ransomware even before the file encryption process had started, making it an effective tool for early ransomware detection (Herrera-Silva & Hernández-Álvarez, 2023).

Recently, Madani et al. conducted a study of ransomware classification employing neural network-based techniques in the year 2022. The study successfully used a Multi-Layer Perceptron (MLP) for binary classification of benign software and malware using a set of 465 files, with an accuracy of 100%. CNNs and RNNs were also tested for classification of ransomware families with the CNN outperforming the MLP with accuracy of 94% and the RNN with 79%. The study found that CNNs performed the best in ransomware classification but noted that there were some drawbacks to the model, such as the limited size of the dataset and the lack of interpretability of deep learning (DL) models. The authors proposed that the data set can be extended and other machine learning algorithms can be investigated to enhance the detection of the algorithm (Madani et al., 2022).

Umara Urooj et al. conducted a study titled "Ransomware Detection Using Dynamic Analysis and Machine learning" to address the challenges of detecting ransomware across

various platforms. The research highlighted the limitations of static analysis and emphasized the effectiveness of dynamic analysis combined with machine learning and deep learning techniques. By reviewing studies from 2019 to 2021 and utilizing datasets from sources like VirusTotal and VirusShare, the study demonstrated the potential of advanced algorithms to detect unseen ransom ware variants, including zero-day threats. The findings proposed a framework for integrating dynamic analysis, enriched datasets, and machine learning to enhance detection accuracy and resilience against evolving ransomware attacks (Urooj et al., 2021).

In 2024, Daniel Ajiga et al. gave a presentation titled “Designing Cyber-security Measures for Enterprise Software Applications to Protect Data Integrity”. The research was dedicated to the issues of data integrity in enterprise software applications and how they are facing new cyber threats. The authors recommended a comprehensive strategy comprising of risk assessment, encryption, access control, secure coding, and incident response planning. The major approaches included were Security throughout the Software Development Lifecycle (SDLC) and the use of Machine Learning (ML) for proactive threat detection. The framework also highlighted the importance of conducting frequent security audits and providing training for employees to ensure strong cyber security practices. The research underscored the need for a holistic and flexible cybersecurity approach to bolster data safeguards, and bolster enterprise resilience to advanced cyber threats (Ajiga et al., 2024).

In 2022, Alsaidi et al. proposed a ransomware detection model using machine learning and DL techniques. The study introduced the Ransomware Detection Dataset (RDD), comprising 405,836 malicious and benign URL records. The authors evaluated Random Forest (RF), Gradient Boosting (GB), Artificial Neural Networks (ANNs), and Long Short-Term Memory (LSTM) models for URL classification. They also introduced a new feature, "Start with https://www," which improved classification performance. The

proposed approach achieved an accuracy of 99.8% in malicious URL detection while maintaining computational efficiency(Alsaidi et al., 2022) .

While the examined studies showed that ML and DL approaches could be very effective for ransomware detection, most of them focussed on high ransomware classification accuracy. The algorithms that consistently achieved an accuracy of over 98%, were DT, RF, eXtreme Gradient Boosting (XGBoost) and Convolutional Neural Networks (CNNs). There are, however, a few studies that use specific datasets with less diversity, which makes it difficult to evaluate the generalizability of the models to new ransomware variants. Furthermore, numerous studies primarily addressed the accuracy, with fewer studies offering in-depth analysis of the computational efficiency, model interpretability and complete evaluation measures such as log loss, which are relevant to real-world cybersecurity deployment. Although some previous studies have reported highly effective results, a detailed comparison of the performance of traditional machine learning algorithms for the detection of Windows Portable Executable (PE) based ransomware is still lacking. Although many existing studies were concentrated on Android ransomware, URL-based detection or DL approaches, few studies compared the conventional classifiers systematically by the same preprocessing and evaluation at the same time. Moreover, most studies focused on accuracy, with little attention given to other performance metrics such as precision, recall, f1-score and log loss. To fill these gaps, the current study conducted a comparative study of LR, DT, SVM, and Gaussian Naïve Bayes (GNB) classifiers on the ransomware dataset of Windows PE and using various evaluation metrics, to get more detailed information about the performance of the classifiers.

## 3. Research Methods

### 3.1 Research Design

The research design is the framework that guides the systematic execution of the entire study.

The overall workflow of the proposed methodology is shown in figure 1.

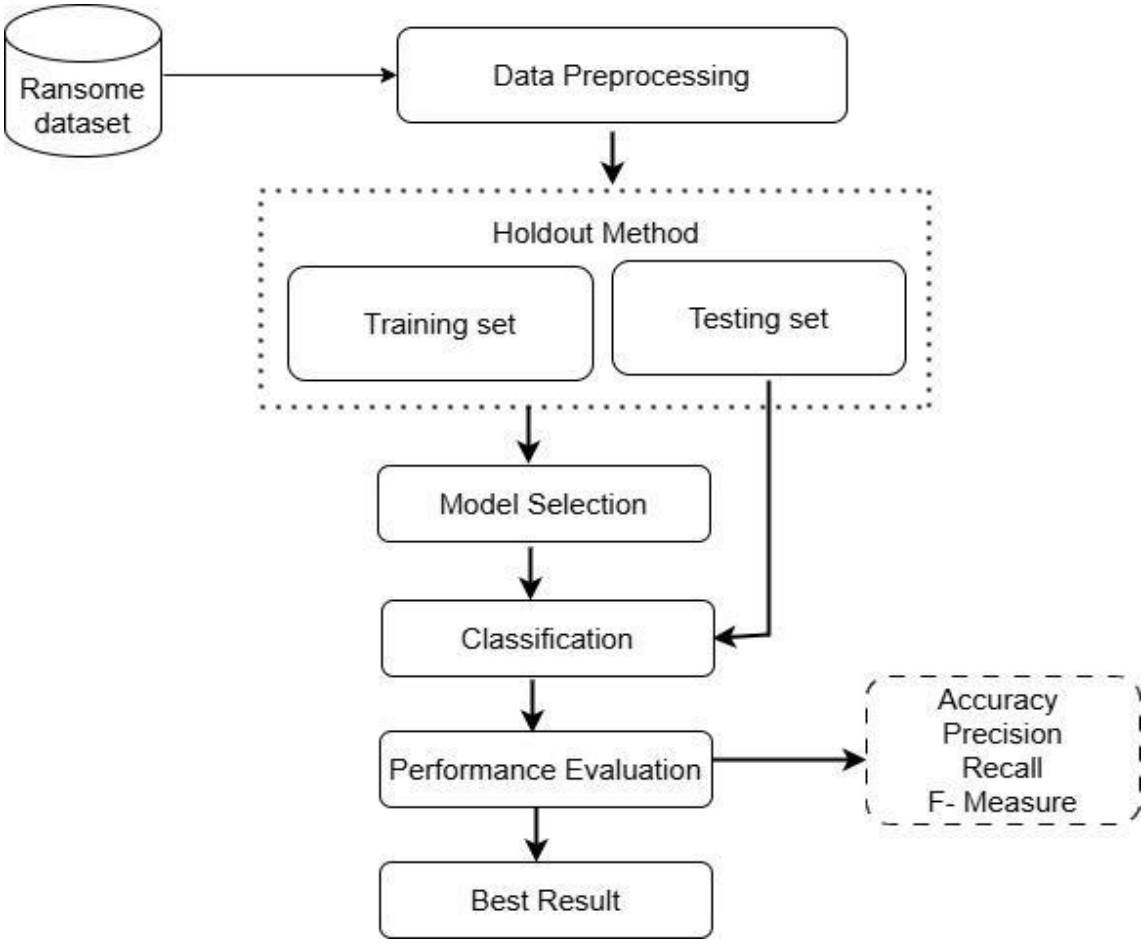



**Figure 1. Block Diagram of Research Framework**

This study uses a **quantitative experimental methodology** to train and evaluate multiple ML algorithms for ransomware detection.

### 3.2 Dataset Information

The dataset used in this research was obtained from a publicly accessible Kaggle repository. It contains labelled samples of both ransomware and benign software, enabling effective training and evaluation of classification models. It includes features extracted from Windows Portable Executable (PE) files, with files identified using VirusShare hashes. While the full dataset has approximately 62,000 .exe and .dll samples, this study focuses on ransomware. Most features are continuous, real-valued attributes, providing quantitative insights into file structure and behavior, making them suitable for statistical modeling and classification. A preview of the dataset is presented below.

**Table 1:**

*Parameter Description*

| Parameters | Description |
|---|---|
| FileName | Name or identifier of the PE file |
| md5Hash | MD5 hash of the file for unique identification |
| Machine | Target machine architecture identifier |
| DebugSize | Size of debug information |
| DebugRVA | Relative Virtual Address of debug information |
| MajorImageVersion | Major version number of the image |
| MajorOSVersion | Major version number of required operating system |
| ExportRVA | Relative Virtual Address of export table |
| ExportSize | Size of export table |
| IatVRA | Relative Virtual Address of Import Address Table |
| MajorLinkerVersion | Major version number of linker |
| MinorLinkerVersion | Minor version number of linker |
| NumberOfSections | Number of sections in the PE file |
| SizeOfStackReserve | Size of stack to reserve |
| DllCharacteristics | DLL characteristics flags |
| ResourceSize | Size of resource section |
| BitcoinAddresses | Number of potential Bitcoin addresses found |
| Benign | Binary label (1 for benign, 0 for malicious) |

### 3.3 Data Pre-processing

To ensure dataset quality and relevance, several preprocessing steps were conducted. Initially, features that held no predictive value, such as FileName and md5Hash were removed. and duplicate or incomplete records were eliminated to maintain data integrity. These fields, although useful for record identification, do not carry meaningful information for learning algorithms and may adversely affect model performance if retained. Duplicate entries and records containing missing values were also removed to ensure data integrity. After cleaning, the dataset was carefully balanced to include an equal proportion of ransomware and benign samples. This is important in balancing the dataset as it ensures that the model is trained on an equitable distribution of classes, thereby reducing the likelihood of overfitting and mitigating bias in predictive outcomes. Finally, all feature values were normalized using Min-Max scaling to ensure numerical stability and improve the performance of subsequent machine learning algorithms. The pre-processed data served as input for model training and evaluation.

### 3.4 Holdout Method

The ML models were evaluated using the holdout method. A 90:10 split was applied, allocating 90% of the data for training and 10% for testing. This ratio maximizes training data to enhance model learning and generalization, while ensuring a robust evaluation of performance on unseen samples.

### 3.5 Model Selection

The selection of algorithms depends on the dataset and the type of prediction required. In this research, four ML algorithms are chosen for their proven effectiveness in classification and ability to handle structured data. The models were selected based on evidence from previous research showing their accuracy in handling complex datasets,

including ransomware-related data. Each of these models is mathematically formulated and set up as described below:

**Naive Bayes (NB)**

In this experiment, GNB is used due to its suitability for continuous features, if values within each class follow a normal distribution. In GNB, the likelihood is modelled using the probability density function (PDF) of the Gaussian (normal) distribution:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (1)$$

Where,

- x is the feature value,
- μ is the mean of the feature values
- σ is the standard deviation of the feature values for that class,
- π is a constant (approximately 3.14159),
- e is the base of the natural logarithm.

**Support Vector Machines (SVM)**

SVM is a powerful supervised machine learning method that is frequently used to applications including outlier detection, regression, and classification. In ransomware detection, SVM finds the best hyperplane in the feature space to distinguish between ransomware activity and regular system activity (Huang et al., 2018). The decision function of SVM can be represented as:

$$f(x) = w^{T\phi(x)} + b \quad (2)$$

Where,

- represents the **weight vector**.
- $x$represents the **input feature vector**.
- $\phi(x)$represents the **feature transformation (kernel mapping) function**, which maps the input data into a higher-dimensional feature space.

- $b$ represents the bias (intercept) term.

**Logistic Regression (LR)**

For this research, the model was trained on the training set of the data, X train containing feature vectors and y train containing class labels. The parameters of the model are optimized during training to minimize the logistic loss function. The sigmoid function is employed as the activation function to transform the output probabilities, ensuring stable model training and reliable classification performance. The probability of a sample being in the positive class is: :

$$P(\mathrm{y} = 1 \mid \mathrm{x}) = \frac{1}{1+\mathrm{e}^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n)}} \qquad (3)$$

Where,

- P(y=1|x) denotes the probability that the dependent variable y belongs to the positive class given the input features x.
- β0 is the intercept (bias) term of the model.
- X = (x1, x2,…,xn) represents the input feature vector.
- β1, β2,…,βn are the coefficients (weights) associated with the corresponding input features.
- e = Euler's number (approximately 2.71828).

**Decision Tree (DT)**

In this study, CART (Classification and Regression Tree) -based DT classifier has been used in this study for the detection of ransomware. The CART algorithm is a recursive partitioning algorithm which splits the feature space binary according to the Gini criterion. The default hyperparameter values were used, and the splitting criterion was Gini impurity, the splitter strategy was best split, the number of samples that can be split

was unlimited, and the minimum number of samples to split was two, with one being a leaf node.

The mathematical formulation for Gini impurity can remain:

$$\text{Gini}(\text{D}) = 1 - \sum_{\text{i}=1}^{\text{n}} \text{p}_\text{i}^2 \qquad (4)$$

Where,

- $Gini(D)$= Gini impurity of dataset $D$
- $p_i$= Proportion (probability) of samples belonging to class $i$
- $n$= Total number of classes

The best split is selected by minimizing the weighted impurity:

$$\text{Gini}_{\text{split}} = \frac{|\text{D}_1|}{|\text{D}|}\text{Gini}(\text{D}_1) + \frac{|\text{D}_2|}{|\text{D}|}\text{Gini}(\text{D}_2) \qquad (5)$$

**Where:**

- $Gini_{split}$= Gini impurity after splitting the dataset.
- $D$= The original dataset before the split.
- $D_1$= The first subset (left child) created after the split.
- $D_2$= The second subset (right child) created after the split.
- $|\ D\ |$= Total number of samples in the original dataset.
- $|\ D_1\ |$= Number of samples in subset $D_1$.
- $|\ D_2\ |$= Number of samples in subset $D_2$.
- Gini($D_1$)= Gini impurity of subset $D_1$.
- Gini($D_2$)= Gini impurity of subset $D_2$.

### 3.5.1 Hyperparameter Settings

To ensure reproducibility and fair comparison between the ML models, default hyperparameters from the Scikit-learn library were used, unless modifications were necessary for the implementation of the model. A DT classifier was implemented using the CART algorithm and the default criterion of Gini impurity. SVM model is trained with a Radial Basis Function (RBF) kernel and the probability estimation option enabled to produce the prediction probabilities required for log loss evaluation. GNB was set to default variance smoothing parameter. A fixed random state (random_state = 42) was also used where applicable to ensure consistent and reproducible experimental results. Full model configurations and hyperparameter values are provided in Table 2: -

**Table 2:**

*Hyperparameter Settings of the ML Models*

| **Model** | **Variant Used** | **Hyperparameter** | **Value** |
|---|---|---|---|
| LR | Binary | Solver | Default (lbfgs) |
| | | Penalty | L2 (default) |
| | | Maximum iterations (max_iter) | 1000 |
| | | Regularization parameter (c) | 1.0 (default) |
| | | Random state | 42 |
| | | Fit intercept | True (default) |
| | | | |
| DT | CART | Criterion | Default (gini) |
| | | Random state | 42 |
| | | | |
| SVM | RBF kernel | Kernel | RBF |
| | | Regularization parameter (c) | Default (1.0) |
| | | Kernel coefficient (gamma) | Default (scale) |
| | | | Enabled (True) |

| | | | |
|---|---|---|---|
| | | Probability estimation | |
| | | Random state | 42 |
| | | | |
| NB | Guassian | Variance smoothing (var_smoothing) | Default ($1 \times 10^{-9}$) |

### 3.6 Performance Evaluation

After compilation, predictions were performed on the test data to evaluate the performance of all four models using the confusion matrix and ROC–AUC score, computed through confusion_matrix(y_test, y_pred) and roc_auc_score(y_test, y_prob). The evaluation process will include the following steps:

#### 3.6.1 Evaluation Metrics

The performance of ML models is evaluated using evaluation metrics. These metrics help in understanding how well a model performs in terms of its ability to make accurate predictions.

#### 3.6.2 Confusion matrix

Confusion matrix is a table with combination of actual and predicted values made by a classifier. It can be used to evaluate the performance of a classification model through the calculation of performance metrics like accuracy, precision, recall, and F1-score.

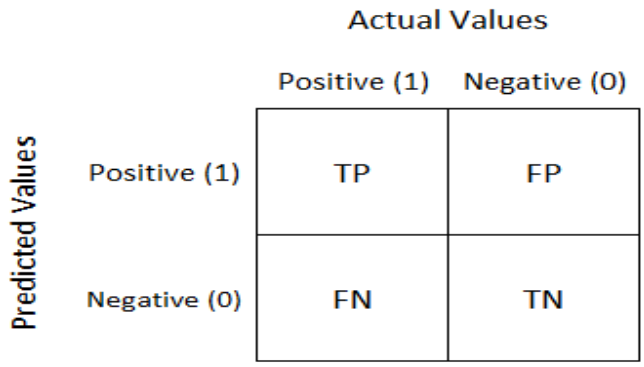



**Figure 2. Standard form of confusion matrix**

### 3.6.3 Classification Accuracy

Accuracy is a performance metric that quantifies how well a model correctly predicts outcomes. It is defined by:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \qquad (6)$$

### 3.6.4 Precision

Precision evaluates the accuracy of a model's positive predictions. It is calculated by using equation 7 formula:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (7)$$

### 3.6.5 Recall

Recall measures how many of the actual positive cases were correctly identified by the model. A high recall value indicates that the model is effective at detecting positive instances, minimizing missed positive cases (false negatives) and is given as:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (8)$$

### 3.6.6 F score

It represents the harmonic mean of precision and recall, balancing both metrics to provide a single evaluation of the model's effectiveness. The score is given by:

$$\mathbf{F\_1 - score} = \frac{\mathbf{2 * Precision * Recall}}{\mathbf{Precision + Recall}} \quad (9)$$

### 3.6.7 ROC-AUC (Receiver Operating Characteristic - Area Under Curve)

The AUC-ROC curve is a graphical tool that illustrates the performance of a binary classification model at various threshold levels. The curve plots the true positive rate against the false positive rate, helping assess the model's ability to make accurate classifications. The AUC value ranges from 0.5 to 1.0, where a value of 0.5 indicates the performance of a random classifier, and a value of 1.0 represents a perfect classifier.

### 3.6.8 Logarithmic Loss (Log Loss)

Logarithmic Loss, also referred to as Log Loss or Cross-Entropy Loss, is an essential metric in ML, especially for evaluating classification problems. Unlike metrics like accuracy, Log Loss considers the uncertainty in predictions and imposes a higher penalty on models that make confident yet incorrect predictions. The formula for Log Loss is given by:

$$Log\ Loss = \left(-\frac{1}{N}\right) \backslash sum_{i=1}^{N} \left(y_i log(p_i) + (1 - y_i) log(1 - p_i)\right) \quad (10)$$

Where:

N → Total number of samples

y_i → True label of sample i (0 or 1)

p_i → Predicted probability that the label is 1

log → Natural logarithm

The minus sign ensures the loss is positive, and smaller values mean better predictions.

### 3.7 Tools Used

The experiments were carried out in Google Colaboratory (Google Colab), is a cloud-based platform provided by Google that enables users to write and execute Python code in a browser (Bisong, 2019). The Scikit-learn library was used mainly for the ML algorithms, feature processing, splitting the dataset and evaluating the model performance with classification metrics like accuracy, precision, recall, f1_score, confusion_matrix, roc_auc and log loss. Pandas and NumPy were used for data handling, numerical computation, and dataset preprocessing. Finally, Matplotlib and Seaborn were employed to create plots and visualizations of experimental results.

## 4. Result and Analysis

This section presents and analyses the performance of four supervised learning algorithms LR**,** DT**,** SVM, and GNB which were evaluated using accuracy, precision, recall, F1-score, log loss, and AUC-ROC with a 90:10 train–test split to assess their effectiveness in ransomware detection.

### 4.1 Confusion Matrix Analysis

The confusion matrix offers detailed analysis by showing True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values for the number of ransomware and benign samples correctly classified. These results can be used to analyse the capability of each model to detect ransomware instances and minimize classification errors.

