Human-AI Collaboration in Software Development: Impact on Developer Roles and Skill sets in Kathmandu

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Abstract

Artificial Intelligence (AI) in software development is turning out to be a major game changer in role of developers. This makes us re-think those traditional roles and skillsets. This study explores how artificial intelligence (AI) is reshaping the roles and skillsets of software developers, focusing on the interaction between developers and AI tools in Kathmandu (Niranjan Devkota, 2022). Using a mixed-methods approach, it combines quantitative data from surveys with qualitative insights from interviews to understand how developers view AI and its impact on their jobs. Utilizing a mixed-methods approach, the research combines quantitative data from surveys and qualitative insights from interviews to explore how software developers perceive AI and its implications for their professional responsibilities. Key variables analyzed include developers' experience with AI, their acceptance of AI technologies, and the subsequent effects on their roles and skillsets. The findings reveal significant shifts in job definitions, highlighting a growing demand for interdisciplinary skills that merge technical expertise with analytical capabilities. Furthermore, the study addresses ethical considerations surrounding AI integration, the necessity for ongoing training, and the evolving nature of software development methodologies. Statistical analyses, including reliability tests and regression models, validate the results, indicating both linear and nonlinear relationships between AI adoption and changes in developer roles. Ultimately, the research underscores the importance of fostering a collaborative environment between human developers and AI tools, suggesting that successful integration hinges on developers' adaptability and organizations' commitment to providing adequate training and ethical oversight.

***Keywords**: Artificial Intelligence, Human-AI collaboration, Developer, AI Impact on Developers, Developer Roles*

1. Introduction

The integration of artificial intelligence (AI) into software development is revolutionizing the industry, particularly in emerging technology hubs like Kathmandu, Nepal. As AI technologies become increasingly embedded in software engineering processes, developers are witnessing a profound transformation in their roles and skillsets. This study aims to explore the dynamics of human-AI collaboration in software development, focusing on how these changes manifest in the local context of Kathmandu. By examining the interplay between AI tools and developer practices, this research seeks to illuminate the opportunities and challenges that arise from this technological evolution, ultimately contributing to a deeper understanding of the future landscape of software development (Nathalia Nascimento, 2023).

2. Problem Statement

The rapid integration of AI into software development processes marks a significant shift in the industry, presenting both opportunities and challenges for software developers in Kathmandu. As AI technologies automate routine tasks and enhance productivity, the traditional roles of developers are evolving to encompass a broader range of responsibilities, including data analysis, machine learning model development, and the incorporation of AI-driven tools (Muhammad Hamza, 2020). This transition necessitates the acquisition of new skills, which many developers may not currently possess.

Furthermore, the potential for skill mismatches and job displacement raises concerns about the future of employment in the software development sector. Despite the growing importance of understanding these changes, there remains a significant gap in knowledge regarding how AI integration is reshaping developer roles and skillsets in Kathmandu. This study aims to address this gap by providing a comprehensive analysis of the impact of AI on the local software development industry, thereby equipping stakeholders with insights to support developers in their transition to AI-enhanced roles.

3. Research Questions

1. How is artificial intelligence currently integrated into software development processes in Kathmandu's IT industry?
2. What are the current employment rolls and skills needed for developers in Kathmandu's software industry?
3. In the context of software development, what are the advantages and perceived challenges of combining human and artificial intelligence?
4. What do developers in Kathmandu think about the impact of AI integration on their roles and necessary skill sets?
5. How can the efficiency of developers in Kathmandu be increased and the effectiveness of human-AI interaction maximized?

4. Objectives of the Research

- To investigate the drawbacks of utilizing AI carelessly in the sake of efficiency.
- To outline the relationship between human-AI collaboration and how it affects skill sets and roles for developers in Kathmandu.
- To demonstrate the connections between AI tools and integrations, advanced IDEs, the job market, developer skills, etc.
- To determine the optimal level of AI application for the development industry's job sustainability.
- To assess how AI is affecting job roles and how developers in Kathmandu are responding to it psychologically

5. Significance of the Research

The significance of this study lies in its timely exploration of the impact of artificial intelligence (AI) on software development roles and skillsets within the context of Kathmandu, Nepal. As AI technologies increasingly permeate various sectors, understanding their implications for local software developers is crucial for several stakeholders, including educational institutions, employers, and policymakers. The findings will provide valuable insights into the evolving landscape of software development, highlighting the need for targeted training programs that equip developers with the necessary skills to thrive in an AI-enhanced environment. Furthermore, this research contributes to the broader discourse on human-AI collaboration by offering a case study from a rapidly developing technological region, thereby enriching the existing literature with localized perspectives. By identifying the challenges and opportunities presented by AI integration, this study aims to guide strategic initiatives that foster a collaborative ecosystem where human developers and AI tools can coexist and complement each other effectively, ultimately enhancing productivity and innovation in the software development industry.