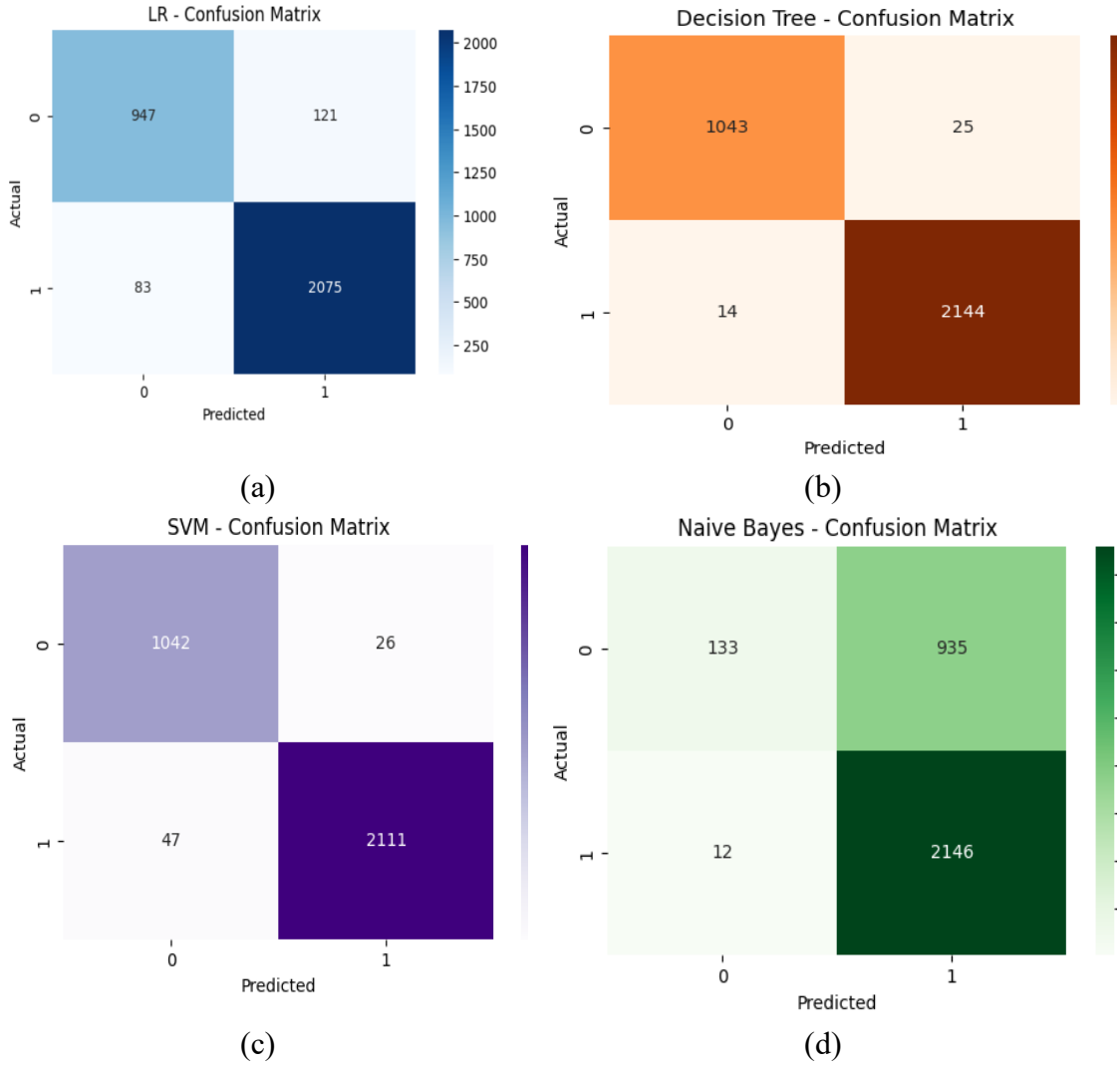


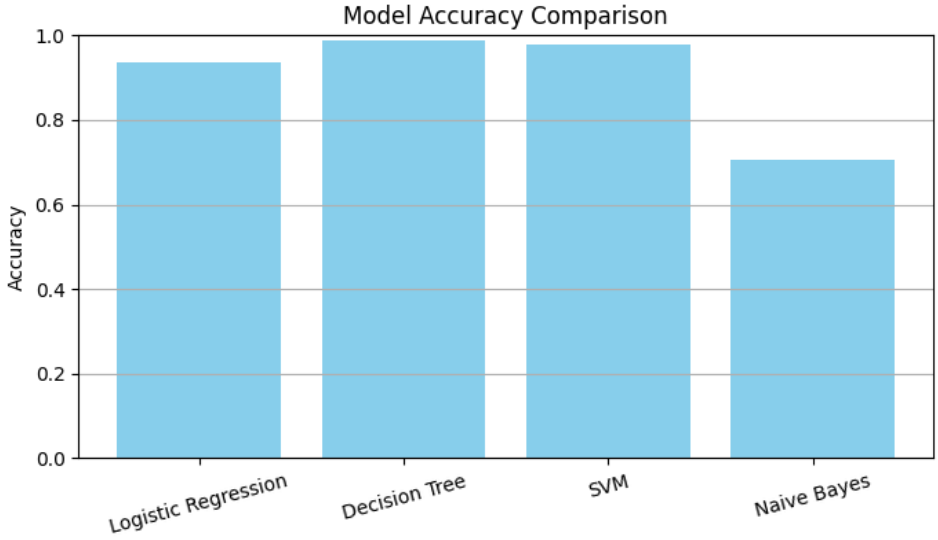

**Figure 3. Confusion matrices of the evaluated machine learning models: (a) LR, (b) DT, (c) SVM, and (d) GNB.**

The numerical values obtained from the confusion matrices are summarized in Table 3.

**Table 3:**

*Performance of Machine Learning Models*

| S.No | Algorithms | Accuracy (%) | Precision (%) | Recall (%) | F-Measure (%) | Log Loss |
|---|---|---|---|---|---|---|
| 1 | LR | 93.68 | 92.00 | 89.00 | 90.00 | 0.168 |
| 2 | DT | 98.79 | 99.00 | 98.00 | 98.00 | 0.424 |
| 3 | SVM | 97.73 | 96.00 | 98.00 | 97.00 | 0.082 |
| 4 | GNB | 70.64 | 92.00 | 12.00 | 22.00 | 1.496 |



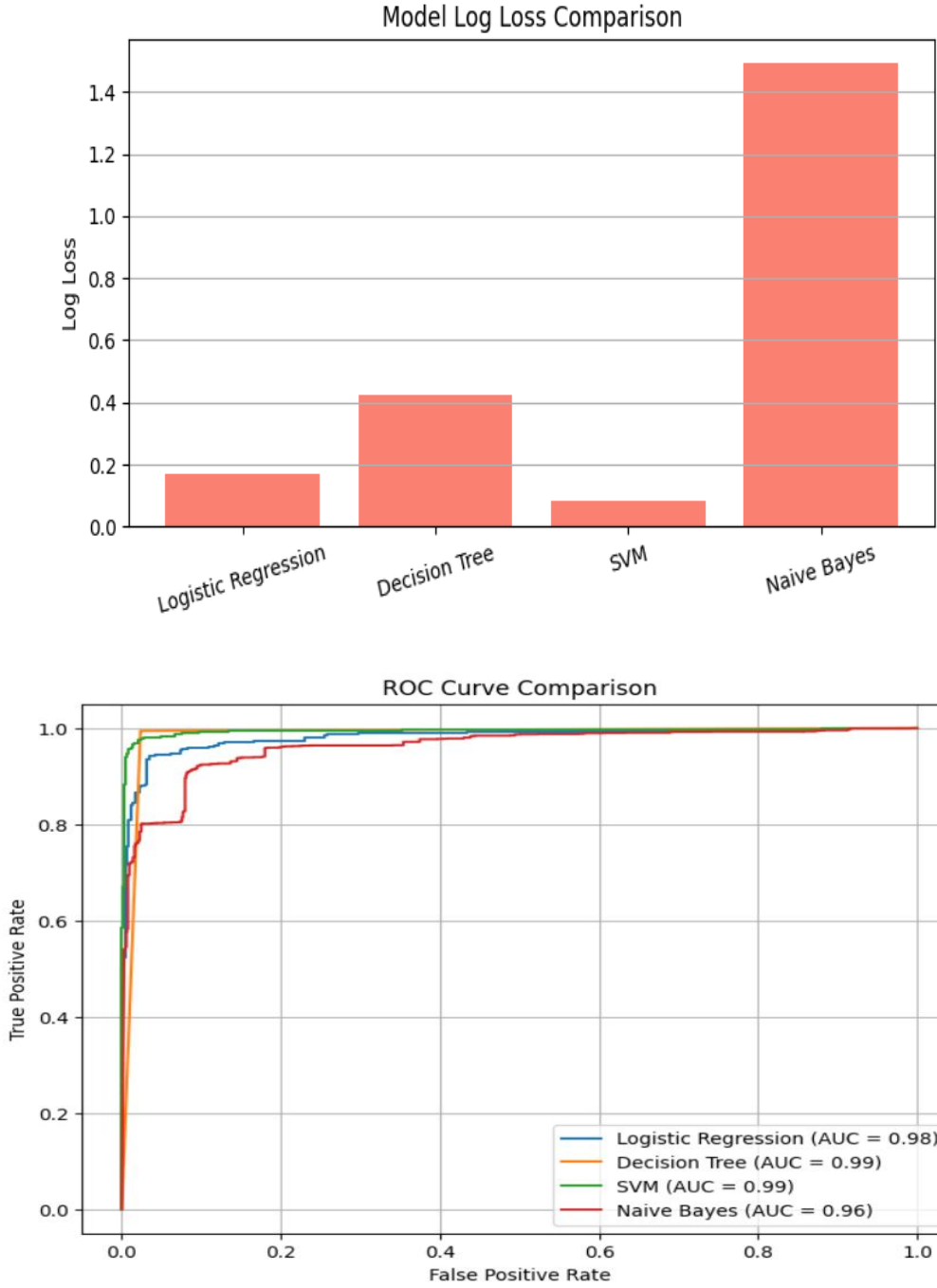



**Figure 4. ROC curves comparing the classification performance of LR, DT, SVM, and GNB models**

The initial comparison based on accuracy revealed that the DT model achieved the highest performance with an accuracy of 98.79%, closely followed by SVM at 97.73%, LR at 93.68%, and GNB at 70.64%. Although accuracy is a useful overall measure, it may not fully capture the performance of a model, especially in cases of class imbalance. Therefore, other metrics such as precision, recall, and F1-score were also analyzed to better understand each model's behaviour.

The SVM model demonstrated a strong balance across all classification metrics, achieving 96% precision, 98% recall, and an F1-score of 97%. These results suggest that the SVM not only identifies the majority of true positives but also maintains a low rate of false positives, making it highly reliable. LR also performed reasonably well, with a precision of 92%, recall of 89%, and an F1-score of 90%. Among the variants of the NB classifier, GNB was selected due to its suitability for continuous-valued features found in ransomware datasets and its computational efficiency. However, its performance revealed significant limitations: despite achieving a high precision of 92%, showed extremely poor recall (12%) and F1-score (22%), indicates that it failed to correctly identify a significant portion of the positive cases, highlighting limitations in its sensitivity despite its strong precision performance. Although the DT achieved the highest accuracy and a strong F1-score of 98%, its reliability in terms of probability calibration was questionable, as highlighted by its comparatively poor performance on the log loss metric. This occurs because DT learn specific patterns from the data in the training set, they can sometimes be overly confident in their predictions, as they are based on the distribution of samples in the leaf nodes. Therefore, although a model may have high accuracy, it may also be less reliable in terms of probability estimates.

SVM outperformed all other models with a log loss of 0.082, suggesting it is both accurate and well-calibrated. LR followed with a moderate log loss of 0.168, while the DT model, despite its high accuracy, produced a significantly higher log loss of 0.424, implying

overfitting and poor probability estimates. NB exhibited the worst performance with a log loss of 1.496, consistent with its low recall and F1-score.

Further evaluation using ROC curves and AUC values provided additional insights into the discriminative power of the models. The AUC values for SVM and DT were both 0.99, indicating excellent capability in distinguishing between classes. LR also performed well with an AUC of 0.98, while NB, though slightly lower at 0.96, still showed acceptable performance in terms of overall class separation.

## 5. Conclusion

The results indicate that the SVM consistently outperformed all the other models, achieving a high accuracy (97.73%), an excellent F1-score (97%), the lowest log loss (0.082), and a strong AUC of 0.99.

While the DT achieved the highest accuracy (98.79%), its relatively higher log loss implies potential overfitting and poor probability calibration. LR emerged as a solid and interpretable baseline model, offering good performance across most metrics. On the other hand, NB was the least effective model in this study, with notably poor recall and high log loss, making it unsuitable for applications where correctly identifying positive cases is critical.

In conclusion, the SVM model emerged as the most robust and reliable classifier, achieving a best balance between predictive performance and probabilistic reliability. It is therefore recommended for deployment in real-world applications requiring high classification accuracy and confidence in output probabilities.

### Future Work

Ransomware detection is one of the research topics from many decades and has been addressed by different methods. From the experiment conducted in this study, the SVM

model showed the best performance**.** However, there are many ways this research can be improved in the future.

**First,** is to test the SVM model in real-time systems to see how well it works when data is changing quickly.

**Second,** while this study focused on ransomware detection, future research could expand the application of these machine learning techniques to detect other types of malware or related objects of interest.

**Third,** future research may explore DL approaches, which are well-suited for identifying complex, non-linear patterns in large-scale datasets.

**Finally,** future research can explore integrating multiple types of data such as network logs, file behaviour, and user activity patterns to build more comprehensive and context-aware detection systems.

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# Perceptions of Local Communities Toward Migrant Students

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**Abstract**

The perspectives of local communities toward migrant students was the goal of this study. A semi-structured interview schedule comprising both open-ended and closed-ended questions based on the study's objectives was used to acquire important primary data. The impact of migrant students in Kirtipur Municipality Ward No. 5, Char Dhara of Panga, was investigated through a personal interview. The respondents were residents of Kirtipur who were at least 60 years old. Purposive sampling was used to choose 50 local respondents between the ages of 20 and 59. The majority of respondents had a positive perception of the migrant students because over 50% of them claimed that they were amiable, helpful, and behaved respectfully toward the locals. Similarly, over 40% of respondents claimed that the locals have a bad opinion of them because of their drinking, smoking, and fashion choices. This result corroborates the findings of Subedi and Upreti's research, which claimed that similar trends may be seen in Nepal, where internal migration creates both economic advantages and social unrest (Subedi & Upreti, 2019).

**Keywords:** perception, migration, student, local community, respondents.

## 1. Introduction

**Perceptions of local communities toward Migrant students**

One of the three aspects of population change that has received less research attention than fertility and mortality is migration. Compared to death and fertility, migration has a varied effect on population size. While both mortality and fertility function within the biological framework, migration is not a biological characteristic, although it is influenced by social, cultural, economic, and political variables. (Kanitkar & Hende, 1978).

Students that come to study in Kathmandu from their native districts or provinces are known as migrant students, and this phenomenon has grown in popularity. Compared to transitory migrant labor, these students typically stay longer, which leads to a deeper level of social connection with local populations. The host community's social structure, way of life, and cultural dynamics are all impacted by their extended presence. Kirtipur, a semi-urban neighborhood in the Kathmandu valley, has seen an increase in the number of out-of-town students because of its close proximity to educational institutions, reasonably priced housing, and enhanced connectivity.

While migration and student inflows have beneficial cultural and economic effects, such as diversity, innovation, and economic activity, they also lead to social conflict, competitiveness, and misunderstandings. Stereotypes and discrimination can arise when locals view immigrant students as rivals for opportunities, resources, or jobs. Disparities in customs, habits, and cultural practices can sometimes lead to miscommunication or bias. Acceptance and mutual respect are therefore essential to fostering peaceful coexistence and integration between the two groups.

In this sense, perception describes how people interpret and comprehend others in light of their experiences, values, and beliefs. The degree of acceptance, collaboration, and peace within a community is determined by how local communities view immigrant pupils. Since every person sees the world through a different lens, perceptions frequently

differ based on social background and individual experiences. This study aims to comprehend how Kirtipur locals see the presence, conduct, and contributions of immigrant students.

In the midst of political unrest, Kumar (2024) noted that students from different provinces temporarily left Kathmandu colleges, demonstrating how macro-level events affect migration patterns. Similar results by Paudel and Bhatt (2021) demonstrate how students' sense of security and belonging are influenced by regional disturbance.

According to Borjas (2017), migration increases the labor supply but, if handled poorly, might lower local wages. Similar effects of rural-to-urban migration on local employment markets and social cohesiveness are reported by Gurung and KC (2020) in Nepal. However, exposure to a variety of people fosters interregional understanding and innovation (World Bank, 2020).

Research by Olneck (1993) and Portes and Rumbaut (1990) connects successful integration with education. Pant (2022) discovered that schools in Nepal that support inclusive pedagogy lessen cultural stereotyping by fostering mutual respect among local and out-of-town pupils.

Putnam (2007) discovered that while ethnic variety initially lowers generic trust, it eventually creates larger networks. Similar patterns may be seen in the mixed communities of Kathmandu, where regular interactions between migrants and locals foster social cohesion despite initial conflict (Upreti, 2010).

The above literature emphasizes the complexity of cultural integration, which includes assimilation, multicultural coexistence, and structural adaptation. Although there is a lot of research conducted worldwide, there are still few empirical studies conducted in Nepal, particularly on local attitudes on migrant students. This study looks at Kirtipur inhabitants' actual experiences in an effort to close that gap.

The evolution of cultural diversity in host societies is explained by theoretical stances such assimilation, multiculturalism, and social capital theory. The advantages and

disadvantages of migration are both demonstrated by empirical data. Fostering peaceful cohabitation and policy frameworks that promote equal integration among Nepal's increasingly varied urban populations require an understanding of local attitudes.

## 2. Theoretical Framework

According to the UK government's Office for National Statistics, international migration is "the movement of people from one country to another and is often defined by the period they live in each country." White (2019). "Shifting of people or an individual or group of individuals from one cultural area to another, which may be permanent or temporary" is the literal definition of migration (Rajan & Neetha, 2018). Atkinson (2015) defines a community as a group of people sharing beliefs that create a single, shared understanding, incorporating the collective character of the group. Community thus reflects social connectedness, shared norms, and a sense of belonging. In the present study, “community” includes both local residents and outstation students living together in Kirtipur, whose interaction shapes social perceptions and integration.

According to Algan (2015), cultural identity and diversity have taken center stage in European political and social discussions. Coexistence, social cohesiveness, and institutional adaptation are all called into question by immigration. These issues are similar to Nepal's internal migration situation, where out-of-town students contribute to cultural diversity in metropolitan areas like Kirtipur (Kshetri, & Thapa, 2022). The process by which various people come to share a common culture is explained by assimilation theory. According to Algan (2015), there are three stages: (a) cultural exchange, (b) the gradual loss of indigenous patterns, and (c) total assimilation. In a similar vein, Gordon (1964) and Alba and Nee (2003) contend that assimilation can result in inclusion within prevailing social structures and can be cultural, structural, or civic. Assimilation for out-of-town students entails incorporating new ideas and habits while adjusting to the conventions of the host society. On the other hand, multiculturalism

encourages the coexistence of various cultural identities. According to Glazer (1997), minority communities actively participate in shared public life while preserving their traditions. By claiming that multiculturalism guarantees the acceptance and equitable participation of minority cultures, Kymlicka (2011) broadens this perspective. Multiculturalism in Nepal's urban environments is demonstrated by the coexistence of linguistic, ethnic, and geographical variety within individual neighborhoods (Gurung et al., 2024).

According to structuralism, integration is based on socioeconomic disparities in power, housing, and educational opportunities. According to Portes (2006), structural impediments prevent migrants from integrating, resulting in class-based divisions. In Kathmandu, social gap between locals and out-of-town students is frequently strengthened by unequal access to inexpensive housing and jobs (Poudel, 2021). According to the economic perspective, integration results from incentives and sensible behavior. According to Algan (2018) and Borjas (1999), migrants modify their cultural preferences in order to optimize their educational and professional opportunities. Similar to this, Shrestha (2024) discovered that community acceptability levels are influenced by perceived academic and economic prospects when it comes to student migration inside Nepal.

Cultural assimilation and adaptability are accelerated by education. Higher education improves intergroup contact and openness, as demonstrated by Lieberson and Waters (1988) and Chiswick and Houseworth (2011). Three mechanisms are identified by Furtado (2006): assortative matching effects, enclave, and cultural adaptability. Pokhrel (2020) found that students in Nepal who have achieved more academically show more tolerance and acceptance of cultural diversity in their host communities.

Assimilation and multiculturalism are two theoretical stances that describe how cultural diversity changes within host nations. Empirical data demonstrates the

advantages and disadvantages of migration. Fostering peaceful cohabitation and policy frameworks that promote equal integration among Nepal's increasingly varied urban populations requires an understanding of local attitudes.

## 3. Methodological Approach

The foundation of scientific inquiry that describes the general study plan is research philosophy. This study views the phenomena assuming objective reality and employs scientific methods to acquire knowledge. The fundamental foundation of this study is a survey that evaluates respondents' socioeconomic backgrounds. A semi-structured interview schedule containing both open-ended and closed-ended questions based on the study's objectives was used to gather the primary data. To learn more about the effects of migrant students in Kirtipur, a firsthand interview was conducted. All adult Kirtipur residents between the ages of 20 and 59 make up the study's universe. The Kirtipur Municipality's ward number 5 was chosen because, in comparison to the other nine wards, it has a significant concentration of migrant students. Fifty locals (respondents) were purposefully chosen from the study area in order to achieve the goal. This method was suitable since it enabled the researcher to choose people who most accurately reflected the attitudes and opinions of the local community regarding out-of-town students. Purposive sampling was used to choose a sample of 50 responders in total. Excel was used to organize, modify, verify, and tabulate the data. Descriptive statistical measures were then used to analyze the results. Informant permission, minimum similarity index, no harm to local customs and culture, and personal security were all upheld in order to preserve academic ethics. This study, however, is restricted to a specific number of producers in Char Dhara, Panga's Kirtipur Municipality ward number five.

## 4. Result and Discussion

The researcher concentrates on evaluating the local population's socioeconomic status and attitudes toward immigrant students. This section covers topics about the respondents' age, level of education, and gender. For this reason, the researcher collected this data.

### *General Information of the Respondents*

Employees, housewives, company owners, and public and private authorities are among the many backgrounds of the research participants in Kirtipur-5, Char Dhara, Panga. The following table displays the age, gender, occupation, education, and religion of 50 respondents that were gathered from the interview schedule.

**Table 1**

*General information of the respondents*

| Variables \ Age Group | | 20-29 | 30-39 | 40-49 | 50-59 | Total | Grand Total |
|---|---|---|---|---|---|---|---|
| **Gender** | Male | 12 | 5 | 5 | 4 | **26** | **50** |
| | Female | 7 | 9 | 5 | 3 | **24** | |
| **Education** | 1st - 5th | 0 | 1 | 1 | 1 | **3** | **50** |
| | 6th - 8th | 2 | 3 | 2 | 0 | **7** | |
| | 9th - 10th | 1 | 5 | 5 | 2 | **13** | |
| | 11th - 12th (diploma) | 4 | 2 | 2 | 2 | **10** | |
| | Bachelor and above | 12 | 1 | 0 | 2 | **15** | |
| | illiterate | 0 | 2 | 0 | 0 | **2** | |
| **Religion** | Hindu | 17 | 10 | 6 | 4 | **37** | **50** |
| | Christian | 2 | 3 | 3 | 3 | **11** | |
| | Muslim | 0 | 1 | 1 | 0 | **2** | |
| **Occupation** | Skilled | 8 | 0 | 0 | 3 | **11** | **50** |
| | Semi-skilled | 4 | 14 | 10 | 4 | **32** | |
| | Students | 7 | 0 | 0 | 0 | **7** | |

Source: Field survey, 2025

The general information of the respondents according to their age group is shown in Table 1. The researcher selected 26 men and 24 women between the ages of 20 and 59 to participate in the study. Two of them were illiterate, while 48 of them had at least a primary education and a bachelor's degree. There were two Muslims, eleven Christians, and 37 Hindus among the responders. Of the respondents, 32 had semi-skilled jobs, 11

had skilled jobs, and 7 were students. There were 19 responders in the 20–29 age group, 14 in the 30–39 age group, 10 in the 40–49 age group, and 7 in the 50–59 age group.

***Perception on helpful attitude of migrant students***

The way people interpret and comprehend others in light of their experiences, values, and beliefs is referred to as perception. The degree of acceptance, collaboration, and harmony within a community is determined by how local communities view out-of-town students. Since every person sees the world through a different lens, perceptions frequently differ based on social background and individual experiences. The perceptions of locals toward immigrant pupils in Kirtipur municipality ward number 5, Char Dhara of Panga, are shown in table 2.

**Table 2:**

*Perception towards attitude of migrant students*

| **Attitude** | **Numbers** | **Percentage (%)** |
|---|---|---|
| **Helpful** | 28 | 56 |
| **Not helpful** | 21 | 42 |
| **No response** | 1 | 2 |
| **Total** | 50 | 100 |

Source: Field survey, 2025

Table 2 shows respondents' perceptions of the usefulness of migrant students. Less than half (42%) of the respondents stated they are not helpful at all, and 2% did not answer the question. Over half (56%) of the respondents claimed they are helpful. When students in the neighborhood need modest amounts of money immediately, the locals, especially the neighbors, approach them and provide assistance. They also assist with environmental cleanup. Regarding not being helpful, they stated that they are mostly

preoccupied with their own kind and don't give a damn about their neighborhood. They are just concerned with paying their rent and using the facilities that come with it.

***Impact of migration in local culture***

In Nepal, migration patterns have become more intense due to urbanization and industrialization. New urban social structures have emerged because of the decline of old social institutions like the joint family system, caste-based hierarchy, and rural communal norms. New social interactions and challenges are arising as migration increases. As a result, migrants also bring their culture with them to their new location. The impact of migration on the destination's culture is displayed in the table below.

**Table 3:**

*Impact of migration in local culture*

| **Impact** | **Numbers** | **Percentage (%)** |
|---|---|---|
| **Dress code and Hair** | 9 | 18 |
| **Food Habits** | 8 | 16 |
| **Lack of Respect** | 6 | 12 |
| **Not affected** | 27 | 54 |
| **Total** | 50 | 100 |

Source: Field survey, 2025

The ways that immigrant students impact the culture of the neighborhood were shown in Table 3. More than half (54%) of the respondents said that the community's culture has not changed since the beginning, while a sizable portion (18%) said that there has been a slight but noticeable change in the youths' dress code and

hairstyles; another sizable portion (16%) said that people, mostly young people, prefer fast food and frequently visit restaurants that serve a variety of foods; and 12% said that moral values, such as respecting the elderly and gender roles, have drastically changed.

***Impact of migration on community life***

While student movement promotes diversity, creativity, and economic activity, it also creates problems with rivalry, miscommunication, and social unrest. Stereotypes and discrimination can arise when locals view immigrant students as rivals for opportunities, resources, or jobs. Disparities in customs, habits, and cultural practices can sometimes lead to miscommunication or bias. Therefore, encouraging peaceful cohabitation and integration between the two groups requires mutual respect and acceptance. The impact of immigrant students on community life is displayed in the following table.

**Table 4:**

*Impact of migrant students on community life*

| **Impact on** | **Numbers** | **Percentage (%)** |
|---|---|---|
| **Bad Influence** | 10 | 20 |
| **Fights** | 4 | 8 |
| **Rent issue** | 2 | 4 |
| **No problem** | 34 | 68 |
| **Total** | 50 | 100 |

Source: Field survey, 2025

The kinds of issues that the community faces as a result of the presence of migrant students were shown in Table 4. Less than one-fourth (20%) of the respondents said that

because the students freely used drugs in the community, they were a detrimental influence. Additionally, they said that the way most girls dress is unacceptable. Young people in the community tend to view college life as less educational and more enjoyable, and they value the freedom of being far from home more than their studies. There is unseen tension between the local youth and students, primarily due to dominance and jealousy over the freedom that out-of-town students have over the local youth, according to a significant portion of the respondents (8%) who said that they fought among themselves, made a big scene, and moved houses overnight. According to 4% of them, neighboring homeowners had issues with late rent payments and complaints from neighbors about students making a lot of noise at night and inviting men or women into their rented homes. Over two thirds of the people claimed that there were no issues or that they had not yet noticed.

***Perception of respondents on migrant students***

The way people interpret and comprehend others in light of their experiences, values, and beliefs is referred to as perception. The degree of acceptance, collaboration, and peace within a community is determined by how local communities view immigrant pupils. Since every person sees the world through a different lens, perceptions frequently differ based on social background and individual experiences. The local community's assessment of the presence, conduct, and contributions of migrant students in their community is displayed in the table below.

**Table 5:**

*Perception of respondents on migrant students*

| Perception | Respondents | Percentage (%) |
|---|---|---|
| **Liked** | 42 | 84 |
| **Dislike** | 7 | 14 |
| **No Response** | 1 | 2 |
| **Total** | 50 | 100 |

Source: Field survey, 2025

The opinions of the local population regarding whether or not migrant students are liked were shown in Table 5. While a sizable minority (14%) of respondents stated that they disliked students and 2% of respondents did not answer the question, the overwhelming majority (84%) of respondents responded that they loved the migrant students.

***Positive perception of respondents towards migrant students***

The process by which various people come to share a common culture is explained by assimilation theory. According to Algan (2015), there are three stages: (a) cultural exchange, (b) the gradual loss of indigenous patterns, and (c) total assimilation. In a similar vein, Gordon (1964) and Alba and Nee (2003) contend that assimilation can result in inclusion within prevailing social structures and can be cultural, structural, or civic. Assimilation for immigrant students entails bringing new viewpoints and actions while adjusting to the standards of the host community.

**Table 6:**

*Positive perception of respondents towards migrant students*

| Positive characteristic / Opinion | Helpful | Educated | Respect | Friendly | Others |
|---|---|---|---|---|---|
| **Noticed** | 28 (56%) | 20 (40%) | 13 (26%) | 28 (56%) | 29 (58%) |
| **Unnoticed** | 22 (44%) | 30 (60%) | 37 (74%) | 22 (44%) | 21 (42%) |

Source: Field survey, 2025

The respondents' perceptions of the migrant students' favorable traits were displayed in Table 6. According to assimilation theory, according to Algan (2015), Gordon (1964), and Alba and Nee (2003), over half (56%) of the respondents reported that they are very helpful and pleasant. The fact that over one-third (40%) of the respondents claimed to be educated is one of their many favorable traits. Few respondents were particularly pleased that people traveled hundreds of kilometers from their hometown to get an education. Of those surveyed, one-fourth (26%) claimed to be courteous to people and to always greet them. When they encountered someone they knew or had previously spoken to, they invariably grinned and bowed slightly. They also discussed the second group of out-of-town students who were peaceful, kept to themselves, and attended college voluntarily. They also talked about how they were able to live distant from home without anyone to help them or keep them under strict supervision. Additionally, respondents stated that traveling far from home allows them to obtain firsthand knowledge of the outside world and other people's lives as well as beneficial experiences, which has contributed to the positive aspects of the migrant students.

***Negative perception of respondents towards migrant students***

Although migration is linked to economic progress, the UNDP Human Development Report (2009) cautions against social strain in the absence of integration initiatives. Adepoju (2003) draws comparisons to West Africa, where war was sparked by unchecked migration. Similar trends can be seen in Nepal, where internal migration causes both social unrest and economic advantages (Subedi & Upreti, 2019).

**Table 7:**

*Negative perception of respondents towards migrant students*

| Negative characteristic / Opinion | Dressing | Drinking | Smoking | Lazy | Others |
|---|---|---|---|---|---|
| **Noticed** | 20 (40%) | 24 (48%) | 23 (46%) | 17 (34%) | 25 (50%) |
| **Unnoticed** | 30 (60%) | 26 (52%) | 27 (54%) | 33 (66%) | 25 (50%) |

Source: Field survey, 2025

The negative traits of the out-of-town pupils were emphasized in Table 7. Less than half (48%) of the respondents claimed to have a bad drinking habit, according to Subedi & Upreti, 2019 (internal migration produces economic benefits but also community friction). According to the aforementioned tables, the majority of migrant students congregate most days, drink in their homes, and then play loud music to disturb social harmony. Smoking is a negative habit, according to slightly less than half (46%) of the respondents. Most of the time, they use their college ID cards to smoke in public, and they don't care whether kids see them. One of the respondents, who operates a retail store and sells cigarettes, stated that the majority of her clients are students and that one individual buys roughly a packet or two in addition to a packet of chewing tobacco. According to the remaining 40% of respondents, one of their bad traits is how they dress.

Respondents expressed dissatisfaction with their own attire and recommended wearing at least respectable clothing when strolling in the neighborhood. Of those surveyed, one-third (34%) claimed to be lazy, wake up late, and attend college. A few of them specifically noted that they witness pupils attending college from early in the morning till four or five o'clock in the evening. Nighttime wandering and public displays of affection like embracing, kissing, and hugging were other negative traits.

## 5. Discussion

The purpose of this study is to ascertain how local populations see immigrant pupils. Migrant students are viewed both favorably and unfavorably by local populations. Positive perceptions of immigrant students in the research area include their helpfulness, education, respect, and friendliness. Similar to this, local people have unfavorable opinions of immigrant students due to their attire, alcohol consumption, smoking, and lethargy. This result was in line with Adepoju's (2003) research. Adepoju draws comparisons to West Africa, where conflict was sparked by unchecked migration. The results of Subedi and Upreti (2019) were consistent with both the positive and negative effects of internal migration. According to Subedi and Upreti, similar trends may be seen in Nepal, where internal migration creates both economic advantages and social unrest (Subedi & Upreti, 2019). The study's conclusions are accepted in theory. According to Sharma and Gurung's (2019) explanation of suggested theoretical methods, multiculturalism in Nepal's urban settings takes the form of linguistic, ethnic, and regional variety coexisting within individual neighborhoods. The coexistence of various cultural identities in the research region is supported by the suggested theoretical approach, multiculturalism. While a sizable number of respondents (14%) disliked migrant students and 2% did not answer the question, the majority of respondents (84%) in the study area preferred migrant students.

## 6. Conclusion

The attitudes of local residents toward immigrant students in Kirtipur Municipality Ward No. 5, Char Dhara, Panga, are the main subject of this study. Local communities have both favorable and unfavorable opinions on immigrant pupils. First off, most respondents said that migrant students are amiable and helpful. Second, they enjoyed the immigrant kids and had no issues. Lastly, locals view immigrant students favorably due to their helpfulness, knowledgeable attitude, respect, and amiable disposition; on the other hand, they view them negatively due to their lethargy, drinking habits, smoking, and fashion choices.

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# Locus of Control as a Mediator in the Relationship Between Hope and Happiness

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**Abstract**

People are pursuing happiness. Being hopeful is thought to make them happy. Locus of control (LOC) is one's degree of belief in control over their life outcomes (such as fate vs. action), and is supposed to affect happiness too. This study aimed to examine whether the locus of control (LOC) and hope predicted happiness among the Nepali sample and if the locus of control mediated the relationship between hope and happiness. A cross-sectional survey was conducted by making a convenience sample of 334 persons ($M_{age}$=26.4 years) in Nepal. Participants filled out the Adult Hope Scale, Subjective Happiness Scale, and Internal-External Locus of Control Short Scale–4, along with 1-item measures of belief in fate/action, and hopefulness, and a sociodemographic questionnaire. Internal locus of control (ILOC)/belief in fate and hope positively predicted happiness. External locus of control (ELOC) negatively predicted it. Belief in action could not significantly predict happiness. Internal and external LoC mediated the relationship between hope and happiness partially. Locus of control and hope are determinants of happiness in one's life. ILOC increases happiness and ELOC decreases it. Hope directly affects happiness but it also affects happiness through ILOC and ELOC. The mediation effect of the internal locus is more than that of the external locus of control.

*Keywords*: Locus of control, happiness, hope, subjective well being (SWB), belief in fate (*bhagya*), belief in action (*karma*)

## 1. Hope and Happiness: Locus of Control as a Mediator

The Nepali are the happiest people in South Asia but the 93rd among 143 countries in the world (Helliwell et al., 2024). We are all pursuing happiness, positive emotion that reflects subjective well-being. Yet the causes are not understood well enough. Being hopeful is supposed to affect one's happiness in life. Happiness consists of purpose, enjoyment, and satisfaction (Brooks & Winfrey, 2023). Intuitively, we can claim that hopeful people are happier and hopeless people are less happy. Locus of control (LOC) is the extent of belief in control over life choices or their consequences (e.g. fate vs. action, system vs. person). It is the perception of control over one's outcomes in life. Internal LOC (ILOC) can be guessed to increase happiness and external LOC (ELOC) can be guessed to decrease it because ILOC people believe they can control life consequences but ELOC believe that external factors like God control life events.

Hope is the confident expectation of achieving goals. It is the expectation that something will turn out to be favorable in the future. Hope is the cognitive ability to set goals and have plans to achieve them (Snyder et al., 1991). Hope consists of two components: agency thinking and pathways thinking (Snyder et al., 1996). Agency thinking is about perceiving oneself as able to attain goals and pathways thinking is about perceiving oneself as capable of finding strategies to attain the goals (Nguyen & McDermott, 2023). These predicted happiness in children. These may enhance one's well-being such as increase flourishing (Belen et al., 2020) by reducing depression and anxiety (Corrigan & Schutte, 2023).

An anthropologist had claimed that the Nepali are fatalists (Bista, 1991). A qualitative study conducted on beliefs about suicide among older adults of Nepal also reiterated that the Nepali believe fate is an important determinant of life consequences (Adhikari et al., 2025). This research got inspired with the question: are Nepali fatalists or believers of fate? Even though this study did not answer this question very well, it

established the norms to decide if they are, should anyone pursue the same question in future. There is a concept in psychology closely related to fatalism: locus of control. There are two types: internal and external LOC. The internal locus of control (ILOC) is one's belief in their ability to effect life's consequences. The external locus of control (ELOC) is one's belief in the external factors (like God, fate, situation of the country) influencing most of life's consequences.

This study aimed to determine whether hope affected happiness, locus of control affected happiness, and hope mediated the relationship between hope and happiness among the Nepali. This study emerged in the backdrop of sparse availability of positive psychological studies in Nepal such as those done in the past (Adhikari, 2022, 2023b, 2023a). The findings of this study are expected to add more understanding on the knowledge of happiness. Moreover, the interventions to increase subjective well-being including happiness may be informed by the findings of this study.

**Hope and Happiness**

Hope consists of agency thinking, pathways thinking and goals. In other words, it is the expectation that one will be able to attain goals by using their agency and strategies. Hope had a significant effect on happiness (Khanzadeh et al., 2019). They were significantly correlated (Ghahremani et al., 2020). Hope, being a positive psychological construct, is intuitively connected with more happiness but needs an empirical exploration.

**Hope and LOC**

In adolescents, locus of control (LoC) was significantly associated with hope (Turan, 2021). It was found to be positively and significantly associated with two measures of external LOC -chance and powerful others (Frankham et al., 2020). Both

agency and pathways components of hope correlated significantly with internal locus of control in pregnant women (Delale et al., 2021).

**LoC and Happiness**

LOC was not significantly associated with happiness (Ramezani & Gholtash, 2015). Internal LOC was not found significantly correlated with happiness in a study (Pannells & Claxton, 2008) but another study (Abedini & Asadi, 2015) showed that it predicted happiness significantly. Moreover, the persons with ILOC differed significantly from ELOC (Pannells & Claxton, 2008). Those with an internal locus of control reported significantly higher happiness scores compared to those with an external locus of control. Happiness may be resulted from the balance of internal and external LOC (April et al., 2012).

**Belief in Fate/Action and Happiness**

Negotiating with fate lets people set delimitations, act, and get outcomes in life (Au & Savani, 2019). This may not be the same as fatalism. Accepting constraints and redefining actions is a part of negotiating with fate and is likely to bring positive outcomes in life. Feeling helpless by believing in the overpowering nature of fate (fatalism) may negatively impact happiness but negotiating with fate may enhance it. Fate control is the belief that life events are decided by external factors but people have the possibility to change it by their actions (Leung et al., 2002). In Chinese teenagers, the belief in freewill had affected their happiness (Li et al., 2017). Belief in fate or action can be important determinants of happiness.

**LOC as Mediator**

Locus of control (LOC) has been tested as a mediator in past studies. There are two types of LOC. Internal LoC is the one in which people believe they have control over life outcomes or their actions cause the life events, and external LOC is the one in which

people believe that external factors cause their life events and control their life outcomes. Internal locus of control was found to mediate relationship between emotional stability and pro-environmental behavior (Chiang et al., 2019). It also mediated the relationship between religiosity and life satisfaction (Fiori et al., 2006). Locus of control is found to mediate two psychological factors often. So, happiness as an outcome of hope can also be expected to be mediated by locus of control. We can hypothesize that internal LOC mediates and external LOC does not mediate the relationship between hope and happiness.

## 2. Theoretical Framework

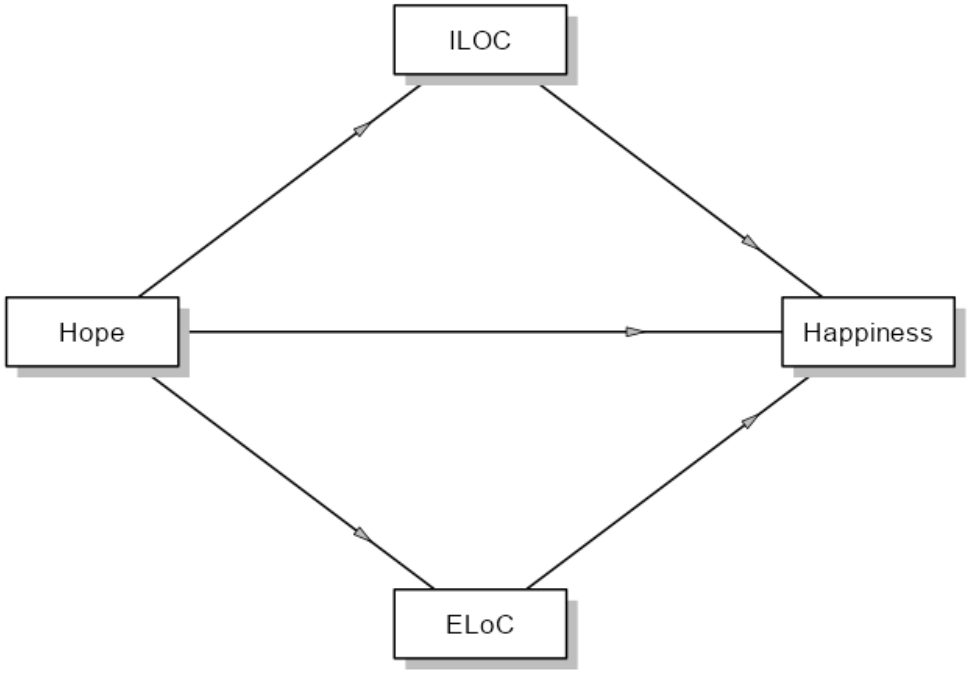
Hope theory (Snyder, 2002) says that hope is perceived capability to adopt pathways with agentic thinking to reach goals. Locus of control theory (Rotter, 1966) says that locus of control is the belief of actions affecting outcomes in life. It is of two types: internal and external. Internals believe in the role of their own efforts and externals believe in the role of external forces to affect outcomes. Subjective well-being theory (Diener, 1984) posits that happiness consists of high positive affect, low negative affect, and high life satisfaction. Hope and perceptions of control (locus of control) can be expected to directly influence subjective well-being such as happiness. Figure 1 shows the conceptual framework.

### Research Gap

It has been established that hope and happiness are significantly related (Botor, 2019). Hope predicts happiness. However, the role of locus of control in this relationship has not been investigated. Locus of control has the potential to mediate the relationship. This study aimed to examine the mediating role of locus of control in the relationship between hope and happiness.

**Figure 1**

*Conceptual Diagram*




*Note.* ILOC Means Internal LOC and ELOC means External LOC

## 3. Methods

The study is based on the ontology of positivism and epistemology of objectivism. Here reality and concepts such as hope is assumed objective and measurable. This quantitative research had a survey design.

### Participants

The mean age of 334 participants was 26.4 (SD=8.28). Participants ranged from 16 to 63 years in age. Half of participants (50.9%) were females, 48.5% were males, 0.6% belonged to the third gender. More than one-fourth (28.7%) participants reported that the district they were living in was the same district they were born in and the remaining said

they lived in a different district. There were participants with 128 surnames, the most frequent being Shrestha (10), Bista (10), Magar (10), Thapa (10), Acharya (10), Adhikari (8), Rai (8), Shakya (7), Bhattarai (6), Dahal (6), Maharjan (6), Pandey (6), Gurung (5), Neupane (5) Sapkota (5), and Tamang (5). Participants belonged to more than 100 professions. In administration and management, there were positions such as administrative assistant, manager, and human resource professionals. The healthcare field included nurses, health workers, and therapists, while the IT sector featured software developers, IT specialists, and digital marketers. Other significant categories included business owners and entrepreneurs, educators, engineers, social workers, and professionals in hospitality like chefs and waiters. Additionally, there were labor roles, government service, military jobs, and creatives like artists and graphic designers, illustrating the diversity of occupations represented. Many of the participants were students

**Measures**

Hope was measured by the Adult Hope Scale (Snyder et al., 1991). It has 12 items: 4 items to measure agency, 4 items to measure pathways, and the remaining filler items. This is an 8-point Likert scale ranging from "Definitely False" to "Definitely True". In this survey, two options– "Slightly False" and "Slightly True"– were eliminated because of being similar to the neighboring options and thus had six points. Too many similar options can make the instrument ineffective as seen in a previous research (McLaren & Adhikari, 2023). This sample had the Cronbach's Alpha of 0.841 for this scale. The Agency Subscale had Cronbach's Alpha of 0.679 and Cronbach's Alpha of 0.795.

The Nepali translation of the English adaptation (Nießen et al., 2022) of Internal–External Locus of Control–4 (Kovaleva et al., 2014) was used to measure internal locus of control. It has two items for internal and two items for external locus of control. This is a 5-point Likert scale ranging from "does not apply at all" to "applies completely". In

this survey, an option "applies somewhat" was removed. For this sample, Cronbach's Alpha for ILOC and ELOC were 0.437 and 0.326. The cause of low values might be due to less number of items: two in each. Inter-item correlation for both ILOC $r=.288$, $p<0.01$ and ELOC $r=.195$, $p<0.001$ was significant. Even though the coefficients are small, they are acceptable for broad concepts.

Happiness was measured by the Subjective Happiness Scale that has four items (Lyubomirsky & Lepper, 1999) and responses are collected in a 7-point Likert scale. This sample had Cronbach's Alpha of 0.369. An example of items in this scale is: "Some people are generally not very happy. Although they are not depressed, they never seem as happy as they might be. To what extent does this characterization describe you?"

One-item measures of fate (translation of *bhagya*), action (translation of *karma*), and hopefulness (translation of *aashabadita*) were used (as shown in appendix) and participants were allowed to rate themselves in scale of 10: 10 meant "completely" and 1 meant "not at all". An example of the question is: How much do you believe in fate? These items combined had a Cronbach's Alpha of 0.621 for this sample.

**Procedures**

Both English and Nepali translations of tests were presented to participants for all the three scales. The data were collected online using Google Forms with the help of research assistants who had been trained beforehand to collect data well. They were the students studying Post-graduate Diploma in Counseling Psychology in a college. They met the participants or called them and informed them about the research. They then sent the link to the form and got it filled. There were information and implied consent in Google Forms also. The data was collected in 2023 between April and September.

**Ethical consideration:** Informed consent was taken. The participation was made voluntary. Confidentiality was maintained by not collecting names. Only surname, age, gender and profession were asked in the sociodemographic questionnaire.

**Data Analysis**

Jamovi 2.6, Excel and SPSS 27 were used to organize and analyze data. The tests such as correlation, regression and mediation analyses were applied to process data. Descriptive statistics were used to summarize the characteristics of the sample.

## 4. Results

Table 1 shows the descriptives of hope, happiness, internal locus of control, belief in fate, action, and hopefulness about future. If future studies use the same instruments used in this study, they may use the following norms to classify the scores: Low Level for <Q1, Mild Level for Q1-Q2, Moderate Level for Q2-Q3, and High Level for >Q3.