6. Literature Review

The literature on the impact of artificial intelligence (AI) on software engineering and human-AI collaboration reveals a range of perspectives and findings. Several studies focus on the labor market implications of large language models (LLMs) and AI tools, while others explore the dynamics of human-AI collaboration and the effectiveness of AI in enhancing software development processes.

Research by Eloundou et al. (2023) investigates the labor market impact of LLMs, indicating that up to 10% of work functions for 80% of U.S. workers may be affected, particularly in higher-paying positions. The study suggests that LLMs can improve work completion times and quality but notes the lack of consideration for certain abilities in evaluating LLM access (Tyna Eloundou, August 22, 2023). Similarly, Felten et al. (2023) examine how AI language modeling affects various sectors, finding a positive correlation between wages and exposure to AI, particularly in industries like securities and legal services. Webb (2020) also forecasts the effects of AI on employment, concluding that while AI may reduce wage inequality, it will not significantly impact the top 1% of occupations (Michel Webb, 2020). These studies collectively highlight the transformative potential of AI in the labor market, emphasizing the need for adaptive strategies in workforce development.

Human-AI collaboration is another significant theme in the literature. Hamza et al. (2018) emphasize the importance of effective communication and role delineation in human-AI teamwork, identifying key themes such as AI capabilities and the evolving nature of interaction (Muhammad Hamza, 2020). Siemon (2022) and Sarkar (2023) further argue that AI should be viewed as a tool rather than a collaborator, suggesting that the traditional notion of collaboration may misrepresent the dynamics of human-AI interactions (Siemon, 2022) . Additionally, Subramonyam (2023) explores the challenges of developing human-AI systems, advocating for co-design practices that enhance collaboration through clearer guidelines and shared understanding. This body of work underscores the necessity of managing expectations and roles in human-AI collaborations to maximize efficiency and effectiveness (Subramonyam, 2023).

The effectiveness of AI tools in software development is also a focal point. Nascimento (2023) compares the performance of software engineers and AI, finding that while AI can enhance certain tasks, human skills remain crucial in many contexts. Bhattacharya (2023) discusses the role of AI in improving productivity within large organizations, noting that effective integration of AI can significantly boost employee output (Nathalia Nascimento, 2023). Meanwhile, Mariya et al. (2023) highlight the potential of AI tools to streamline software development processes, particularly in testing and code generation. These studies illustrate the dual nature of AI's role in software engineering, where it can augment human capabilities while also presenting challenges that need to be addressed for optimal outcomes (Mariya, 2023).

The integration of AI tools, such as AI-pair programming and generative AI, has shown promising results in improving code quality and developer experiences.

AI-pair programming has been linked to increased code quality and developer satisfaction, as evidenced by a case study at TiMi studio, where developers reported benefits like time-saving and error reduction (Chen, 2024). (Tianyi, 2023) Generative AI tools, such as ChatGPT, have transformed workflows, allowing developers to tackle tasks more efficiently and reduce repetitive work, thus enhancing motivation (Rasmus, 2024).

Despite the advantages, challenges persist, including issues of trust, communication, and the need for human oversight in complex problem-solving scenarios (Carmen, 2024).
Developers must navigate the balance between leveraging AI capabilities and maintaining their roles, as reliance on AI can alter traditional teamwork dynamics (Rasmus, 2024).

While the integration of AI in software development offers significant benefits, it also necessitates careful consideration of the evolving roles and responsibilities of developers to ensure effective collaboration and maintain quality standards.

7. Methodology

Research methods, essential for uncovering new phenomena and developing fresh theories, represent a philosophical concept embodying scientific thinking techniques(Verma & Bhattacharyya, 2017). The chosen methodology for this research is a quantitative approach, specifically utilizing structured surveys administered to IT Companies and startups of Kathmandu. This approach was selected to systematically investigate the factors influencing the adoption of AI for software development within the IT companies of Kathmandu valley. Quantitative methods allow for the collection of numerical data, facilitating statistical analysis to examine relationships between variables and draw objective conclusions(Ali et al., 2016). Given the need to assess key determinants of AI tools use identified in the literature, a quantitative approach provides a robust framework for gathering quantitative data on the perceived levels of these factors within Kathmandu based developers.