**Table 1**

*Descriptives of Main Variables*

| | Mean | SD | Minimum | Maximum | Quartile (Q) 1 | 2 | 3 |
|---|---|---|---|---|---|---|---|
| Belief in Fate | 5.88 | 2.57 | 1 | 10 | 4 | 6 | 8 |
| Belief in Action | 7.92 | 2.27 | 1 | 10 | 7 | 9 | 10 |
| Hopeful about future | 7.13 | 2.50 | 1 | 10 | 6 | 8 | 9 |
| Happiness | 18.18 | 4.78 | 5 | 28 | 15 | 18 | 21 |
| ELoC | 4.13 | 1.30 | 2 | 8 | 3 | 4 | 5 |
| ILOC | 6.04 | 1.30 | 2 | 8 | 5 | 6 | 7 |
| Agency | 17.79 | 3.54 | 4 | 24 | 16 | 18 | 20 |
| Pathways | 18.71 | 3.72 | 4 | 24 | 17 | 19 | 22 |
| Hope* | 36.51 | 6.67 | 8 | 48 | 32 | 37 | 42 |
| Age | 26.39 | 8.28 | 16 | 63 | 21 | 24 | 28 |

*Note*. ELOC=External LOC, ILOC=Internal LOC. *Response options had six possibilities unlike original scale

Figure 2 shows the frequency of belief in fate and action on the scale of 10. The frequencies indicate that most of the people had higher belief in action compared to fate. While responding to belief in fate, they remained neutral indicated by average rating being the most frequent.

**Figure 2**

*Histograms for Belief in Fate/Action*

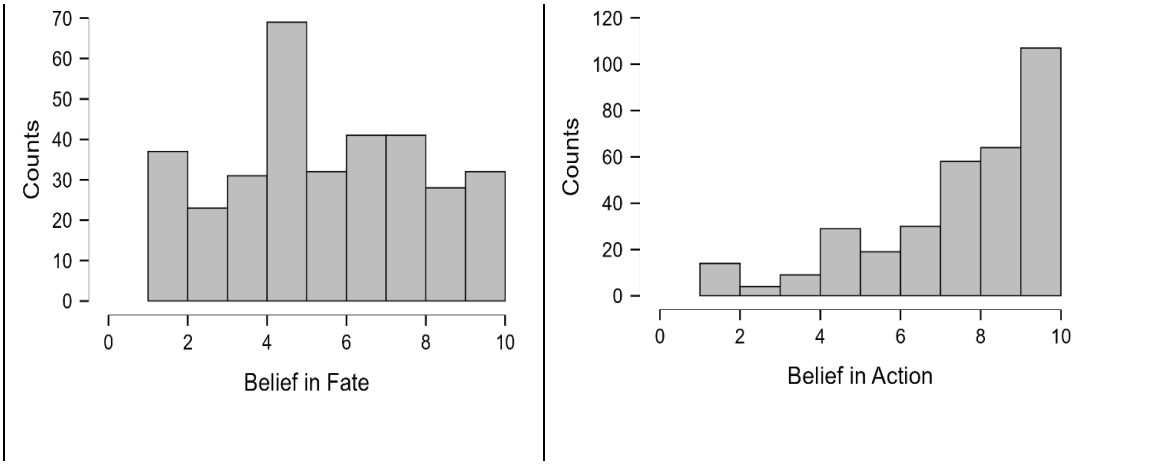
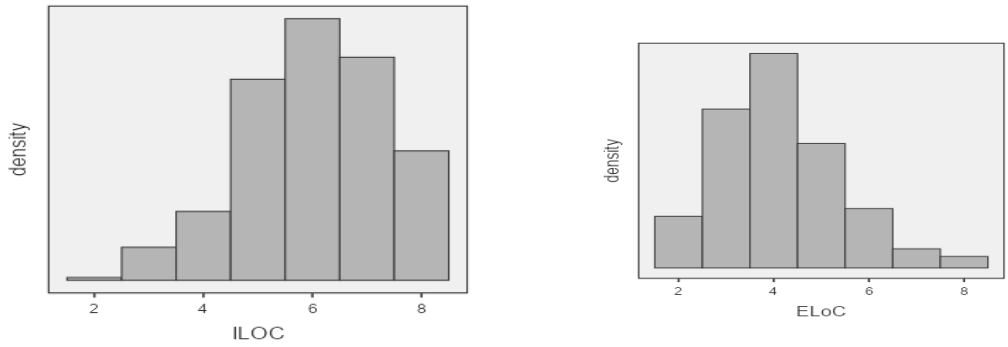



Figure 3 shows the histograms for people with internal and external locus of control. Most of the people had more internal LoC than external LOC. Shapiro-Wilk test showed that ILOC, $W$=0.93, $p$<0.01 and ELOC, $W$=0.92, $p$<0.01 did not follow normal distribution. However, their skewness and kurtosis were within ±2 or an acceptable range. So, parametric tests have been used given a large sample size of 334.

**Figure 3**

*Histogram for Internal/External LOC*



**Correlation**

Table 2 shows that hope, happiness, and LoC (internal and external) are significantly correlated with each other. Hope and hopefulness both correlated significantly and positively with happiness. ELOC correlated significantly and negatively with happiness and hope (and its components), but did not correlate with belief in fate. ILOC correlated significantly and positively with them.

**Table 2**

*Correlation Matrix*

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Belief in Fate | | | | | | | | | |
| 2 | Belief in Action | 0.31*** | | | | | | | | |
| 3 | Hopefulness | 0.28*** | 0.49*** | | | | | | | |
| 4 | Age | -0.19*** | -0.15** | -0.07 | | | | | | |
| 5 | ILoC | 0.12* | 0.36*** | 0.25*** | -0.01 | | | | | |
| 6 | ELoC | 0.01 | -0.33*** | -0.24*** | 0.07 | -0.19*** | | | | |
| 7 | Happiness | 0.23*** | 0.30*** | 0.42*** | 0.07 | 0.32*** | -0.28*** | | | |
| 8 | Agency | 0.19*** | 0.26*** | 0.37*** | 0.05 | 0.39*** | -0.24*** | 0.47*** | | |
| 9 | Pathways | 0.29*** | 0.32*** | 0.31*** | -0.06 | 0.39*** | -0.21*** | 0.45*** | 0.69*** | |
| 10 | Hope | 0.24*** | 0.32*** | 0.37*** | -0.01 | 0.42*** | -0.24*** | 0.50*** | 0.91*** | 0.92*** |

*Note.* * p < .05, ** p < .01, *** p < 1

**Regression Analysis**

The first regression analysis was run to examine if belief in fate/action and hopefulness about future predict happiness. As shown in the Table 3, belief in fate and hopefulness about the future significantly predicted happiness. The model was significant, $F$ (3, 330) = 27.5, $p$ < 01 and 20% variance was explained by the independent variables.

**Table 3**

Regression model with belief in fate/action and hopefulness as predictors

| Predictor | B | SE | t | P | β |
|---|---|---|---|---|---|
| Intercept | 10.69 | 0.94 | 11.36 | <1 | |
| Belief in Fate | 0.20 | 0.10 | 2.04 | **0.04** | 0.11 |
| Belief in Action | 0.21 | 0.12 | 1.70 | 0.09 | 0.10 |
| Hopefulness | 0.66 | 0.11 | 6.06 | <**1** | 0.35 |

*Note*. All independent variables were measured by 1-item scale.

The second regression analysis was run to examine if agency and pathways (components of hope), and locus of control predicted happiness. As shown in the Table 4, all of them significantly predicted happiness. The model was significant, $F$ (4, 329) = 33.8, $p$ < 01 and 29.1% variance was explained by the independent variables.

**Table 4**

*Regression model with internal/external locus of control, agency and pathways as predictors*

| Predictor | B | SE | t | p | β |
|---|---|---|---|---|---|
| Intercept | 7.04 | 1.74 | 4.04 | <1 | |
| ILOC | 0.44 | 0.19 | 2.34 | 0.**02** | 0.12 |
| ELOC | -0.57 | 0.18 | -3.22 | 0**1** | -0.16 |
| Agency | 0.34 | 0.09 | 3.82 | <**1** | 0.25 |
| Pathways | 0.26 | 0.08 | 3.09 | 0**2** | 0.20 |

In the third model, hope (as a whole) and LoC significantly predicted happiness. The model was significant, $F$ (2, 330) = 67.6, $p < 01$ with 29% explanation of variance as shown in Table 5.

**Table 5**

Regression model with internal/external locus of control and hope as predictors

| Predictor | B | SE | t | p | β |
|---|---|---|---|---|---|
| Intercept | 7.07 | 1.74 | 4.06 | <1 | |
| ILOC | 0.44 | 0.19 | 2.35 | 0.019 | 0.12 |
| ELoC | -0.57 | 0.18 | -3.25 | 01 | -0.16 |
| Hope | 0.30 | 0.04 | 7.95 | <1 | 0.41 |

In both the second and third models, prediction of internal LoC was positive and that of external LOC was negative. In other words, internal LOC increases happiness and external LOC decreases happiness.

**Mediation**

The first mediation model was run to examine if LoC mediated the relationship between hope and happiness. The Table 6 shows that both direct and indirect effects were significant. So, the mediation effect of internal locus of control on the relationship between hope and happiness was partial. So was the effect of external locus of control, but to a smaller extent, β=0.038. Positive coefficient suggests that hope increased happiness through an increased sense of internal control. To a smaller extent, hope influenced happiness through changes in external locus of control. Hope had a strong direct effect on happiness, even when controlling for the mediators

**Table 6**

Mediation model with internal/external locus of control as mediators in relationship of hope and happiness

| | | | | 95% C.I. (a) | | | | |
|---|---|---|---|---|---|---|---|---|
| Type | Effect | B | SE | Lower | Upper | β | z | p |
| Indirect | Hope ⇒ ILOC ⇒ Happiness | 0.04 | 0.02 | 0.01 | 0.07 | 0.05 | 2.28 | **0.02** |
| | Hope ⇒ ELoC ⇒ Happiness | 0.03 | 0.01 | 0.01 | 0.05 | 0.04 | 2.66 | **0.01** |
| Component | Hope ⇒ ILOC | 0.08 | 0.01 | 0.06 | 0.10 | 0.42 | 8.48 | <1 |
| | ILOC ⇒ Happiness | 0.44 | 0.19 | 0.08 | 0.81 | 0.12 | 2.36 | 0.02 |

| Type | Effect | B | SE | 95% C.I. (a) | | β | z | p |
|---|---|---|---|---|---|---|---|---|
| | | | | Lower | Upper | | | |
| | Hope ⇒ ELoC | -0.05 | 0.01 | -0.07 | -0.03 | -0.24 | -4.59 | <1 |
| | ELoC ⇒ Happiness | -0.57 | 0.18 | -0.92 | -0.23 | -0.16 | -3.27 | 0 |
| Direct | Hope ⇒ Happiness | 0.30 | 0.04 | 0.22 | 0.37 | 0.41 | 8 | <1 |
| Total | Hope ⇒ Happiness | 0.36 | 0.03 | 0.29 | 0.43 | 0.50 | 10.60 | <1 |

*Note*. Confidence intervals computed with method: Standard (Delta method)

The second mediation model was run with components of hope as independent variables and LoC as mediator. The Table 7 shows that both direct and indirect effects were significant. So, ELoC mediated the relationship between agency and happiness significantly but the effect size was small, β = 0.0288. The direct effect of agency on happiness is much stronger, B=0.3379.

**Table 7**

Mediation model with internal/external locus of control as mediators in relationship of agency/pathways and happiness

| Type | Effect | B | SE | 95% C.I. (a) Lower | 95% C.I. (a) Upper | β | z | p |
|---|---|---|---|---|---|---|---|---|
| Indirect | Agency ⇒ ILOC ⇒ Happiness | 0.04 | 0.02 | −4.40e−4 | 0.08 | 0.03 | 1.94 | 0.05 |
| | Agency ⇒ ELoC ⇒ Happiness | 0.04 | 0.02 | 0 | 0.08 | 0.03 | 2 | **0.05** |
| | Pathways ⇒ ILOC ⇒ Happiness | 0.04 | 0.02 | −6.45e−4 | 0.07 | 0.03 | 1.92 | 0.05 |
| | Pathways ⇒ ELoC ⇒ Happiness | 0.02 | 0.02 | -0.01 | 0.05 | 0.01 | 1.04 | 0.30 |
| Component | Agency ⇒ ILOC | 0.09 | 0.03 | 0.04 | 0.13 | 0.23 | 3.39 | <1 |
| | ILOC ⇒ Happiness | 0.44 | 0.19 | 0.08 | 0.81 | 0.12 | 2.36 | 0.02 |
| | Agency ⇒ ELoC | -0.07 | 0.03 | -0.12 | -0.02 | -0.19 | -2.54 | 0.01 |
| | ELoC ⇒ Happiness | -0.57 | 0.18 | -0.91 | -0.23 | -0.15 | -3.24 | 0 |
| | Pathways⇒ ILOC | 0.08 | 0.02 | 0.03 | 0.13 | 0.23 | 3.32 | <1 |
| | Pathways ⇒ ELoC | -0.03 | 0.03 | -0.08 | 0.02 | -0.08 | -1.10 | 0.27 |
| Direct | Agency ⇒ Happiness | 0.34 | 0.09 | 0.17 | 0.51 | 0.25 | 3.85 | <1 |
| | Pathways ⇒ Happiness | 0.26 | 0.08 | 0.10 | 0.42 | 0.20 | 3.11 | 0 |
| Total | Agency ⇒ Happiness | 0.41 | 0.09 | 0.24 | 0.59 | 0.31 | 4.71 | <1 |
| | Pathways ⇒ Happiness | 0.31 | 0.08 | 0.14 | 0.47 | 0.24 | 3.69 | <1 |

*Note*. Confidence intervals computed with method: Standard (Delta method)

The third mediation model was run with belief in fate/action as mediators, hope as independent and happiness as dependent variables. The Table 8 shows that belief in action mediated the relationship partially but belief in fate could not. Mediation effect was not very strong, β=0.0422.

**Table 8**

*Mediation Model with Belief in Fate/Action as Mediators in Hope–Happiness Relationship*

| Type | Effect | B | SE | 95% C.I. (a) | | β | z | p |
|---|---|---|---|---|---|---|---|---|
| | | | | Lower | Upper | | | |
| Indirect | Hope ⇒ Belief in Fate ⇒ Happiness | 0.01 | 0.01 | 0 | 0.03 | 0.02 | 1.64 | 0.10 |
| | Hope ⇒ Belief in Action ⇒ Happiness | 0.03 | 0.01 | 0.01 | 0.05 | 0.04 | 2.42 | **0.02** |
| Component | Hope ⇒ Belief in Fate | 0.09 | 0.02 | 0.05 | 0.13 | 0.24 | 4.43 | <1 |
| | Belief in Fate ⇒ Happiness | 0.16 | 0.09 | -0.02 | 0.34 | 0.09 | 1.76 | 0.08 |
| | Hope ⇒ Belief in Action | 0.11 | 0.02 | 0.07 | 0.14 | 0.32 | 6.07 | <1 |
| | Belief in Action ⇒ Happiness | 0.28 | 0.11 | 0.07 | 0.49 | 0.13 | 2.64 | 0.01 |
| Direct | Hope ⇒ Happiness | 0.31 | 0.04 | 0.25 | 0.38 | 0.44 | 8.89 | <1 |
| Total | Hope ⇒ Happiness | 0.36 | 0.03 | 0.29 | 0.43 | 0.50 | 10.60 | <1 |

*Note*. Confidence intervals computed with method: Standard (Delta method)

## 5. Discussion

Hope and hopefulness both predicted happiness. Internal and external locus of control predicted happiness but external LOC predicted it negatively. They mediated the relationship between hope and happiness. Internal LOC was a more effective mediator in this relationship. External LOC mediated the relationship between agency and happiness too. Belief in fate predicted happiness significantly. Belief in action mediated the relationship between hope and happiness.

### Interpretation of Results

A rough indication is that the Nepali are less fatalist than believers of actions. They are more believers of action than those of fate. They believe in action more than they do in fate. However, these concepts need not be interpreted as antonymous. The believers of fate may also be the believers in action. Belief in fate predicted happiness but belief in action indirectly affected happiness caused by hope. Having hope is empirically proven to increase happiness in the Nepali sample. Being hopeful is different from being optimistic. Being optimist involves doing nothing and expecting good results to come but hope involves both agency and pathways. In other words, hope is the belief that triggers one to do the actions and adopt various strategies.

Result of mediation analysis has shown that people with higher hope experience more happiness due to an increased internal locus of control. ELOC has a weaker effect compared to ILOC. Hope contributes to happiness through both direct pathways and its effects on locus of control, with ILOC being a more influential mediator compared to ELOC. Agency thinking is motivational in nature, and related well with happiness but was mediated by external LOC feebly. This is an interesting interaction and mixes the action-orientation and fate-orientation. This also indicates that belief in fate and action should not be disjoint concepts; they need not be antonymous and can coexist. Result of regression analysis has pointed to the fact that ELOC may decrease happiness.

**Comparison with Past Studies**

Various psychological causes of happiness have been identified. Enjoyment is making pleasure with people and creating memories. Joy after struggle is satisfaction. Having purpose in life gives meaning. Happiness is made up of enjoyment, satisfaction, and meaning (Brooks & Winfrey, 2023). Meaning consists of coherence, significance and purpose. Happiness is not a destination but a direction. The happiness experts have suggested developing family, friendship, faith, and meaningful work. This study has established that hope and locus of control predict happiness. So, it has posited that cognitive factors are important to determine one's happiness.

External LOC was negatively associated with happiness in the past (Devin et al., 2012). This study also showed that it predicted happiness negatively. Internal LOC was significantly associated with subjective well-being (Kesavayuth et al., 2022). This study also showed that internal LOC predicted happiness positively. Hope and happiness were significantly related (Lonkar, 2024). This study also showed that hope and its components predicted happiness significantly. In addition, this study showed that LOC mediated the relationship of hope and happiness.

**Limitations**

The measures of LOC and happiness had low internal reliability. So, validity and thus accuracy of measurement may be questionable. The sample was non-probabilistic. So, we should be cautious during generalization of the findings. The demographic factors were not accounted for in the regression models. Some demographic variables like marital status, employment, and age may play an important role in happiness. Global conclusion for all age groups or all genders may lead to overgeneralization or missing of specific patterns of happiness. This sample was dominated by emerging adults i.e. adults below 30 (Arnett, 2015). Additionally, the cross-sectional nature of this study may undermine causality claimed in it.

**Implications**

This study has contributed to the theory of happiness. This study has reiterated that happiness depends on both hope and locus of control (an indicator of perception of control). It also depends on belief in fate and action. The finding that locus of control mediates the relationship between hope and happiness should be helpful to understand the pathways to happiness. This study also supported the notion that belief in fate and belief in action are overlapping concepts, not contradictory ones. As predicted by hope theory, hope predicts happiness. As predicted by the locus of control theory, internal LOC leads to more happiness than external LOC does.

If the interventions are designed to increase happiness, they should account for hope and locus of control. Hope (or hopefulness) needs to be increased. So does the internal locus of control. The external locus of control needs to be checked/controlled. Belief in action (*karma*) also contributes to overall happiness indirectly. Belief in fate is also helpful but negotiating with fate may be better than considering fate as unchangeable.

There are methodological implications. One-item measure of action and hopefulness correlated well with related concepts. One-item measure of fate did not correlate well with external locus of control but correlated significantly with belief in action and internal locus of control. One-item measures show the possibility of measuring the constructs well when researchers need to assess them quickly. This study somewhat validated the Nepali versions of the scales used to measure hope, happiness, and locus of control.

**Future Research**

Future studies can investigate other predictors of happiness. Studies have concluded that happiness results from having meaning in life, helping others (Aknin & Whillans, 2020), having family, cultivating friendship, doing enjoyable work, and finding

faith/spirituality, being connected to community, and developing intent to develop habit friendly to creating happiness (Brooks & Winfrey, 2023). Moreover, metacognition is helpful to cultivate happiness. Beyond these, there may be other psychological and social factors.

Happiness may not be the result of existing traits and abilities. So, the cultivation of happiness is a possibility (Sheldon & Lyubomirsky, 2019). The future studies may focus on this aspect. However, biological factors such as genetically decided "set point" may be majorly responsible for the level of happiness one has in life (Cummins, 2012). So, exploring happiness from the biological perspective is needed too.

In addition, the mediating role of LOC was established by the current research. Future studies may figure out other mediators in the relationship between hope and happiness. For example, extraversion may be another factor. Moreover, the theories about happiness made in the developed nations may be verified in the Nepali context.

## 6. Conclusion

The Nepali may be less fatalist and more believers of action (karma). It may be possible that they are both at the same time. A new cross-national study is needed to confirm this conclusion. The norms developed in this study can clarify this thing in future. Happiness is being searched by us all but many causes are unclear yet. This study showed that three cognitive factors–hope, belief in fate, and locus of control– are important determinants. Moreover, LOC mediates the relationship between hope and happiness. So does belief in action (not fate). Future studies should further identify other psychological, biological, and social determinants. Furthermore, other mediators need to be identified in the relationship between the determinants and happiness.

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## Appendix

**Fate, Action & Hope Scale भाग्य, कर्म र आशा जाँच**

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Indicate by tick mark in a scale of 10.<br>ठीक चिह्न लाएर १० को स्केलमा आफूलाई उपयुक्त ठाउँमा राख्नुहोस् | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| How much do you believe in fate?<br>तपाईं भाग्यमा कति विश्वास गर्नुहुन्छ? | Not at all<br>ठ्याक्कै गर्दिनँ<br>1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Completely<br>पूरै गर्छु<br>10 |
| How much do you believe in action?<br>तपाईं कर्ममा कति विश्वास गर्नुहुन्छ? | Not at all<br>ठ्याक्कै गर्दिनँ<br>1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Completely<br>पूरै गर्छु<br>10 |
| How hopeful are you about future? तपाईं कति आशावादी हुनुहुन्छ? | Not at all<br>ठ्याक्कै छैन<br>1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Completely<br>पूरै छु<br>10 |

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# Lecturer Competencies, Teaching Delivery and Student Academic Performance in Nepalese Higher Education

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**Abstract**

Improving the quality of teaching in higher education remains a significant challenge in developing-country contexts, where traditional instructional practices continue to shape academic systems. This review examines the relationship between teacher delivery, lecture quality, lecturer competencies, and student academic performance, with specific reference to Nepalese higher education. The study seeks to identify the gap between teacher delivery and student performance, assess the effectiveness of quality lecture delivery, and analyze the extent to which student grades depend on lecturer competencies. A structured narrative review methodology was employed, drawing on peer-reviewed journal articles, policy documents, and scholarly studies related to higher education teaching and learning. Owing to the limited availability of Nepal-specific empirical research, international and developing-country literature was synthesized to provide contextual insight. A conceptual framework was developed to illustrate the sequential relationship between lecturer competencies, lecture delivery, student engagement, and academic performance. The review reveals a persistent mismatch between teaching delivery and student academic outcomes, largely attributed to lecture-centered pedagogy and examination-oriented assessment systems. While quality lecture delivery and lecturer competencies positively influence student engagement and learning processes, their impact on academic performance is frequently constrained by institutional limitations, assessment practices, and gaps in policy implementation.

**Keywords:** Developing countries, Teacher delivery, Lecturer competencies, Student academic performance, Higher education

## 1. Introduction

In higher education, student learning results are significantly impacted by high-quality instruction. Universities around the world are increasingly being assessed on the quality of instruction and lecturer competencies in addition to research production and curriculum design (Hattie, 2009). Deeper learning, more student engagement, and better academic performance are all linked to effective teaching strategies. Nepal's higher education system is made up of central institutions that oversee a large network of colleges that are linked to or associated with them. These include Tribhuvan University, Pokhara University, Purbanchal University, and Kathmandu University. While universities establish curricula, evaluations, and quality requirements, affiliated colleges are mainly in charge of daily education. According to the University Grants Commission Nepal (n.d.), this distinction frequently leads to notable variations in the quality of education and the student experience between institutions.

Nepal has been in a positive trajectory towards global literacy rate. Nepal's rapid expansion in enrollment and educational institutions has positive effect on improving literacy rate but worries about the effectiveness of instruction and the employability of graduates persist. Classroom instruction at many associated colleges is still mostly lecture-centered, emphasizing syllabus completion and exam preparation rather than active, student-centered learning (Poudel & Sharma, 2019; Molung Educational Frontier, 2018). By restricting opportunities for critical thinking, problem-solving, and applied learning, these approaches produce a persistent gap between teachers' instruction and students' demonstrated learning. One of the main causes of this discrepancy is the fact that many professors at associated colleges lack possibilities for continuous professional development and pedagogical training. Recruitment is often based only on publication records and subject qualifications, while formal training in pedagogy, assessment design, and instructional methodologies is either nonexistent or inconsistent (Tamang, Shrestha, & Dhungana, 2022; British Council/Simon Borg &

Vertex Consult, 2023). Because of this, there is more variety between institutions because the quality of lectures is mostly based on the skills of individual lecturers rather than on frameworks for standardized teaching ability.

Assessment practices further confuse the relationship between teaching and performance. In Nepal's university-college system, summative assessments that are administered centrally and emphasize memorization and rote responses over higher-order skills (including analysis, synthesis, and application) are commonly employed to assess student progress. As a result, exam results could not fairly reflect actual learning or the pedagogical effectiveness of instruction at affiliated colleges (Ghimire, Bhattarai, & Rajbhandari, 2022). Because of this mismatch, it is difficult to determine the percentage of grade difference attributable to institutional features and assessment design vs lecturer talents.

Quality assurance, outcome-based education, and faculty development have been prioritized at the policy level by the University Grants Commission (UGC) and other stakeholders; however, implementation across affiliated colleges is still uneven because of resource constraints, a lack of oversight, and deeply embedded academic protocols (UGC Nepal; British Council report). Therefore, improving pedagogy, coordinating assessment with learning objectives, and expanding systematic faculty development are crucial to closing the achievement gap between teachers and students in Nepalese universities and their associated colleges.

Given these systemic realities, the purpose of this review paper is to: (1) identify gaps between teachers' instructional delivery and students' academic performance in Nepal's university-college system; (2) evaluate the effectiveness of quality lecture delivery in promoting learning in affiliated college settings; and (3) investigate the extent to which student grades are dependent on lecturer competencies. The report aims to inform institutional and UGC-level policies that might improve teaching quality and student outcomes by integrating worldwide literature with Nepalese research. For

gathering information for this review, we used a method and built a conceptual. Framework to work upon and conclude the study's objective.

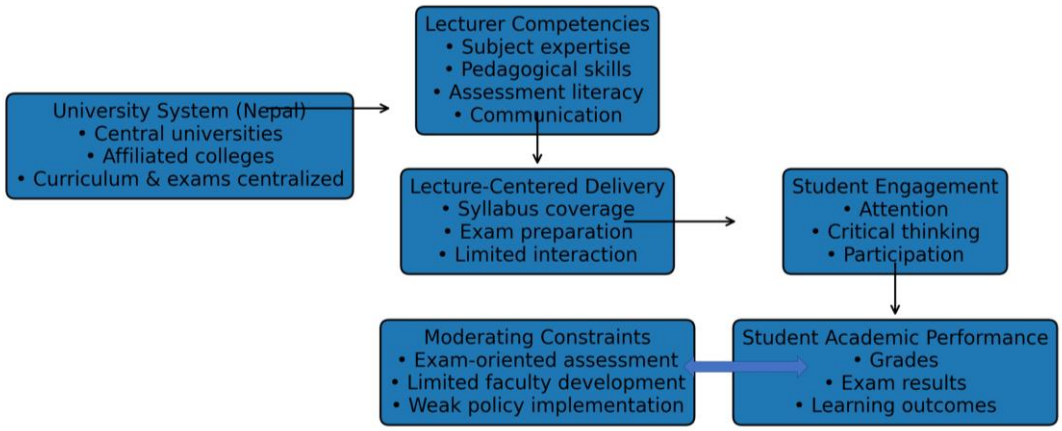


*Figure 1 Conceptual framework illustrating the relationship between lecturer competencies, lecture delivery, student engagement, and academic performance in Nepalese higher education*

## 2. Methods of data collections

This study adopts a structured narrative review to examine the relationship between teacher delivery, lecture quality, lecturer competencies, and student academic performance in Nepalese higher education. A narrative review is appropriate due to the limited Nepal-specific empirical evidence and the need to synthesize theoretical and policy literature (Tight, 2012; Trowler, 2010). Literature was collected from Google Scholar, ERIC, Scopus, policy documents, quality assurance reports, and Nepalese institutional studies (World Bank, 2018; OECD, 2019). Studies were selected based on relevance to higher education teaching, lecture delivery, lecturer competencies, student engagement, and academic performance. The literature was analyzed thematically around the study's three objectives (Biggs & Tang, 2011; Ramsden, 2003). As only

secondary sources were used, ethical approval was not required. Although Nepal-specific empirical studies remain limited, combining international and regional evidence strengthens the study's contextual validity.

### 2.1 Conceptual Framework

The conceptual framework (Figure 1) explains how lecturer competencies influence lecture delivery quality, which shapes student engagement and ultimately affects academic performance in Nepalese higher education. It assumes that student performance depends not only on learner ability but also on instructional processes within institutional and assessment contexts (Biggs, 1999; Prosser & Trigwell, 1999). Lecturer competencies include subject knowledge, pedagogical skills, communication, assessment literacy, and classroom facilitation (Shulman, 1986; Darling-Hammond, 2000; Kreber & Cranton, 2000). Lecture delivery quality, characterized by clarity, organization, interaction, and feedback, mediates the relationship between competencies and engagement (Hativa, 2000; Sweller, 1998; Mayer, 2009). Student engagement is the key mechanism linking instruction to academic performance (Kuh, 2009; Carini et al., 2006). These relationships are moderated by contextual factors in Nepalese higher education, including examination-oriented assessment, large class sizes, limited pedagogical training, and traditional academic culture (Bista & Gaulee, 2017; Altbach, 2015).

## 3. Literature Review

### 3.1 Teaching Delivery and Student Academic Performance

A substantial body of higher education research highlights a persistent misalignment between instructional delivery and student academic performance. Although effective teaching is often associated with clear content transmission,

evidence indicates that content-focused delivery alone does not necessarily improve learning outcomes (Biggs & Tang, 2011; Hattie, 2009). This disconnect is especially evident where instructional practices emphasize syllabus completion rather than conceptual understanding and higher-order cognitive skills (Anderson & Krathwohl, 2001). Research across higher education contexts shows that traditional lecture-based instruction often promotes surface learning, particularly when assessment systems reward factual recall instead of analytical or applied knowledge (Entwistle & Ramsden, 1983; Ramsden, 2003).

Consequently, student attendance and exposure to instruction do not always translate into meaningful learning gains or sustained academic performance. Research on student engagement shows that passive learning environments weaken the link between teaching and learning outcomes by limiting opportunities for critical thinking, reflection, and knowledge construction (Prince, 2004; Brookfield, 1995). Empirical studies also associate low classroom interaction with reduced motivation, lower attention, and weaker long-term knowledge retention, whereas active learning strategies improve student performance and reduce achievement gaps, even in large classes (Carini et al., 2006; Kuh, 2009; Freeman et al., 2014).

In the Nepalese context, this gap between instructional delivery and student learning is particularly pronounced. Teaching effectiveness is commonly evaluated through content coverage rather than learning outcomes, reinforcing teacher-centered practices with limited student participation (Bista, 2015; Bista & Gaulee, 2017). Examination-oriented assessment further encourages memorization-based learning, enabling students to obtain acceptable grades without developing conceptual understanding or analytical competence. This structural misalignment contributes to inconsistent academic performance and undermines the broader goals of higher education in Nepal.

### 3.2 Quality of Lecture Delivery and Learning Effectiveness

Despite critiques of traditional lecturing, research acknowledges that lectures remain a central mode of instruction in higher education, particularly in resource-constrained contexts. The effectiveness of lectures depends less on their format and more on their quality of delivery. High-quality lectures are characterized by clear organization, logical sequencing, and alignment with explicitly stated learning objectives (Hativa, 2000; Gibbs, 2010). Effective lecture delivery supports learning when new content is meaningfully connected to prior knowledge, real-world contexts, and practical examples (Biggs & Tang, 2011; Mayer, 2009). Such instructional coherence reduces extraneous cognitive load and enables students to integrate and apply new information more effectively (Sweller, 1998). Clarity of explanation, appropriate pacing, and emphasis on key concepts are consistently identified as critical determinants of lecture effectiveness. Interaction and feedback further enhance the impact of lecture delivery. Opportunities for questioning, discussion, and formative feedback allow students to monitor their understanding and adjust learning strategies accordingly (Hattie & Timperley, 2007). However, research suggests that such practices are unevenly implemented, particularly in higher education systems characterized by large class sizes and limited pedagogical training (Gibbs & Coffey, 2004). In Nepal, structural constraints—including overcrowded classrooms, limited instructional resources, and insufficient professional development opportunities—restrict the adoption of interactive and student-centered lecture practices (Bista & Gaulee, 2017). As a result, lectures often remain transmission-oriented, limiting their potential contribution to deeper learning and academic achievement.

### 3.3 Lecturer Competence and Student Academic Outcomes

Lecturer competence is widely recognized as a multidimensional construct encompassing pedagogical knowledge, subject expertise, communication skills, and assessment literacy. Shulman's (1986) concept of pedagogical content knowledge emphasizes the importance of integrating disciplinary expertise with an understanding of how students learn specific subject matter. Empirical studies demonstrate that lecturers with strong pedagogical and communication competencies are more effective in fostering student engagement and supporting learning (Darling-Hammond, 2000; Kane et al., 2002). Meta-analytic evidence indicates a positive relationship between teaching quality and student achievement; however, this relationship is often mediated by assessment practices and institutional contexts (Hattie, 2009). When assessment systems emphasize recall-based examinations, improvements in teaching quality may not be reflected in student grades, thereby obscuring the impact of lecturer competence on measurable academic outcomes (Harvey & Green, 1993). In Nepalese higher education, assessment practices are predominantly examination-driven, with limited integration of formative or continuous assessment (Bista, 2015). Grades function as the primary indicator of academic success, shaping both teaching strategies and student learning behavior. This grading culture constrains the influence of pedagogical innovation and limits the extent to which lecturer competence translates into improved student performance.

### 3.4 Teaching Practices in Developing-Country Contexts: Implications for Nepal

Higher education systems in developing countries face shared structural and institutional challenges, including limited funding, high student–teacher ratios, inadequate infrastructure, and weak professional development systems (Altbach et al., 2009; Henard & Roseveare, 2012). In such contexts, teaching practices often remain

traditional and teacher-centered, despite growing recognition of the importance of student-centered learning. Policy frameworks frequently prioritize access and enrollment expansion over instructional quality, resulting in limited accountability mechanisms for teaching effectiveness (World Bank, 2018). Although quality assurance discourse has gained prominence, implementation remains uneven, particularly with respect to pedagogical practices and assessment reform. Resistance to pedagogical change further complicates reform efforts. Established academic cultures, heavy workloads, limited incentives, and examination-dominated assessment systems discourage sustained instructional innovation (Barnett, 2000). In Nepal, initiatives aimed at promoting active learning and reflective teaching often encounter cultural and structural barriers, limiting their long-term impact on student learning outcomes.

*Table 1 Key References and Their Significance to understand Conceptual Relationship between Lecturer Competencies, Lecture Delivery, Student Engagement, and Academic Performance in Nepalese Higher Education*

| ***Reference*** | ***Theoretical*** | ***Core Contribution*** | ***Significance*** |
|---|---|---|---|
| *Shulman (1986)* | *Pedagogical Content Knowledge* | *Introduced the integration of pedagogy and subject knowledge* | *Provides the conceptual foundation for defining lecturer competencies* |
| *Biggs (1999)* | *Student-centered learning* | *Emphasized learning as a function of what students do* | *Supports the shift from delivery to engagement* |

| ***Reference*** | ***Theoretical*** | ***Core Contribution*** | ***Significance*** |
|---|---|---|---|
| *Biggs & Tang (2011)* | *Constructive alignment* | *Alignment of teaching, learning outcomes, and assessment* | *Explains why misaligned assessment weakens teaching impact* |
| *Hattie (2009)* | *Meta-analysis of teaching effectiveness* | *Identified feedback, clarity, and instruction as high-impact factors* | *Justifies focus on lecture quality and feedback* |
| *Hativa (2000)* | *Lecture effectiveness* | *Identified clarity, structure, and explanation as core lecture qualities* | *Directly informs the lecture delivery component* |
| *Entwistle & Ramsden (1983)* | *Student learning approaches* | *Distinguished surface vs deep learning* | *Explains exam-driven surface learning in Nepal* |
| *Ramsden (2003)* | *Teaching in higher education* | *Linked assessment design to learning approaches* | *Supports discussion on grade–learning mismatch* |
| *Prince (2004)* | *Active learning* | *Demonstrated superiority of active learning over passive lectures* | *Highlights limitations of* |

| ***Reference*** | ***Theoretical*** | ***Core Contribution*** | ***Significance*** |
|---|---|---|---|
| | | | *lecture-centered pedagogy* |
| *Freeman et al. (2014)* | *Active learning meta-analysis* | *Empirical evidence of improved performance through engagement* | *Strengthens engagement–performance linkage* |
| *Kuh (2009)* | *Student engagement* | *Engagement is linked to achievement and persistence* | *Supports engagement as a mediating variable* |
| *Darling-Hammond (2000)* | *Teacher quality* | *Connected pedagogical competence with student outcomes* | *Reinforces the importance of lecturer competencies* |
| *Kane et al. (2002)* | *Teaching effectiveness* | *Showed teaching quality affects student learning experiences* | *Supports competence → delivery pathway* |
| *Gibbs & Coffey (2004)* | *Teacher training* | *Found pedagogical training improves teaching quality* | *Supports recommendations for faculty development* |

| ***Reference*** | ***Theoretical*** | ***Core Contribution*** | ***Significance*** |
|---|---|---|---|
| *Hattie & Timperley (2007)* | *Feedback* | *Feedback as a key driver of learning* | *Justifies the inclusion of feedback in lecture quality* |
| *Sweller (1998)* | *Cognitive load theory* | *Structured instruction reduces cognitive overload* | *Explains the importance of lecture organization* |
| *Bista (2015)* | *Teaching in Nepal* | *Identified exam-oriented and teacher-centered practices* | *Provides Nepal-specific empirical grounding* |
| *Bista & Gaulee (2017)* | *Nepalese higher education* | *Highlighted structural and pedagogical challenges* | *Supports moderating institutional factors* |
| *Paudel (2020)* | *Assessment practices in Nepal* | *Identified dominance of summative exams* | *Explains weak teaching–grade alignment* |
| *Henard & Roseveare (2012)* | *Quality teaching policy* | *Institutional support critical for teaching quality* | *Information institutional implications* |

| *Reference* | *Theoretical* | *Core Contribution* | *Significance* |
|---|---|---|---|
| *World Bank (2018)* | *Learning outcomes* | *Emphasized instructional quality over access* | *Supports policy-level reform arguments* |
| *Altbach et al. (2009)* | *Developing-country HE* | *Identified systemic constraints* | *Contextualizes Nepal within global South* |
| *Fullan (2007)* | *Educational change* | *Change requires system-wide alignment* | *Supports system-level recommendations* |

## 4. Result and Discussion

### 4.1 Gap Between Teacher Delivery and Student Performance

The literature indicates a persistent gap between teacher delivery and student performance when teaching effectiveness is defined primarily by content coverage rather than learning outcomes (Biggs & Tang, 2011; Entwistle & Ramsden, 1983). In such contexts, instructional effort does not necessarily translate into improved performance, particularly when assessments emphasize recall.

In Nepalese higher education, this gap is intensified by lecture-centered pedagogy and examination-oriented evaluation practices (Bista, 2015). Emphasis on syllabus completion limits interaction and deep learning, making student performance an inconsistent indicator of actual learning.

### 4.2 Role of Lecture Quality in Shaping Learning Outcomes

The literature consistently shows that well-structured lectures enhance student understanding and engagement (Hativa, 2000; Sweller, 1998). Interactive elements and feedback further support learning (Prince, 2004; Hattie & Timperley, 2007). However, in Nepal, large class sizes and limited resources constrain interaction and feedback, reducing the impact of lecture quality on academic outcomes (Bista & Gaulee, 2017). This supports the framework's view that lecture quality operates within contextual limits.

### 4.3 Lecturer Competencies and Student Grades

Lecturer competencies, including pedagogical skills, communication, and assessment literacy, are central to effective teaching (Shulman, 1986; Darling-Hammond, 2000). Competent lecturers are associated with higher student motivation and engagement (Hattie, 2009). Nonetheless, in Nepal, examination-driven assessment systems weaken the link between teaching quality and grades (Bista, 2015). Conceptual teaching may not yield higher results when assessments reward memorization, limiting the measurable impact of lecturer competence.

### 4.4 Teaching Practices in Developing Countries: Implications for Nepal

Studies from developing countries identify shared constraints such as limited funding, rising enrollments, and weak professional development, reinforcing reliance on traditional lectures (Altbach, Reisberg, & Rumbley, 2009). In Nepal, weak policy implementation and evaluation systems further restrict instructional reform (World Bank, 2018). Resistance to change, shaped by institutional culture and workload pressures, also hinders sustained innovation (Fullan, 2007).

### 4.5 Integration with the Conceptual Framework

The discussion aligns with the conceptual framework, showing that lecturer competencies influence lecture delivery and student engagement, while assessment practices and institutional constraints moderate their effect on academic performance.

### 4.6 Summary of Discussion

Overall, the gap between teacher delivery and student performance in Nepalese higher education is systemic rather than purely pedagogical. While lecturer competence and lecture quality are necessary, their impact is constrained by examination dominance, institutional limitations, and resistance to reform. Addressing these interconnected factors is essential for improving learning outcomes. The discussion further indicates that improvements in student academic performance require changes beyond individual lecturer competence. While effective lecture delivery and strong pedagogical skills remain important, their influence depends on supportive assessment practices and institutional conditions. Without greater alignment between teaching methods, assessment systems, and learning objectives, improvements in lecture quality alone are unlikely to produce consistent gains in student performance, particularly within the Nepalese higher education context (Biggs & Tang, 2011; Hativa, 2000; Shulman, 1986; Bista, 2015; Bista & Gaulee, 2017).

## 5. Conclusion

This review examines the gap between teacher delivery and student academic performance, the role of lecture quality, and the influence of lecturer competencies in Nepalese higher education. Drawing on global, developing-country, and Nepal-specific literature, it finds that student performance is shaped by an interaction of pedagogy, institutional structures, and assessment systems. The gap between teaching and

performance is rooted less in teacher effort and more in traditional instructional models and exam-oriented assessments, where syllabus completion and high-stakes examinations dominate. While quality lecture delivery—marked by clarity, organization, interaction, and feedback—enhances student engagement, its impact on academic performance is limited by large class sizes, scarce resources, and restricted professional development. Lecture competencies, including pedagogical skills, communication, and assessment literacy, are important but insufficient in contexts that emphasize rote memorization over conceptual understanding. Overall, the review concludes that improving student performance in Nepal requires system-wide reforms that align teaching practices, assessment methods, and institutional support, rather than focusing solely on lecture quality or lecturer competence.

## 6. Implication and recommendation

Teaching effectiveness should be viewed as a continuous process rather than measured solely through examination results, as overreliance on grades obscures student engagement and conceptual understanding (Gibbs, 2010). Effective teaching requires not only subject expertise but also strong pedagogical and assessment-related competencies (Kreber & Cranton, 2000), particularly in higher education systems where recall-based assessments limit meaningful evaluation of student learning. Although incremental improvements in lecture delivery, including clear learning objectives, structured interaction, and timely feedback, can enhance student engagement (Fry, Ketteridge, & Marshall, 2009), their impact remains limited when assessment practices continue to emphasize memorization rather than deeper learning, underscoring the importance of constructive alignment between teaching, assessment, and intended learning outcomes (Ramsden, 2003). At the institutional level, teaching quality should be recognized as a core academic priority through sustained investment in faculty development, mentoring, peer learning, and teaching support systems

(Henard & Roseveare, 2012). Likewise, teaching evaluation should extend beyond examination performance to incorporate peer observation, reflective practice, student feedback, and broader indicators of instructional quality and learning effectiveness (Harvey & Green, 1993). From a policy perspective, strengthening higher education requires translating quality improvement goals into effective classroom practice through clear implementation strategies, continuous monitoring, adequate institutional resources, and assessment reforms that encourage deeper learning and stronger alignment between teaching practices and student outcomes (Altbach, 2015; Boud & Falchikov, 2007). Accordingly, Nepalese higher education institutions should institutionalize regular pedagogical training, align teaching with assessment and intended learning outcomes, strengthen faculty development initiatives, and implement comprehensive teaching evaluation systems to promote sustainable improvements in teaching quality and student academic performance.

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# Cascaded AI Task Decomposition: A Generalizable Framework for Multi-Stage Computer Vision Pipeline Validated on Automatic Number Plate Recognition for Nepali License Plates

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**Abstract**

Detecting, localizing, and reading a license plate in a single pass usually lowers accuracy. Each of these sub-tasks is manageable on its own, but a single model must handle all of them together, across spatial scales that differ by more than an order of magnitude, so it settles for a compromise that is only moderate at each. This paper formalizes *Cascaded AI Task Decomposition* (CATD), which splits a compound vision problem into a sequence of tasks, each handled by a model trained only for that task and operating on a progressively cropped Region of Interest (ROI). The pipeline connects to any IP camera over the Real-Time Streaming Protocol (RTSP) and requires no hardware changes. To evaluate the framework, we built a three-stage Automatic Number Plate Recognition (ANPR) system for Nepali embossed plates: (1) a YOLOv8n-COCO vehicle detector, (2) a custom-trained YOLOv11n plate localizer, and (3) an RF-DETR Base character recognizer covering 61 classes. On the held-out test set the plate localizer reached 97.1 percent mAP@50 and the character recognizer 97.8 percent mAP@50. We integrated the pipeline into a parking-management system that automates the flow from plate capture to billing. We estimate the end-to-end precision at about 90.4 percent; this is not a direct measurement but a combination of the per-stage precisions, and validation on real Nepali embossed plates remains future work.