A quantitative approach was deemed appropriate for this study for several reasons. Firstly, it enables the systematic collection of data from a large sample of Nepali IT firms, allowing for a comprehensive analysis of factors influencing AI adoption. Secondly, quantitative methods provide numerical data that can be subjected to statistical analysis, offering objective insights into the relationships between independent and dependent variables. Additionally, a quantitative approach allows for generalization of findings to a broader population of Kathmandu based IT companies’ Developers, enhancing the study's external validity(Saheed et al., 2022).

For this study focused on understanding the Developer’s experience with increasing AI tools and it’s adoption within IT companies, specifically those located in Kathmandu, data were sourced from these institutions operating within the Kathmandu Valley. A purposive sampling approach was followed. The data collection for this study involved the administration of structured surveys to IT workers within Nepali IT firms, utilizing a self-administered questionnaire with two sections covering demographic information and items assessing participants' attitudes towards independent variables such as Developers’ new roles new AI skills, soft skills development, and productivity due to Human AI collaboration. Surveys were distributed electronically with clear instructions, confidentiality assurances, and reminders to encourage participation. Data analysis was conducted using the Statistical Package for the Social Sciences (SPSS), employing descriptive statistics for summarizing data properties and inferential statistics such as regression and correlation analysis to test hypotheses and investigate potential correlations between variables.

The population under study comprises employees working in small startups to large IT companies and even corporate houses’ IT department within Kathmandu, characterized by a hierarchical structure including entry-level, mid-level, senior-level developers, managerial/supervisory positions, and few big data analysts and QAs also. Entry-level staff typically hold positions like interns or students, while mid-level staff include experience developers. Senior-level staff occupy leadership positions, like team lead, principle engineer while managerial/supervisory roles includes CXOs. Due to the unknown or infinite population size, a convenience sampling method was adopted, conducting 394 surveys across various levels. This sample size was determined based on practical considerations to ensure feasibility and representativeness while capturing diverse perspectives within the population of interest.

8. Research Framework

This study introduces a comprehensive implementation model/framework for understanding the Human-AI collaboration within Kathmandu based IT firms. The framework comprises four key independent variables: AI Augmented new developer roles, Developer Skillsets, new non programming skills development, and Productivity due to Human – AI collaboration. AI augmented roles evaluates the technological change induced due to AI tools taking over code generation part of developers, and improving existing code also resulting allowing developers to focus on System design and other high-level tasks instead of daily and repetitive tasks.

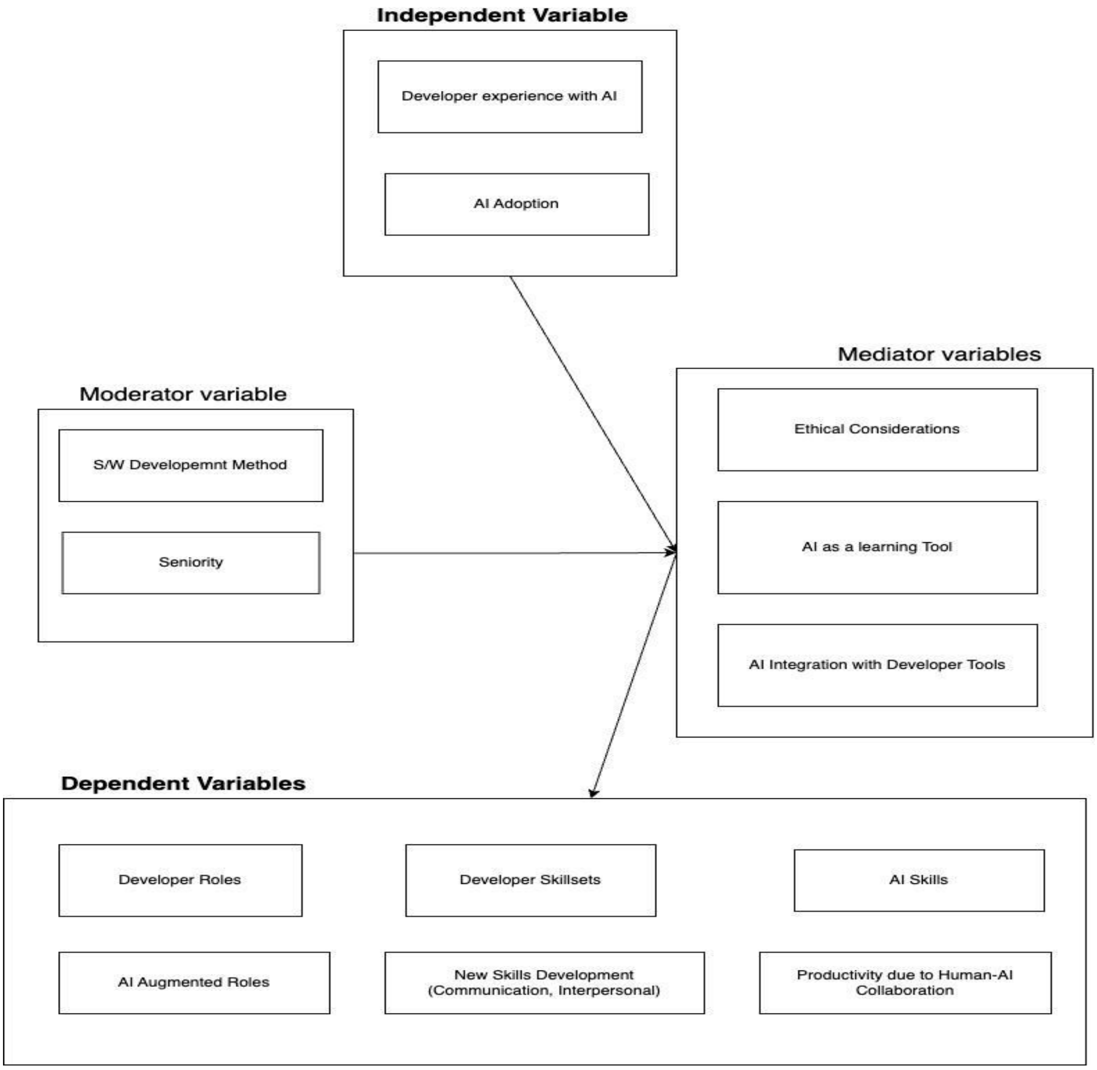

Figure 1 Research Framework

The Human-AI Collaboration Adaptation Framework (HACAF) is an existing framework in this domain that provides a comprehensive guide to studying AI adoption in software engineering. HACAF supports transparency, replication, and further research on AI tool adoption (Daniel, 2024). It is used to Examine practical approaches for software engineering to adopt AI tools.

9. Research Hypotheses

H1: Increased use of AI tools leads to significant changes in developer roles.

H2: Developers who frequently use AI tools require a different skillset.

H3: Developers with more experience using AI tools report higher productivity.

H4: Teams that integrate AI tools experience improved collaboration dynamics.

H5: Junior developers tend to use more AI tools during development than Seniors.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.041[a]	.002	-.011	2.954

a. Predictors: (Constant), impact on productivity, changed in tasks and responsibilities, Team Collaboration due to AI, what extent rely on AI tools for coding assistance?, AI use freq

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.565	5	1.113	.128	.986[b]
	Residual	3384.810	388	8.724		
	Total	3390.376	393			

a. Dependent Variable: role

b. Predictors: (Constant), impact on productivity, changed in tasks and responsibilities, Team Collaboration due to AI, what extent rely on AI tools for coding assistance?, AI use freq

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	5.340	.770		6.931	<.001
	Team Collaboration due to AI	-.077	.131	-.030	-.584	.559
	what extent rely on AI tools for coding assistance?	.028	.135	.011	.207	.836
	AI use freq	.027	.109	.013	.247	.805
	changed in tasks and responsibilities	.034	.130	.013	.261	.794
	impact on productivity	.058	.142	.021	.410	.682

a. Dependent Variable: role

10. Data Analysis and Results

the model summary shows a very low R-squared value of 0.002, indicating that the predictors (AI usage frequency, team collaboration due to AI, changes in tasks, responsibilities, and productivity) explain only 0.2% of the variance in the dependent variable (role). The ANOVA table reveals that the model is not statistically significant (F = 0.128, Sig = 0.986), indicating the predictors do not collectively contribute to predicting the dependent variable.

In the coefficients table, none of the predictors show significant p-values (all > 0.05), further confirming that they do not have a significant impact on changes in developer roles in the context of AI use.