**Keywords:** cascaded pipeline; task decomposition; YOLOv11; RF-DETR; ANPR; OCR; multi-agent orchestration; computer vision; Nepal; parking management.

## 1. Introduction

Most computer vision applications involve more than one problem at once: an object must first be detected, then localized, and a specific attribute must finally be extracted from it. A common approach is to train a single model to perform all of these tasks jointly. This forces the model to handle very different spatial scales and feature distributions simultaneously, and the result is typically a model that performs adequately on every subtask but excels at none.

This paper formalizes CATD: rather than relying on a single model to perform every subtask, a pipeline of specialized models is constructed, each solving one well-scoped subproblem and passing a refined crop to the next stage. The structure mirrors multi-agent LLM orchestration, microservice design, and classical signal-processing cascades. Multistage cascades are themselves well established; what this paper adds is to articulate the pattern as a reusable design framework with explicit criteria for when spatial-scale decomposition helps, particularly for dual-script, low-data regional ANPR, together with a quantified comparison against monolithic alternatives.

We validate CATD using a three-stage ANPR system. This system works with any IP camera over RTSP. It does not require any hardware changes. The reason is simple: vehicle registration in the Kathmandu valley increases every year. Many places still record information by hand. This leads to repeated mistakes. For example, a digit might be copied incorrectly. Handwriting can be hard to read after a week. An attendant might make errors near the end of a shift. Plate recognition solves this problem. We use it as part of a parking-management application. This application logs when vehicles enter and exit. It also bills for each session. At the end of the day it summarizes the traffic. CATD is a part of this process. The ANPR system helps to read vehicle plates. This makes the parking-management application more reliable.

**Key Contributions:**

- A multi-stage model of the CATD framework, along with some rules to help design a cascade and a test to see if the extra complexity is worth it.
- A CCTV-agnostic three-stage pipeline achieving 97.1% mAP@50 plate localization and 97.8% mAP@50-character recognition on the held-out test set.
- A data strategy that pairs Nepali flat-plate images with Indian embossed-plate images in two ways, layout and surface, which helps the pipeline read Nepali embossed plates it was not trained on.
- An integrated parking-management use case demonstrating end-to-end automation from RTSP capture to billing, session management, and analytics.

## 2. Theoretical Framework: Cascaded AI Task Decomposition

### 2.1 Formal Definition

Let us consider a compound task $C$. This compound task $C$ has to find an attribute $A$ from a big scene $S$. The attribute $A$ is really small compared to the scene $S$. We write the CATD pipeline as an ordered chain $M = \{M_1, M_2, \dots, M_N\}$. The first model $M_1$ turns the full scene into a region $\mathrm{ROI}_1 \subseteq S$; every later model $M_i$ $(i > 1)$ takes the previous region $\mathrm{ROI}_{i-1}$ and tightens it to $\mathrm{ROI}_i$; the last model $M_N$ returns $A$.

If we treat stage failures as statistically independent, the end-to-end precision multiplies:

$$N$$

$$P_{\text{e2e}} = \prod_{i=1} P_i.$$

where each $P_i$ is the precision of stage $i$. With the measured values 98.5%, 96.5%, and 95.1% (Table 5), Equation [eq:e2e] gives $P_{\text{e2e}} \approx 0.985 \times 0.965 \times 0.951 \approx 90.4\%$ . Treat this as a modelled figure rather than a measurement. It leans on two conveniences. The first, independence, flatters the result: the stages actually move together to some degree, since a half-occluded vehicle crop out of Stage 1 makes Stage 2 likelier to miss as well, so the real end-to-end precision should sit a little below 90.4%. Second, because each stage must also *detect* its target before the next stage can run, overall read *yield* is additionally bounded by per-stage recall; Equation [eq:e2e] therefore characterizes the precision of the cascade rather than the fraction of plates read correctly end-to-end. An empirical end-to-end measurement is reported as pending in Section 4.5.

### 2.2 Why Cascading Beats Monolithic Models

Each stage passes a cropped ROI to the next model, stripping background clutter that would otherwise confuse downstream predictions. RF-DETR Base accounts for the majority of total pipeline compute but only runs when Stage 1 confirms a vehicle is present, so it is never invoked on empty frames.

### 2.3 Analogy to Multi-Agent Orchestration

CATD and multi-agent LLM orchestration line up almost one to one. A complex task is split into sub-tasks, each handed to a specialist; every agent's output narrows what the next one has to deal with; the later agents fire only once confidence clears a threshold; and any agent can be replaced on its own. In both, the design question that matters is where to cut the task apart. For CATD the cut goes at the spatial-scale transition, since that is exactly where a single model starts losing accuracy and a cascade wins it back.

## 3. Literature Review

### 3.1 From Classical Vision to Deep Learning

Early ANPR systems relied on Scale-Invariant Feature Transform (SIFT) descriptors, Support Vector Machine (SVM) classifiers, and Canny edge detection (Canny, 1986), dropping below 70% accuracy in adverse weather (Shaikh and Tawde, 2024). Single-pass detectors from the YOLO family first made real-time recognition practical (Redmon et al., 2016). On Chinese plates LPRNet (Zherzdev and Gruzdev, 2018) hit 95%, but glare on the plate surface and any departure from the standard layout still threw it off. Nepali work built on YOLOv3/v4 topped out near 87%, where embossed plates broke character segmentation (Gajurel et al., 2024).

### 3.2 Transformer Architectures for Fine-Grained Recognition

By attending over image patches rather than fixed neighbourhoods, the Vision Transformer handles characters that are tilted or half-hidden (Dosovitskiy et al., 2021). RF-DETR (Robinson et al., 2026) puts a DINOv2 backbone (Oquab et al., 2024) through neural architecture search; it tops RF100-VL, and, what matters more for us, it transfers well across domains, which helps when Nepali training data is thin. Others have bolted spatial transformer networks onto YOLO detectors and held up under plate tilt and uneven lighting (Wang et al., 2025).

### 3.3 Cascaded and Multi-Stage Architectures

Viola and Jones (2001) showed that cascaded face detection substantially outperformed single classifiers at equivalent compute. Ammar et al. (2023) validated the multistage pattern in a production parking deployment for Saudi plates but did not address dualscript plates, embossed surface reflectance, or cross-domain adaptation for low-data settings.

Our approach maintains explicitly decoupled, independently trained stages with clean ROI boundaries at each handoff.

Hence, existing Nepali ANPR literature is missing three things: a clear explanation of why cascading improves accuracy; a cross-domain data strategy for regional datasets with limited coverage; and end-to-end accuracy measurement that accounts for compounded stage errors. Direct comparison with systems like LPRNet is not possible because no shared Nepali embossed-plate benchmark exists. This paper addresses all three, and additionally demonstrates the system in a deployed parking-management context. In particular, although cascaded detection is itself well established (Viola and Jones, 2001) and has been applied to plate recognition in single-script production settings (Ammar et al., 2023), few prior works articulate the spatial-scale decomposition principle as an explicit, reusable design framework or quantify its accuracy advantage for dual-script, low-data regional plates.

## 4. Research Methods

Our research methodology focuses on the design, implementation, and empirical evaluation of the Cascaded AI Task Decomposition (CATD) framework. The approach is structured into four main phases: We formalize the CATD framework by decomposing the compound task of ANPR into a sequential chain of isolated sub-tasks. By establishing an ordered sequence from scene to attribute, each successive model progressively refines the Region of Interest (ROI). This phase also mathematically models the end-to-end precision as a product of individual stage probabilities, assuming statistical independence, to establish a theoretical performance baseline for the multi-stage pipeline.

### 4.1 Data Strategy and Proxy Adaptation

A significant hurdle in regional ANPR is the scarcity of training data, particularly for Nepali embossed plates. To address this, we employed a two-dimensional proxy adaptation strategy. The training corpus was constructed by combining 1,380 Nepali traditional flat plates (to teach the system the layout, Devanagari characters, and province tokens) with 1,127 Indian embossed plates (to simulate specular highlights and metallic shadows). This zero-shot transfer approach forces the model to generalize to unseen Nepali embossed plates during inference.

### 4.2 Model Training and Pipeline Integration

The pipeline consists of three independently trained models orchestrated sequentially:

- **Vehicle Detection (Stage 1):** Utilizes a YOLOv8n model pre-trained on the COCO dataset to isolate vehicles from the raw RTSP camera feed without further fine-tuning.
- **Plate Localization (Stage 2):** Employs a YOLOv11n model trained specifically on the vehicle crops from Stage 1, using Complete-IoU (CIoU) loss to handle tight bounding boxes and minimize glare interference.
- **Character Recognition (Stage 3):** Deploys an RF-DETR Base model that treats every character out of 61 possible classes as an independent detection target.

These models are integrated into a cohesive pipeline that only invokes computationally heavy stages (like Stage 3) when earlier stages confirm a detection, optimizing overall system inference.

### 4.3 Empirical Evaluation

The models were empirically validated on a held-out test set, capturing key performance metrics such as mAP@50 for both plate localization and character recognition. Beyond static dataset metrics, the pipeline was deployed in a live parking-management application. This real-world integration verified the system's operational viability, demonstrating its ability to automate vehicle entry/exit logging and billing while confirming the practical advantages of spatial-scale task decomposition.

## 3.5 The CATD Design Framework

### 3.5.1 Task Decomposition Analysis

Begin by listing the spatial scales the problem contains: scene, object, sub-object, attribute. Put the scale with the most training data first, at Stage 1, and save your strongest model for whichever scale has to be most accurate. In ANPR the chain runs vehicle (scene) → plate (object) → character (sub-object).

### 3.5.2 Dataset Strategy: Two-Dimensional Proxy Adaptation

The data shortage here runs in two directions. Nepali plates are already thin in public datasets, and Nepali *embossed* plates are almost absent. We fill the two gaps from different sources. For *layout*, 1,380 Nepali traditional flat-plate images teach the Devanagari character set, the province tokens, and how a Nepali plate is laid out. For the *embossed surface*, 1,127 Indian embossed-plate images teach specular highlights and the shadow that metallic relief throws. No Nepali embossed plate is in the training set; the model meets one only at inference, where it has to put the two together.

### 3.5.3 Training Protocol

Stage 1 runs on stock COCO (Common Objects in Context) weights; we do not fine-tune it. To build Stage 2's training data we push raw images through Stage 1 and keep the vehicle crops, so at training time Stage 2 already sees the exact input distribution it will meet in production. Stage 2 applies the Complete-IoU (CIoU) loss,

$$\mathcal{L}_{\text{CIoU}} = 1 - \text{IoU} + \frac{\rho^2(b, b^{gt})}{c_2} + \alpha v,$$

Here $\rho(\cdot)$ is the distance between the centres of the predicted box $\boldsymbol{b}$ and the ground-truth box $\boldsymbol{b}^{gt}$, $c$ is the diagonal of the smallest box enclosing both, and the aspect-ratio term is

$$v = \frac{4}{\pi^2}\left(\arctan\frac{w_{gt}}{h_{gt}} - \arctan\frac{w}{h}\right)^2, \qquad \alpha = \frac{v}{(1 - \text{IoU}) + v}.$$

Stage 3 trains on the Stage 2 crops in turn. We label every character as its own detection target, which keeps recognition working when part of the plate is blocked.

### 3.5.4 Iterative Refinement and Per-Stage Visualization

The stages are separate, so you can fix one stage without affecting the other stages. When a problem happens as something moves from one stage to another, it usually becomes clear what is going wrong.

- **Stage 1 output:** Review vehicle bounding-box crops; tune the confidence threshold if motorbikes or tuk-tuks are missed.
- **Stage 2 output:** Inspect plate-crop tightness; adjust the IoU threshold or retrain with additional monsoon-condition images if glare causes loose boxes.

- **Stage 3 output:** Look at the per-character confidence scores; when the regex check starts failing on a rare class such as LUMBINI or MADESH, retrain on more of it.

So the system gets better one step at a time. You fix one part of the process, not the whole thing. The main controls for each stage are the confidence threshold, the IoU threshold, the NMS overlap, the input resolution, and how much you modify the input.

### 3.6 Datasets

#### 3.6.1 Stage 2: Plate Localization

We pooled 2,507 plate images for training: 1,380 Nepali traditional flat plates (55.0%), drawn from Roboflow Universe and the Inspiring Lab Kaggle dataset, plus 1,127 Indian embossed-plate proxies (45.0%). Roboflow augmentation took that to 9,366 images, a

3.7 × expansion, which we split 7,058 / 1,835 / 473 across train, validation, and test (75.4%, 19.6%, 5.0%). We drew every bounding box ourselves.

#### 3.6.2 Stage 3: Character Recognition

The same 2,507 plates supplied the character data: 21,648 boxes over 61 classes, about 8.6 per image, at a median resolution of $324 \times 121$ pixels. The split was 17,722 training (81.9%), 3,072 validation (14.2%), and 854 test annotations (3.9%). Eleven classes, among them LUMBINI, MADESH, VE, HA, and KA, carry fewer than three annotations each and never reach the test set. So the 97.8% test-set mAP@50 covers only the classes we could actually score; Table 6 gives the per-class numbers, and the regex check in Section 3.7.4 catches the rare tokens the model misreads.

### 3.7 Implementation: Three-Stage ANPR for Nepali Plates

#### 3.7.1 Domain Challenges

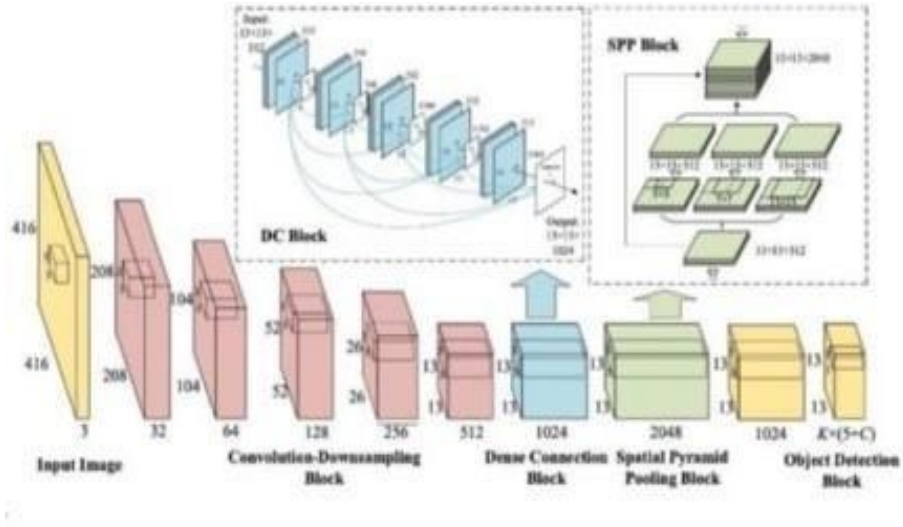
Several difficulties stack up on a Nepali plate. Two scripts share it, which pushes the recognition model to 61 classes, well beyond what Latin-only ANPR needs. The embossed finish throws specular glare that edge-gradient OCR cannot handle. Monsoon months swing the lighting around and load the air with haze and dust. And since public datasets barely cover the range of Nepali plate formats, a supervised model starts out short of data.

The radio-frequency identification (RFID) tags on Nepal's official embossed plates are worth noting here, because they complement the vision pipeline rather than compete with it. An RFID tag returns a digital identifier when a compatible reader is in range, but it depends on dedicated hardware, a functioning tag, and a close-range read, and it carries no visual confirmation of the physical plate. The CATD pipeline needs only a standard camera and the existing video stream, works on legacy and non-RFID plates, and produces a plate image that a human can verify. Used together, the two channels crosscheck each other: the camera covers cases where RFID is absent or fails, and the plate image serves as an audit trail for disputed sessions. The system presented here is therefore designed to work alongside RFID, not to replace it.


*Representative samples from the training corpus of Nepali traditional and Indian embossed license plates used for cross-domain proxy adaptation.*

### 3.7.2 Stage 1: Vehicle Gating (YOLOv8n-COCO)

A pre-trained YOLOv8n (Jocher et al., 2023) processes every incoming RTSP frame at $640 \times 640$ resolution. Frames with no vehicle detections are discarded immediately, so Stages 2 and 3 only run when there is something worth processing. This selective activation reduces effective compute by 61–73% depending on vehicle density in the scene.

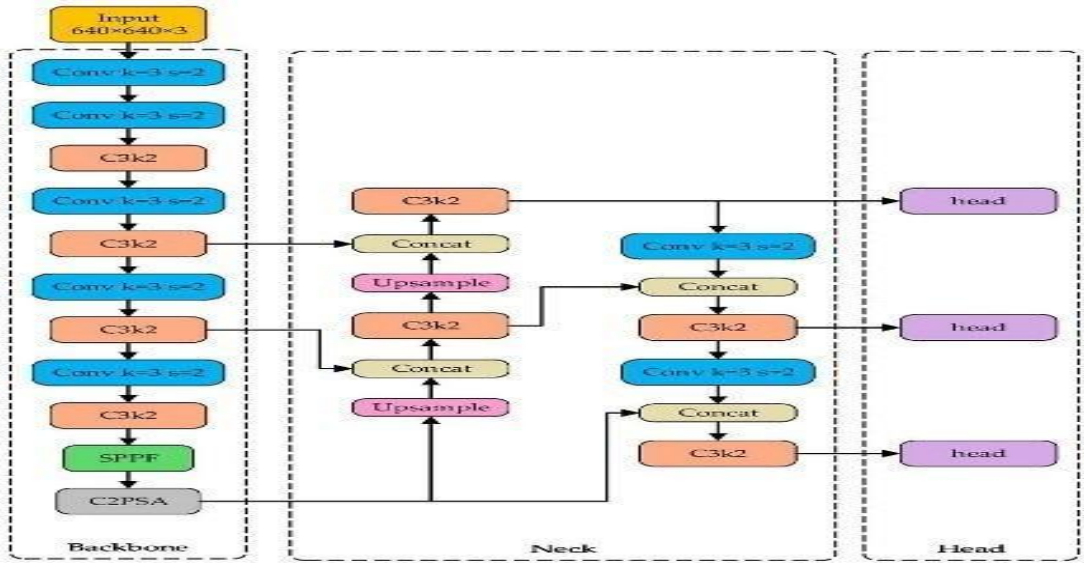



*YOLO single-stage detector architecture used for Stage 1 vehicle gating: convolutional downsampling backbone, dense-connection and spatial-pyramid-pooling blocks, and the detection head.*

### 3.7.3 Stage 2: Plate Localization (YOLOv11n)

The cropped vehicle region goes to a custom-trained YOLOv11n (Khanam and Hussain, 2024). The architecture introduces the C3k2 block (Cross-Stage Partial with kernel size 2),

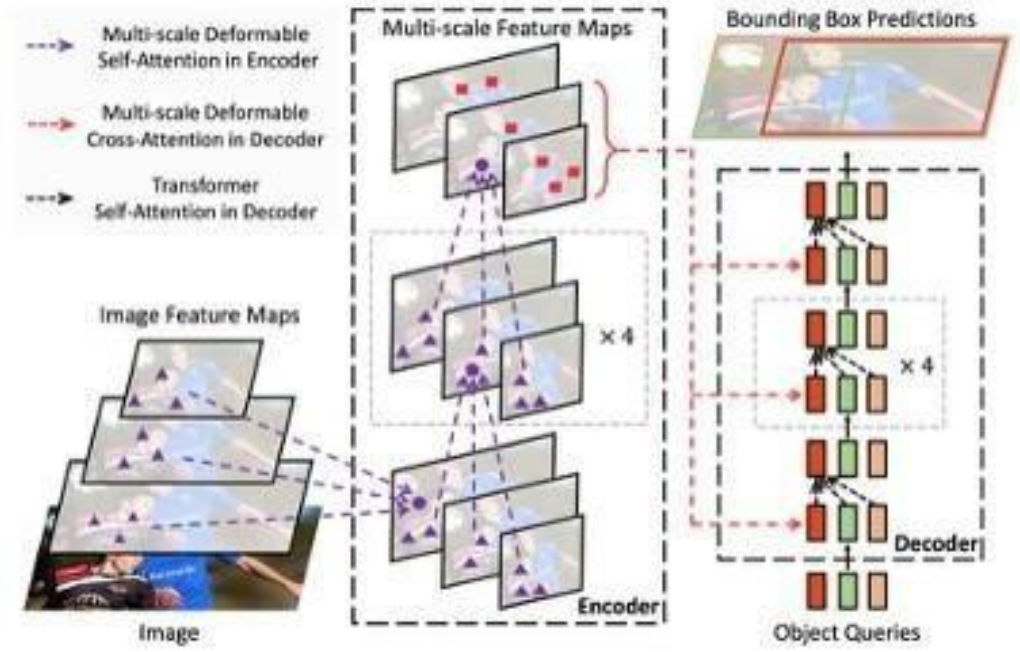
SPPF (Spatial Pyramid Pooling-Fast), and C2PSA (Convolutional block with Parallel Spatial Attention). This model was trained using the CIoU loss of Equation [eq:ciou] on the two dimensional proxy dataset described in Section 3.6.




*YOLOv11n architecture (Stage 2 plate localizer): backbone with C3k2, SPPF, and C2PSA blocks, a feature-pyramid neck with up-sampling and concatenation, and three detection heads.*

### 3.7.4 Stage 3: Character Recognition (RF-DETR Base)

The localized plate crop goes to RF-DETR Base, configured for 61-class character detection and built on a DINOv2 backbone (Oquab et al., 2024; Robinson et al., 2026). Each character is detected as an independent object; the recognized boxes are then ordered left-to-right (*x*-sort) and passed through regex post-validation to assemble and validate the final plate string.