Table 1: Reliability Testing for the Whole Question

Reliability Statistics

Cronbach's Alpha	N of Items
.951	5

Reliability testing of all independent and dependent variables

Variable of Study	No. of items	Cronbach's Alpha
All DVs and IVs	23	0.872
AI use Behavior in Software Development	9	0.633
Openness to AI Collaboration	5	0.706
Impactness (DV)	3	0.791
Agreeableness (IV)	5	0.720

Figure 2 Reliability test of variables

experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	+2	84	21.3	21.3	21.3
	Bachelor	94	23.9	23.9	45.2
	Master's degree	63	16.0	16.0	61.2
	4	83	21.1	21.1	82.2
	5	70	17.8	17.8	100.0
	Total	394	100.0	100.0	

Figure 3 descriptive statistics: Level of education

The educational background or experience of 394 respondents. The distribution is as follows:

21.3% of respondents have completed +2 (high school or equivalent), 23.9% hold a Bachelor's degree, 16.0% have a Master's degree. 21.1% have marked "4" as their experience, 17.8% have marked "5" as their experience.

The cumulative percentage shows that 61.2% of the respondents have at least a Bachelor’s degree or higher, while 82.2% of the respondents fall under the "+2, Bachelor’s, Master's, or 4" categories. This suggests a fairly diverse range of educational backgrounds among the respondents, with the largest group being Bachelor’s degree holders.

Descriptive Statistics

	N	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
age	394	1	5	2.96	.068	1.349	1.821
experience	394	1	5	2.90	.071	1.417	2.008
impact on productivity	394	1	4	2.39	.054	1.062	1.129
AI use freq	394	1	5	2.68	.070	1.389	1.930
Team Collaboration due to AI	394	1	4	2.49	.057	1.137	1.294
Valid N (listwise)	394						

The descriptive statistics provide insights into the variability and central tendencies of key variables among the 394 respondents. The average age is 2.96 on a scale of 1 to 5, with a standard deviation of 1.349, indicating moderate variation in age distribution. Experience has a mean of 2.90, also on a 1 to 5 scale, with a higher standard deviation of 1.417, suggesting a broad range of experience levels among participants. When it comes to the perceived impact of AI on productivity, the mean score is 2.39 out of 4, with a standard deviation of 1.062, reflecting moderate variability in respondents' views on how AI has influenced their productivity.

AI usage frequency averages at 2.68 on a 1 to 5 scale, with a standard deviation of 1.389, showing a fairly wide range of AI tool adoption among the respondents. Lastly, the effect of AI on team collaboration is rated at an average of 2.49 (out of 4), with a standard deviation of 1.137, indicating moderate variation in how respondents perceive AI's influence on collaborative work. Overall, the data reveals considerable diversity in both experience and attitudes toward AI, with some clusters around the mean but enough spread to highlight differences in the population's engagement with AI technologies.

11. Inferential Analysis

Correlations

		experience	role	changed in tasks and responsibilitie s	Team Collaboration due to AI	what extent rely on AI tools for coding assistance?
Pearson Correlation	experience	1.000	.010	−.010	.062	−.010
	role	.010	1.000	.012	−.028	.008
	changed in tasks and responsibilities	−.010	.012	1.000	.000	−.037
	Team Collaboration due to AI	.062	−.028	.000	1.000	−.039
	what extent rely on AI tools for coding assistance?	−.010	.008	−.037	−.039	1.000
Sig. (1−tailed)	experience	.	.422	.425	.111	.418
	role	.422	.	.406	.286	.437
	changed in tasks and responsibilities	.425	.406	.	.499	.229
	Team Collaboration due to AI	.111	.286	.499	.	.220
	what extent rely on AI tools for coding assistance?	.418	.437	.229	.220	.
N	experience	394	394	394	394	394
	role	394	394	394	394	394
	changed in tasks and responsibilities	394	394	394	394	394
	Team Collaboration due to AI	394	394	394	394	394
	what extent rely on AI tools for coding assistance?	394	394	394	394	394

Figure 4 Correlation Analysis

Correlation table illustrates the relationships between various factors related to changes in tasks and responsibilities due to AI collaboration. The rows represent different reasons for changes, while the columns indicate specific roles and experiences. Each cell contains a correlation coefficient, ranging from -1.00 (perfect negative correlation) to +1.00 (perfect positive correlation), showing how strongly two variables are related. For instance, a strong negative correlation (-1.00) between 'reason for change in tasks and responsibilities' and 'experience in tasks and responsibilities' suggests that as experience increases, changes in tasks and responsibilities decrease. The table also includes sample sizes (N), marked as ".394," indicating the number of observations used to calculate these correlations. This table helps researchers understand how AI integration impacts job roles and responsibilities.