*RF-DETR detection-transformer architecture (Stage 3 character recognizer): multiscale deformable self-attention in the encoder and cross-attention in the decoder map image features to per-character bounding-box predictions over object queries.*

### 3.7.5 Software Stack

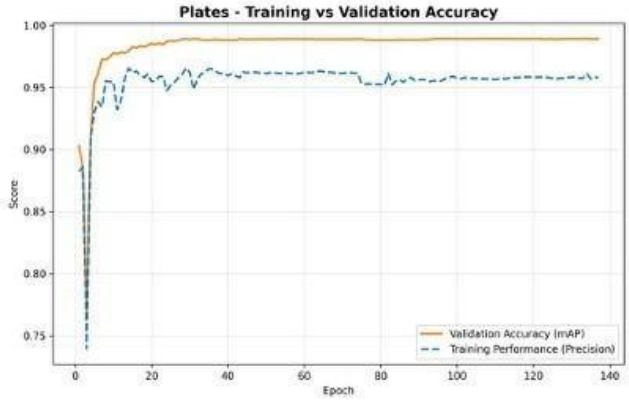
*Software stack for the three-stage ANPR pipeline.*

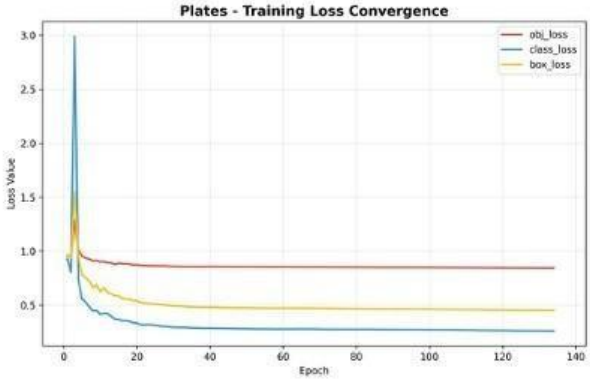
| Component | Technology | Role |
|---|---|---|
| Stage 1 Detector | YOLOv8n (COCO) | Vehicle gating |
| Stage 2 Localizer | YOLOv11n (Custom) | Plate localization |
| Stage 3 OCR | RF-DETR Base (DINOv2) | Character recognition |
| Stream Input | RTSP (IP camera) | Frame acquisition |
| Post-processing | Regex + *x*-sort | Format validation & plate string |
| Training Platform | Roboflow, Google Colab | All stages |

## 4. Results Analysis

### 4.1 Stage 2: YOLOv11n Plate Localization: Training Analysis

The figures below show how the Stage 2 localizer learned. When you look at these curves one at a time you can see what you need to change. If the precision and the recall are not close to each other, you should change the confidence threshold. If the box loss stops getting better quickly, you should look at the learning-r

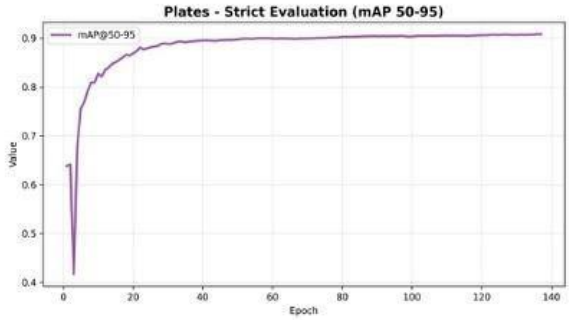


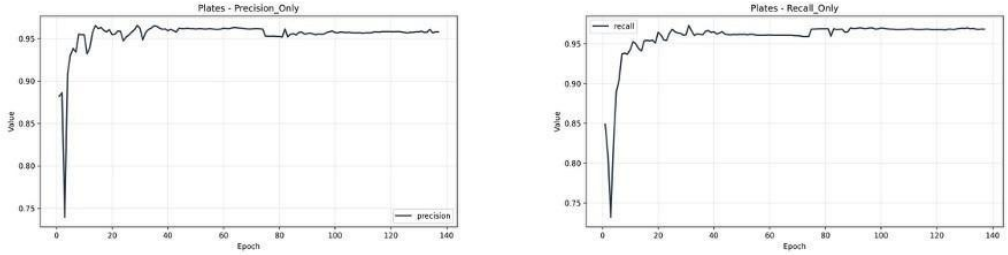

ate schedule again.

*Stage 2 YOLOv11n plate detector: (a) training against validation accuracy, and (b) how the training loss converges.*

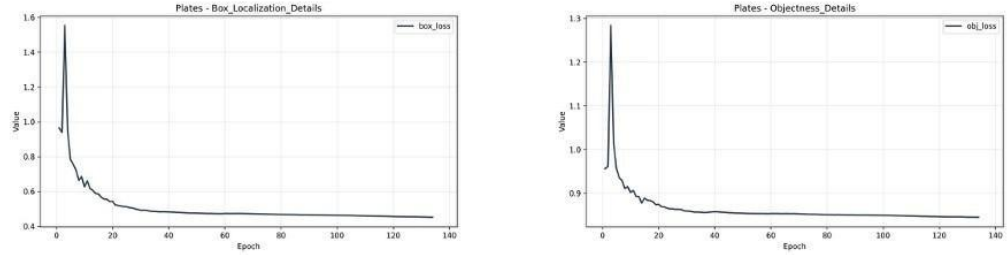
mAP@50 climbs above 97% early and holds there. mAP@50:95 levels off around 91% (Figure 6). That gap is no surprise: the tighter IoU cutoffs are hard to meet when plate boxes vary so much in aspect ratio.




*YOLOv11n (Stage 2): strict mAP@50:95, plateauing near 91%.*




*Stage 2 YOLOv11n: (a) precision and (b) recall over training.*




*Stage 2 YOLOv11n loss curves: (a) box loss, falling monotonically, and (b) objectness loss, settling smoothly.*

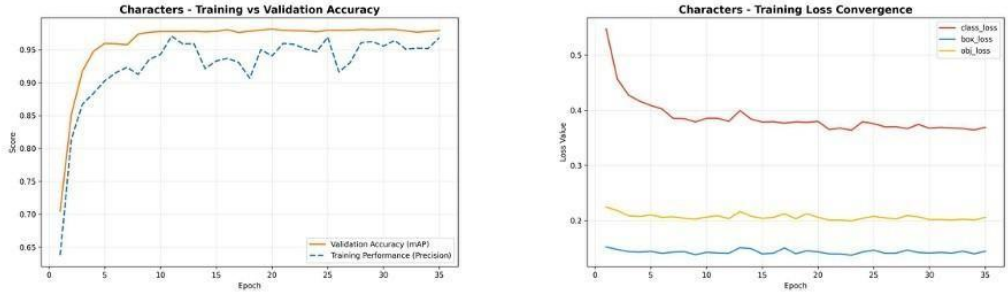
*Stage 2 YOLOv11n plate localization: final metrics.*

| **Metric** | **Value** |
|---|---|

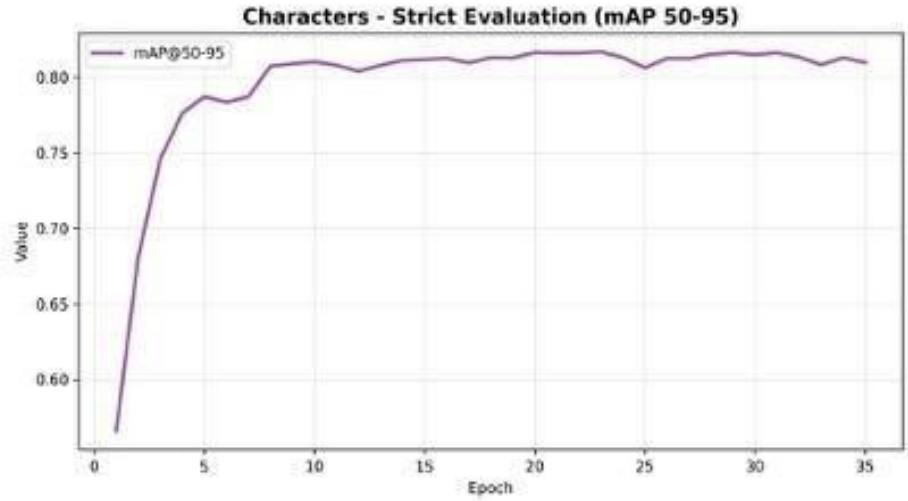
| | |
|---|---|
| mAP@50 | 97.1% |
| mAP@50:95 | 91.0% |
| Precision | 96.5% |
| Recall | 93.7% |
| F1-score | 95.1% |

### 4.2 Stage 3: RF-DETR Base Character Recognition: Training Analysis

RF-DETR Base converges quickly, reaching ≈95% mAP@50 early in training and remaining between 97% and 99% thereafter. The oscillatory but bounded loss behavior is characteristic of DINOv2-backbone transformer fine-tuning.




*RF-DETR Base (Stage 3): (a) training vs. validation accuracy; (b) training-loss convergence.*




*RF-DETR Base (Stage 3): strict mAP@50:95, plateauing near 81%.*

The substantial difference between the Stage 3 mAP@50 (97.8%) and mAP@50:95 (≈ 81%) metrics is expected and reflects what each metric measures rather than a recognition weakness. mAP@50 counts a character as correctly detected when its predicted box overlaps the ground truth by at least 50% IoU, capturing whether the correct character class is identified at the correct location. mAP@50:95 averages precision over progressively stricter IoU thresholds up to 95%, penalizing even minor bounding-box looseness. Because the downstream task only requires reading the correct character and preserving its left-to-right order, not pixel-perfect box geometry, mAP@50 is the operationally relevant metric, while the lower mAP@50:95 simply reflects small boxtightness variation on low-resolution embossed glyphs.

*RF-DETR Base character recognition: final test-set metrics (Stage 3).*

| **Metric** | **Value** |
|---|---|
| mAP@50 | 97.8% |

mAP@50:95 ≈81.0% Precision

95.1%

Recall 93.8%

F1-score 94.4%

### 4.3 Per-Stage and End-to-End Performance *Training*

*hyperparameters for all pipeline stages.*

| **Hyperparameter** | **Stage 1** | **Stage 2** | **Stage 3** |
|---|---|---|---|
| Learning rate | Pre-trained | $1.0 \times 10^{-2}$ | $5.0 \times 10^{-4}$ |
| Weight decay | N/A | $5.0 \times 10^{-4}$ | $1.0 \times 10^{-4}$ |
| Augmentation | COCO | Mosaic, Mixup | Crop, Rotate |

*Per-stage and end-to-end metrics.*

| **Stage** | **mAP@50** | **Prec.** | **Recall** | **F1** |
|---|---|---|---|---|
| Stage 1: Vehicle Detection (YOLOv8n-COCO) | N/A | 98.5% | 99.1% | 98.8% |
| Stage 2: Plate Localization (YOLOv11n) | 97.1% | 96.5% | 93.7% | 95.1% |
| Stage 3: Character OCR (RF-DETR Base) | 97.8% | 95.1% | 93.8% | 94.4% |

### 4.4 End-to-End Precision: A Model-Based Estimate

The independence model (Equation [eq:e2e]) combines the measured per-stage precisions (98.5%, 96.5%, 95.1%) into an estimated end-to-end precision of 90.4%. This is an estimate derived from the per-stage metrics rather than a directly measured fullstring read

accuracy (Section 4.5). The independence assumption is expected to be mildly optimistic: when Stage 1 crops a vehicle partially out of frame (edge vehicles, vehicles in occlusion), Stage 2 receives an incomplete input and is significantly more likely to fail. The two stages are therefore not fully independent for edge cases, and the product-ofprecisions formula overestimates performance. This correlation can be reduced by expanding Stage 1 training to include partially occluded vehicle instances, or by adding a Stage 1.5 quality filter that discards crops below a bounding-box-area threshold before passing to Stage 2.

### 4.5 Test-Set Evaluation and Per-Class Performance

We evaluated the pipeline on the held-out test split drawn from the 9,366-image corpus of Nepali traditional and Indian embossed plates. Stage 1 uses the pre-trained YOLOv8n detector; Stage 2 (YOLOv11n) attains 97.1% mAP@50 (precision 96.5%, recall 93.7%, F1 95.1%); and Stage 3 (RF-DETR Base) attains 97.8% mAP@50 on the test set (precision 95.1%, recall 93.8%, F1 94.4%), with a macro-average per-class mAP@50 of 97.0% on test and 98.0% on validation. Combining the measured per-stage precisions via Equation [eq:e2e] yields an estimated end-to-end precision of 90.4%.

Table 6 reports the per-class Stage 3 mAP@50. Most classes exceed 95% on both splits. The principal outlier is the rare token “U”, which scores 100% on validation but only 3.0% on the test split. This large gap reflects its very small test support rather than a systematic recognition weakness: with only a handful of test annotations, a single miss collapses the per-class average. It is consistent with the broader class-imbalance limitation (Section 4.8.2). A few other low-frequency tokens also lag (for example “W” 90% and “Y” 95% on test, and “PRA” 83% and “O” 89% on validation), while the bulk of digits, Latin letters, and common Devanagari tokens reach 95–100%.

*Scope of this evaluation.* The corpus contains only a small number of true Nepali embossed plates; most embossed examples are Indian proxies and most Nepali examples

are traditional flat plates. These figures therefore measure in-distribution performance together with the compositional cross-domain transfer; a dedicated held-out benchmark of real Nepali embossed plates remains the principal target for future validation (Section 4.9).

*Per-class Stage 3 character mAP@50 (%) on the validation and test splits. "−" is the province/number separator; classes absent from a split are marked "–". Macro-average (all classes): 98.0% validation, 97.0% test.*

| Cls | Val | Test | Cls | Val | Test | Cls | Val | Test |
|---|---|---|---|---|---|---|---|---|
| 0 | 93 | 100 | 1 | 97 | 98 | 2 | 99 | 100 |
| 3 | 99 | 100 | 4 | 97 | 97 | 5 | 99 | 100 |
| 6 | 98 | 100 | 7 | 98 | 100 | 8 | 99 | 100 |
| 9 | 100 | 100 | − | 98 | 97 | A | 100 | 95 |
| B | 95 | 100 | C | 98 | 100 | D | 100 | 100 |
| E | 92 | 100 | F | 100 | 100 | G | 91 | 100 |
| H | 99 | 95 | I | 100 | 100 | J | 99 | 100 |
| K | 100 | 100 | L | 100 | 100 | M | 100 | 100 |
| **Cls** | **Val** | **Test** | **Cls** | **Val** | **Test** | **Cls** | **Val** | **Test** |
| N | 95 | 100 | O | 89 | 100 | P | 99 | 100 |
| Q | 100 | 100 | R | 96 | 100 | S | 100 | 100 |
| T | 100 | 100 | U | 100 | 3 | V | 100 | 100 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| W | 100 | 90 | X | 100 | 100 | Y | 100 | 95 | |
| Z | 88 | 100 | BA | 95 | 100 | BAGMATI | 99 | 100 | |
| CHA | 100 | 100 | GA | 100 | 100 | GANDAKI | 100 | 100 | |
| JA | 100 | – | KHA | 100 | – | KO | 100 | 100 | |
| LU | 100 | 100 | ME | 100 | – | NA | 97 | 100 | |
| PA | 98 | 100 | PRA | 83 | 100 | PRADESH | 100 | 100 | |
| RA | 100 | 100 | SU | 100 | – | YA | – | 100 | |

### 4.6 Cross-Domain Transfer Validation

The two-axis proxy adaptation bears out the compositional zero-shot claim: Stage 3, which never saw a Nepali embossed plate, still reads one by combining the layout it learned from Nepali flat plates with the embossed surface it learned from Indian plates. Where it does fail, the failures track the edges of the training data: plates damaged past roughly 30% of their surface, old multi-row layouts, and rare provincial tokens with only a handful of annotations. None of these calls for a new architecture, only for more of the right data.

We can line these numbers up against earlier systems, but not read them head-to-head. No shared Nepali embossed-plate benchmark exists (Section 2.4), and our 97.1% and 97.8% are per-stage mAP@50 *detection* scores, whereas the older figures are end-to-end full-string *read* accuracies; a fair comparison has to wait for the measurement in Section 4.5. For reference, the LPRNet system gets 95 percent correct when it comes to standard Chinese license plates (Zherzdev and Gruzdev, 2018), and there was also some work done on license plates using YOLOv3 and YOLOv4 that was able to get around 87 percent correct before it started having trouble with the raised letters on the plates (Gajurel et al.,

2024). Ammar et al. (2023) showed that a similar system could work in production in 2023, but they were only working with Saudi license plates that had one set of letters and no raised surfaces that could cause glare. Our system is different because it can handle license plates with two sets of letters, and it gets 97.1% mAP@50 when it comes to finding the plate and 97.8% when it comes to reading the letters. Our system also folds the per-stage errors into a single end-to-end estimate, which most other systems leave out because they look at only one part of the process rather than from start to finish.

### 4.7 Refinement Pathway and Adaptive Metrics

*Per-stage monitoring metrics and the triggers that prompt refinement.*

| | Primary Metric | Secondary Metric | Refinement Trigger |
|---|---|---|---|
| Stage 1 (Vehicle) | Precision @0.5 | False-positive rate | FP rate > 5% (billboards) |
| Stage 2 (Plate) | mAP@50 | Recall (rainy) | Recall drop > 2% in monsoon |
| Stage 3 (OCR) | mAP@50/class | Regex fail rate | Fail rate > 1% triggers retrain |
| End-to-End | Full-plate read | Manual override | Override > 10% of sessions |

## 5. Discussion

### 5.1 When to Apply CATD

A cascade is worth using only when three conditions hold together. First, the task must span at least two spatial scales that differ by roughly an order of magnitude. Second, the fine-grained sub-task must reach high per-element accuracy, on the order of 90 percent, which a single model rarely achieves when it processes the whole scene at once. Third, the deployment must tolerate the added latency of running several stages in sequence. When any of these fails, whether the scales are close together, the accuracy target is modest, or the response must be near-instant, a single model is usually the better choice.

### 5.2 Limitations

- **Stage 3 class imbalance.** The macro-average mAP@50 looks good, but the rare tokens are shaky. “U” scores 100% on validation yet just 3.0% on the test split (Table 6), a swing driven by its tiny test support rather than by a recognition failure; separately, eleven other classes have fewer than three annotations and no test-set coverage at all.

- **Inter-stage error correlation.** Equation [eq:e2e] assumes that the stages fail independently. This is a big assumption: when a vehicle gets in the way and blocks part of the view, it usually causes problems for Stage 1 and Stage 2 at the same time. So the actual precision from start to finish is probably lower than 90.4%. We do not yet know how much lower; we still need to measure it, which we discuss in Section 4.5.

- **Training-data transfer.** We did not have any Nepali embossed plates to train on. The system relies entirely on compositional cross-domain transfer, which works

well in our tests but has not been evaluated on a held-out embossed-plate benchmark (which does not yet exist).

- **Physical damage and non-standard formats.** Plates with more than ≈30% surface occlusion degrade Stage 2 localization. Royal, Tempo, and diplomatic plates fall outside Stage 3's training distribution. The spatial-sorting algorithm does not support multi-row legacy Nepali plates.

**Future Work**

Six directions seem most worth pursuing:

- Direct end-to-end accuracy measurement on a held-out Nepali embossed-plate test set, since the model-predicted 90.4% figure needs empirical validation (Section 4.5).
- Continual learning for Stage 3 by retraining on accumulated recognition failures for underrepresented classes (LUMBINI, MADESH, and the nine other sub-threeannotation tokens).
- Edge deployment via TensorRT optimization, enabling on-device frame filtering without cloud GPU dependence.
- Construction of a public, held-out Nepali embossed license-plate benchmark, so that the cross-domain transfer hypothesis can be validated against real targetdomain data and compared directly with prior systems such as LPRNet and earlier Nepali ANPR work.
- Fusion with the RFID infrastructure already embedded in Nepal's official embossed plates, treating the vision pipeline and the RFID tag as complementary,

mutually cross-validating identification channels that remain robust under glare, occlusion, or tag-read failure.

- Extension of the spatial-sorting and recognition logic to multi-row legacy plate formats and to special categories (Royal, Tempo, and diplomatic plates) that currently fall outside the Stage 3 training distribution.

## 6. Conclusion

This paper has presented CATD as a design pattern for high-accuracy computer-vision pipelines and demonstrated it on a concrete, difficult problem: ANPR for Nepali embossed license plates, which combines a 61-class dual-script character set, specular reflectance from embossed surfaces, monsoon-season illumination variability, and a training-data situation where the exact target domain appears in no public dataset.

On the held-out test set the YOLOv11n plate localizer reaches 97.1% mAP@50 and the RF-DETR Base character recognizer 97.8% mAP@50. The estimated end-to-end precision is 90.4%. The two-dimensional cross-domain data strategy, combining Nepali flat-plate images for format knowledge with Indian embossed-plate images for surfaceproperty knowledge, transfers to Nepali traditional and embossed plates at inference without any direct training examples. The pipeline is integrated as the computer-vision backbone of a prototype smart parking-management system handling live RTSP streams, session management, billing, and analytics. These figures are validation-set metrics for the individual stages; the 90.4% end-to-end precision remains a model prediction, and the cross-domain transfer has not yet been tested on a held-out set of real Nepali embossed plates, the most important remaining limitation. Constructing such a benchmark, broadening coverage of rare provincial tokens and non-standard plate

formats, and fusing the pipeline with the existing RFID identification infrastructure are the primary directions for future work.

The CATD framework generalizes to any compound visual recognition task where there is a meaningful spatial-scale transition between stages. The system can be improved bit by bit. This is because it uses a refinement approach that happens in stages. We can see how each stage is doing, and we can also change how we measure success and retrain parts of the system. This all happens without affecting the rest of the system.

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# The Adaptation of Online Learning During Covid-19: Perspectives of Undergraduate Students

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**Abstract**

The COVID-19 pandemic compelled educational institutions worldwide to transition abruptly from traditional face-to-face instruction to online learning. This study investigates the factors influencing undergraduate students' adaptation to online learning during the pandemic, with a specific focus on the context of Nepal. Drawing on a review of relevant scholarly literature, the research examines the relationship between three independent variables— availability of IT infrastructure, effectiveness of online learning, and computer self-efficacy—and the dependent variable, students' adaptation to online learning. A quantitative research design was adopted, and data were collected through a structured questionnaire survey administered to 351 undergraduate students. The collected data were coded and analyzed using the Statistical Package for the Social Sciences (SPSS), employing reliability testing, descriptive statistics, correlation analysis, and linear regression. The findings indicate that the availability of IT infrastructure has a statistically significant, positive relationship with students' adaptation to online learning, while effectiveness and computer self-efficacy demonstrate weaker associations. The study concludes with practical recommendations for the government, colleges, faculty members, and students to enhance the adaptation and delivery of online learning, and it identifies avenues for future research.

**Keywords:** online learning, COVID-19, undergraduate students, IT infrastructure, computer self-efficacy, e-learning adaptation, Nepal

## 1. Introduction

Online learning has expanded rapidly in recent years and is projected to grow further owing to the widespread availability of high-speed internet and the accelerating pace of technological development, including 4G and emerging 5G networks (Lemay,D.J, 2021). This growth was dramatically intensified by the onset of the COVID-19 pandemic, which fundamentally reshaped the delivery of education across the globe.The COVID-19 outbreak, first identified in Wuhan, China, in late 2019, quickly escalated into a global pandemic. Within a matter of months, a term that was largely unknown until early 2020 became part of everyday discourse for the majority of the world's population (Qazi, 2021). The education sector was among the most heavily affected. Following the imposition of restrictions on physical contact between students and instructors, many countries responded by closing schools and adopting online teaching and learning as an alternative mode of instruction (Rusman1,T, 2021)

.

As the pandemic progressed, faculty members increasingly shifted their curricula to online or hybrid environments. Even where face-to-face instruction was partially restored, the capacity to deliver knowledge through online platforms and to operate within a fully virtual setting became a new standard of educational practice (Al-Mawee & Gharaibeh, 2021).

Nepal, a small nation situated between China and India, is characterized by considerable geographical, cultural, and social diversity. The spread of COVID-19 affected the country's social, technological, economic, environmental, and educational development in profound ways (Paudel, 2021). The first confirmed case in Nepal was recorded on 25 January 2020, involving a 32-year-old Nepali student who had returned from Wuhan, China; this marked the initial phase of viral transmission, largely associated with the return of citizens from abroad (Maqableh & Alia, 2021). To contain the spread, the

government imposed a nationwide lockdown from 24 March 2020 (Sharma & Neupane, 2020)

Despite these measures, the number of COVID-19 cases rose sharply. Schools and higher education institutions in Nepal remained closed for more than five months. A UNESCO assessment of the pandemic's impact on education reported that school and university closures, adopted as a preventive strategy, affected millions of students in Nepal (UNESCO, 2021). Within this context, understanding how undergraduate students adapted to online learning is of considerable academic and practical importance.

## 2. Literature Review

### 2.1. Adaptation and Perception of Online Learning during COVID-19 Pandemic by Albanian University Student

This study examined the perceptions, adaptation, and challenges experienced by Albanian university students during online learning implemented due to the COVID-19 pandemic. The respondents were invited via email to participate by completing an online questionnaire. The collected data were preprocessed and statistically analyzed using SPSS 26.0. Initially, the data were explored using frequency distributions, descriptive statistics, and graphical visualizations. The Shapiro-Wilk test was then conducted to determine whether the numerical data followed a normal distribution. Furthermore, the Chi-square test was used to examine the relationships between the general characteristics of the respondents and several selected nominal variables included in the questionnaire(Xhelili & Sheme, 2021).

### 2.2. Adaptation to Online Technology for Learning during COVID-19 Pandemic: An Observational Study of Effectiveness and Student's Perception in Various Universities

The study was designed to understand the effectiveness of online classes and students' perspectives, attitudes, and readiness toward online learning at the university level. The respondents were invited to participate by completing an online questionnaire. A semi-structured, self-administered questionnaire containing both open-ended and close-ended questions was prepared using Google Forms and circulated among university students through WhatsApp and email. The study used a questionnaire-based observational descriptive research design and employed both qualitative and quantitative methods. The collected data were tabulated using Google Sheets and analyzed using SPSS. The study also highlighted the lack of a conceptual framework for describing students' adaptation to online learning during the COVID-19 pandemic (Kumar & Singh, 2021).

### 2.3. Adaption of distance learning to continue the academic year amid COVID-19 lockdown

This study investigated the use of distance learning as a means of continuing students' academic year during the COVID-19 lockdown. The study examined how situational awareness and readiness influenced the adoption of distance learning, with trust in information sources related to distance learning playing an important role. The researchers proposed a model in which awareness, readiness, and adoption were key factors, with predictive relevance ($Q^2$) values of 0.377 for awareness, 0.559 for readiness, and 0.309 for the adoption of distance learning. Data were collected through a semi-structured, self-administered questionnaire prepared using Google Forms and distributed to university students through WhatsApp and email. The collected data were tabulated using Google Sheets and analyzed using SPSS. The research followed a questionnaire-based observational descriptive design and employed both qualitative and quantitative approaches. However, the study had a limitation in that it lacked a comprehensive conceptual framework for explaining students' adaptation to online learning during the COVID-19 pandemic (Qazi, 2021).

The sudden shift from traditional classroom instruction to online learning during the COVID-19 pandemic posed significant challenges for both students and educational institutions, particularly in developing countries such as Nepal. Many students faced difficulties arising from inadequate IT infrastructure, unstable internet connectivity, limited access to appropriate devices, and varying levels of familiarity with digital tools. In addition, concerns relating to the perceived effectiveness of online instruction and students' confidence in using technology raised questions about how well learners were able to adapt to this new mode of education.

While a substantial body of international research has explored online learning during the pandemic, comparatively little empirical evidence exists concerning the experiences of undergraduate students in Nepal. There remains a limited understanding of which specific factors most strongly influence students' adaptation to online learning within this context. This study seeks to address that gap by empirically examining the relationships between the availability of IT infrastructure, effectiveness, computer self-efficacy, and students' adaptation to online learning during COVID-19.

## 3. Research Objectives

The primary aim of this study is to examine the factors influencing undergraduate students' adaptation to online learning during the COVID-19 pandemic. The specific objectives are:

1. To examine the relationship between the availability of IT infrastructure and students' adaptation to online learning during COVID-19.
2. To assess the influence of the perceived effectiveness of online learning on students' adaptation to online learning during COVID-19.
3. To investigate the relationship between students' computer self-efficacy and their adaptation to online learning during COVID-19.

4. To provide recommendations to relevant stakeholders for improving the adaptation and delivery of online learning.

## 4. Research Methods

This study adopted a quantitative research design to investigate the factors influencing undergraduate students' adaptation to online learning. A research framework was developed to guide the investigation and to define the scope of the study. In examining a cause-and-effect relationship, two categories of variables were identified: the independent variables and the dependent variable (Lemay et al., 2021).

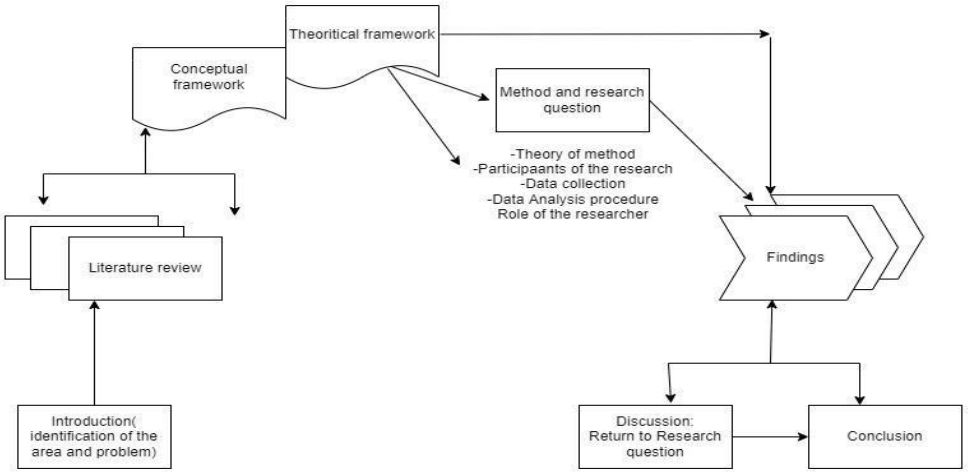


***Figure1. Research Model***

### 4.1. Research Framework and Variables

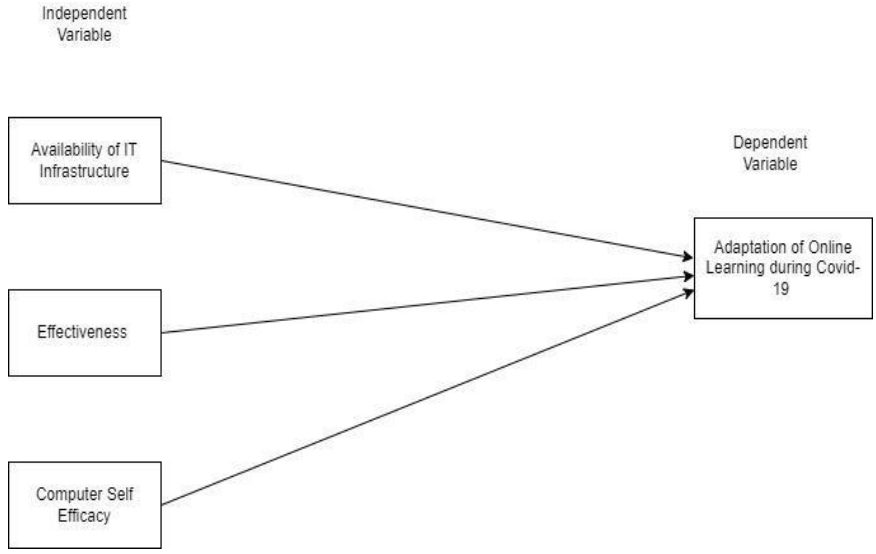


***Figure2. Research Framework***

**Independent Variables:** The independent variables are the factors hypothesised to influence students' adaptation to online learning. These are: Availability of IT Infrastructure, Effectiveness and Computer Self-Efficacy

**Dependent Variable:** The dependent variable is the outcome being measured, assumed to depend on the values of the independent variables, namely the Adaptation of Online Learning during COVID-19. The proposed relationships are illustrated in the research model and framework (Figures 1 and 2).

### 4.2. Data Collection and Sampling

Primary data were collected through a structured questionnaire survey. The questionnaire consisted of demographic items and Likert-scale items mapped to each research objective. A total of 351 valid responses were obtained from undergraduate students. Convenience sampling was employed owing to the practical constraints imposed by the pandemic. Items targeting each research objective were averaged to produce a single composite value for each construct, enabling subsequent statistical analysis.

### 4.3. Data Analysis

The collected data were coded and analyzed using the Statistical Package for the Social Sciences (SPSS). The analysis comprised reliability testing (Cronbach's alpha), descriptive statistics, correlation analysis, and linear regression. Ethical considerations, including voluntary participation, informed consent, anonymity, and confidentiality of responses, were observed throughout the research process.

### 4.4. Pilot Test

A pilot test—a small preliminary study conducted prior to the full-scale research— was carried out to evaluate the feasibility and clarity of the proposed instrument. The pilot followed the same procedures as the main study and was used to refine the questionnaire and to estimate the appropriate sample size before full-scale data collection.

### 4.5. Reliability Testing (Cronbach's Alpha)

Cronbach's alpha coefficient measures the internal consistency of a scale and ranges from 0 to 1. Higher values indicate that the items share greater covariance and are more likely to measure the same underlying construct. Methodologists commonly recommend a minimum coefficient of between 0.65 and 0.8; coefficients below 0.5 are generally considered unacceptable, particularly for unidimensional scales.

The reliability results for each construct and for the overall instrument are summarized in Table 1.

**Table 1.**

*Reliability Test Results*

| Construct | Cronbach's Alpha | Standardized Alpha | N of Items |
|---|---|---|---|
| **Availability of IT Infrastructure** | 0.719 | 0.718 | 4 |
| **Effectiveness** | 0.736 | 0.736 | 6 |
| **Computer Self-Efficacy** | 0.719 | 0.718 | 4 |
| **Overall** | 0.738 | 0.706 | 33 |

All constructs and the overall instrument achieved Cronbach's alpha values above the acceptable threshold of 0.65, confirming satisfactory internal reliability of the measurement scales.

## 5. Discussion and Results

### 5.1. Respondents' Demographic Profile

Demographic data were collected regarding respondents' age, gender, qualification, and university affiliation.

**Table 2.**

*Demographic Profile of Respondents (N = 351)*

| Variable | Category | Frequency | Percent (%) |
|---|---|---|---|
| **Age** | Below 20 | 75 | 21.4 |
| | 20–30 | 273 | 77.8 |
| | Above 30 | 3 | 0.9 |
| **Gender** | Male | 180 | 51.3 |
| | Female | 171 | 48.7 |

| | | | |
|---|---|---|---|
| **Qualification** | +2 | 57 | 16.2 |
| | Bachelor's | 285 | 81.2 |
| | Master's | 9 | 2.6 |
| **University** | Tribhuvan University | 333 | 94.9 |
| | Kathmandu University | 3 | 0.9 |
| | Pokhara University | 3 | 0.9 |
| | Foreign University | 12 | 3.4 |

**Interpretation:**

The majority of respondents (77.8%) belonged to the 20–30 age group, while 21.4% were below 20 and 0.9% were above 30. Gender distribution was relatively balanced, with 51.3% male and 48.7% female respondents. In terms of qualification, 81.2% were pursuing a bachelor's degree, 16.2% held a +2 qualification, and 2.6% were at the master's level. The overwhelming majority (94.9%) were affiliated with Tribhuvan University.

### 5.2. Access to Internet Connectivity

**Table 3.**

*Modes of Internet Access*

| Mode of Access | Responses (N) | Percent | Percent of Cases |
|---|---|---|---|
| **Broadband/Fibre/DSL** | 339 | 81.3% | 96.6% |
| **Cellphone data** | 63 | 15.1% | 17.9% |
| **Computer shop** | 3 | 0.7% | 0.9% |
| **Relative/friend's home** | 12 | 2.9% | 3.4% |
| **Total** | 417 | 100.0% | 118.8% |

**Interpretation:**

Most respondents (81.3%) used broadband connections to access the internet, followed by cellphone data (15.1%), a relative's or friend's home (2.9%), and computer shops (0.7%).

### 5.3. Devices Used for Online Learning Table 4.

*Devices Used for Online Learning*

| Device | Responses (N) | Percent | Percent of Cases |
|---|---|---|---|
| **Desktop** | 57 | 8.8% | 16.2% |
| **Laptop** | 336 | 52.1% | 95.7% |
| **Smartphone** | 234 | 36.3% | 66.7% |
| **Tablet** | 18 | 2.8% | 5.1% |
| **Total** | 645 | 100.0% | 183.8% |

**Interpretation:**

The laptop was the most widely used device (95.7%), followed by the smartphone (66.7%), desktop (16.2%), and tablet (5.1%). These results suggest that the majority of students possessed adequate IT infrastructure to support online learning, facilitated by the availability of affordable hardware, software, and internet services in the market.

### 5.4. Platforms Used for Online Learning

**Table 5.**

*Platforms Used for Online Learning*

| Platform | Responses (N) | Percent | Percent of Cases |
|---|---|---|---|
| **Zoom** | 330 | 60.8% | 94.0% |
| **Microsoft Teams** | 72 | 13.3% | 20.5% |
| **Google Meet** | 126 | 23.2% | 35.9% |
| **Others** | 15 | 2.8% | 4.3% |
| **Total** | 543 | 100.0% | 154.7% |

**Interpretation:**

Zoom was the most commonly used platform (94.0%), followed by Google Meet (35.9%), Microsoft Teams (20.5%), and other platforms (4.3%).

### 5.5. Hours Spent on Online Classes

**Table 6.**

*Hours Spent on Online Classes per Day*

| Category | Frequency | Percent (%) |
|---|---|---|
| **No access to online class** | 12 | 3.4 |
| **Less than 3 hours** | 81 | 23.1 |
| **3–7 hours** | 252 | 71.8 |
| **8 hours or more** | 6 | 1.7 |
| **Total** | 351 | 100.0 |

**Interpretation:**

A majority of respondents (71.8%) spent between 3 and 7 hours per day on online classes, while 23.1% spent less than 3 hours, 1.7% spent 8 hours or more, and 3.4% had no access to online classes.

### 5.6. Availability of IT Infrastructure

**Table 7.**

*Descriptive Statistics – Availability of IT Infrastructure*

| Item | Mean | Median | Mode | Std. Dev. |
|---|---|---|---|---|
| **Adequate access to internet connectivity** | 2.93 | 3.00 | 3 | 0.737 |
| **Adequate access to computer hardware** | 2.67 | 3.00 | 3 | 0.980 |
| **Stable and sustainable internet connection** | 3.32 | 3.00 | 3 | 1.021 |
| **Equipped workplace for student and teacher** | 2.36 | 2.00 | 2 | 0.791 |
| **Availability of digital educational resources** | 2.61 | 3.00 | 3 | 0.907 |

**Interpretation:**

The mean values ranged from 2.36 to 3.32, with an overall average of 2.78. This suggests that the availability of IT infrastructure has a meaningful bearing on students' adaptation to online learning. The findings indicate that a stable and sustainable internet connection is a particularly important requirement for successful adaptation.

### 5.7. Effectiveness

**Table 8.**

*Descriptive Statistics – Effectiveness of Online Learning*

| Item | Mean | Median | Mode | Std. Dev. |
|---|---|---|---|---|
| **Saving time getting ready** | 2.14 | 2.00 | 2 | 0.979 |
| **Saving time commuting** | 2.34 | 3.00 | 3 | 0.918 |
| **Saving transportation cost** | 1.78 | 1.00 | 1 | 1.120 |
| **Getting easily distracted** | 1.87 | 2.00 | 1 | 0.884 |
| **Attending while doing other tasks** | 2.43 | 2.00 | 2 | 0.974 |
| **Feeling less committed without instructor's presence** | 2.09 | 2.00 | 2 | 0.935 |
| **Positive impact on academic performance** | 3.15 | 3.00 | 3 | 0.922 |
| **Physical classes better than online learning** | 1.94 | 2.00 | 1 | 0.991 |

| | | | | |
|---|---|---|---|---|
| **Managing study time and** | 2.44 | 3.00 | 3 | 0.948 |
| **submitting on time** | | | | |
| **Online platforms user-friendly and easy to use** | 2.32 | 2.00 | 2 | 0.877 |

**Interpretation:**

The mean values ranged from 1.78 to 3.15, with an overall average of 2.25. This indicates that the perceived effectiveness of online learning contributes to students' adaptation to online learning during COVID-19, although the effect is comparatively modest.

### 5.8. Computer Self-Efficacy

**Table 9.**

*Descriptive Statistics – Computer Self-Efficacy*

| Item | Mean | Median | Mode | Std. Dev. |
|---|---|---|---|---|
| **Lacking selfdiscipline for a fully online environment** | 2.98 | 3.00 | 3 | 1.006 |
| **Experiencing personal growth during online learning** | 2.93 | 3.00 | 3 | 0.737 |
| **Difficulty accessing materials due to devices** | 2.67 | 3.00 | 3 | 0.980 |

| | | | | |
|---|---|---|---|---|
| **Technology skills improved during online learning** | 3.32 | 3.00 | 3 | 1.021 |

**Interpretation:**

The mean values ranged from 2.93 to 3.32, with an overall average of 2.98. This indicates that computer self-efficacy plays a role in students' adaptation to online learning during COVID-19, with respondents reporting notable improvements in their technology skills.

### 5.9. Overall Descriptive Summary

**Table 10.**

*Overall Descriptive Statistics*

| Construct | N | Mean | Std. Dev. |
|---|---|---|---|
| **Availability of IT Infrastructure** | 351 | 2.70 | 0.288 |
| **Effectiveness** | 351 | 2.25 | 0.453 |
| **Computer Self-Efficacy** | 351 | 2.98 | 0.365 |

## 6. Inferential Analysis

### 6.1. Correlation Analysis

**Table 11.**

*Correlation Matrix*

| | Availability | Effectiveness | Self-Efficacy | Adaptation |
|---|---|---|---|---|
| **Availability** | 1 | | | |
| **Effectiveness** | 0.233** | 1 | | |
| **Self-Efficacy** | 0.577** | 0.205** | 1 | |
| **Adaptation** | 0.182** | 0.026 | 0.089 | 1 |

*** Correlation is significant at the 0.01 level (2-tailed). N = 351.*

The correlation analysis reveals a positive and statistically significant, though weak, relationship between the availability of IT infrastructure and students' adaptation to online learning ($r = 0.182$, $p < 0.01$). The relationships between effectiveness ($r = 0.026$) and computer self-efficacy ($r = 0.089$) and adaptation were positive but weak. Notably, the independent variables were positively and significantly correlated with one another, with the strongest association observed between availability of IT infrastructure and computer self-efficacy ($r = 0.577$).

### 6.2. Linear Regression Analysis

**Table 12.**

*Model Summary*

| Model | R | R Square | Adjusted R Square | Std. Error | Sig. F Change |
|---|---|---|---|---|---|
| **1** | 0.195 | 0.038 | 0.030 | 0.71519 | 0.004 |

*Predictors: (Constant), self-efficacy, effectiveness, availability.*

**Table 13.**

*ANOVA*

| Model | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| **Regression** | 7.007 | 3 | 2.336 | 4.566 | 0.004 |
| **Residual** | 177.491 | 347 | 0.512 | | |
| **Total** | 184.498 | 350 | | | |

*Dependent Variable: Adaptation.*

**Table 14.**

*Coefficients*

| Model | B | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| **(Constant)** | 1.599 | 0.393 | | 4.070 | 0.000 |
| **Availability** | 0.309 | 0.137 | 0.123 | 2.257 | 0.025 |
| **Effectiveness** | 0.094 | 0.087 | 0.059 | 1.084 | 0.279 |
| **Self-Efficacy** | 0.158 | 0.107 | 0.079 | 1.473 | 0.142 |

*Dependent Variable: Adaptation.*

The regression analysis indicates positive coefficients for all three independent variables. The R-square value of 0.038 indicates that approximately 3.8% of the variation in students' adaptation to online learning can be explained by the combined effect of availability of IT infrastructure, effectiveness, and computer self-efficacy.

The F-test yielded F = 4.566 with a p-value of 0.004, which is below the 0.05 threshold, indicating that the overall model is statistically significant. Among the individual predictors, only the availability of IT infrastructure was a statistically significant predictor of adaptation ($\beta = 0.123$, $p = 0.025$), while effectiveness ($p = 0.279$) and computer self-efficacy ($p = 0.142$) were not statistically significant at the 0.05 level.

## 7. Conclusion

This study set out to examine the relationships between the availability of IT infrastructure, effectiveness, and computer self-efficacy, and undergraduate students' adaptation to online learning during the COVID-19 pandemic in Nepal. The findings demonstrate that students were, on the whole, neutral in their adaptation to online learning. The availability of IT infrastructure showed the strongest and only statistically significant relationship with adaptation, confirming that reliable devices, appropriate software, and stable internet connectivity are essential for effective online learning. Effectiveness and computer self-efficacy, while positively associated with adaptation, played comparatively smaller roles. These results highlight that infrastructural readiness is a foundational determinant of successful online learning adaptation, particularly in a developing-country context such as Nepal.

### Recommendations

Based on the findings and conclusions, the following recommendations are proposed for the key stakeholders. Given the significant influence of IT infrastructure on adaptation, and considering that many people in Nepal reside in remote areas with limited financial means to afford devices and internet access, the government should support the provision of internet connectivity and devices to rural areas and government educational institutions. It is further recommended that the government conduct training and awareness programmed across both rural and urban areas to strengthen digital readiness.

A notable number of students reported challenges relating to self-discipline, personal growth, and disruptions to their academic flow during the pandemic, which affected their adaptation. Colleges should organize mental health awareness and support initiatives, avoid placing undue pressure on students, and foster supportive learning environments. Since limited interaction was identified as a key weakness of online classes, college

administrations should implement strategies to enhance student participation. Institutions should also train students in the effective use of online platforms, as ease of use is positively associated with adaptation.

As the primary point of contact with students, faculty members are encouraged to engage with students not only on academic matters but also on their broader wellbeing. They should provide support to students who face difficulties operating online platforms or sitting online examinations, and should design their classes to encourage the active involvement of all participants, thereby improving interaction.

Students are advised to select better internet plans where feasible, as connection quality directly affects the smooth delivery of online classes. They are also encouraged to take the initiative to interact during online classes, given that limited interaction was identified as a major drawback of online learning.

**Limitations and Future Research**

This study is subject to several limitations. The sample was drawn predominantly from Tribhuvan University students through convenience sampling, which limits the generalizability of the findings. The relatively low R-square value (3.8%) indicates that other factors not captured in this model contribute to students' adaptation to online learning. Future research could incorporate additional variables—such as social support, motivation, learning environment, and instructor quality—and employ probability sampling across a wider range of institutions to enhance representativeness and explanatory power.

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