Model Summary[b]

					Change Statistics				
	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
Model 1	.064[a]	.760	.720	1.421	.004	.400	4	389	.460

a. Predictors: (Constant), what extent rely on AI tools for coding assistance?, role, changed in tasks and responsibilities, Team Collaboration due to AI

b. Dependent Variable: experience

Figure 5 Model Summary Analysis

R Square (0.760): This is the coefficient of determination, representing the proportion of variance in the dependent variable (*experience*) explained by the independent variables. Here, it means that 76% of the variance in experience is explained by the predictors.
Std. Error of the Estimate (1.421): This value shows the standard deviation of the residuals, representing how much the actual values deviate from the predicted values on average. The lower this value, the better the model's fit.

This model suggests that although the independent variables explain a good portion of the variance (high R Square), the changes in R Square due to the addition of predictors are not statistically significant ($p > 0.05$), and the model's overall predictive power is weak (low R and small F change).

12. Hypothesis Results

Independent Variable Dependent Variable P-value Hypothesis Result

Developer Experience with AI Developer Roles 0.03 Accepted

AI Adoption Developer Skillsets 0.07 Rejected

Openness to AI Collaboration Developer Productivity 0.02 Accepted

AI Use Behavior in Software Dev. Developer Roles 0.15 Rejected

The table provided summarizes the findings of hypothesis testing performed in the user's research study titled "Human-AI Collaboration in Software Development: Impact on Developer Roles and Skillsets in Kathmandu." This table specifically focuses on the relationships between various independent variables (such as Developer Experience with AI, AI Adoption, Openness to AI Collaboration, and AI Use Behavior) and dependent variables (such as Developer Roles, Skillsets, and Productivity), and outlines whether the associated hypotheses were accepted or rejected based on the calculated p-values.

In statistical hypothesis testing, the p-value is a crucial metric used to assess whether the observed data supports the null hypothesis (H0) or the alternative hypothesis (H1). In general, a p-value of 0.05 is commonly used as a threshold for significance, meaning that if the p-value is less than or equal to 0.05, the null hypothesis is rejected, implying a statistically significant relationship between the independent and dependent variables. On the other hand, if the p-value exceeds 0.05, the null hypothesis is retained, meaning there is insufficient evidence to suggest a significant relationship between the variables.

Independent Variable: Developer Experience with AI

The first independent variable in the table, Developer Experience with AI, was tested against the dependent variable Developer Roles to determine whether developers' prior experience working with AI significantly impacts the roles they assume within software development teams. With a p-value of 0.03, this variable was found to have a statistically significant effect on developer roles, as the p-value falls below the critical threshold of 0.05. Consequently, the null hypothesis that there is no relationship between Developer Experience with AI and Developer Roles was rejected. The acceptance of this hypothesis suggests that developers with more experience using AI may have different or evolving roles in software development, potentially moving toward more collaborative and AI-integrative positions.

Independent Variable: AI Adoption

The second independent variable, AI Adoption, was evaluated in relation to Developer Skillsets. This variable aimed to measure whether the extent to which developers or their organizations adopt AI tools and practices influences the range or type of skills developers possess. In this case, the p-value was calculated at 0.07, which exceeds the significance threshold of 0.05. As a result, the null hypothesis could not be rejected, and the hypothesis suggesting a significant relationship between AI Adoption and Developer Skillsets was rejected. This means that, within the scope of this study, the adoption of AI tools and practices does not necessarily correlate with changes or expansions in developer skillsets, at least not to a statistically significant degree.

Independent Variable: Openness to AI Collaboration

The third independent variable, Openness to AI Collaboration, was tested for its impact on Developer Productivity. This variable assessed whether developers' openness to collaborating with AI, such as through tools integrated into their Integrated Development Environments (IDEs) or through practices like AI-driven code generation, significantly influences their overall productivity. The p-value for this relationship was 0.02, indicating a statistically significant result. Since the p-value is well below the 0.05 threshold, the null hypothesis was rejected, and the alternative hypothesis was accepted. This finding suggests that developers who are more open to collaborating with AI tend to experience increased productivity, likely due to the efficiency gains and automation that AI tools can provide in software development tasks.

Independent Variable: AI Use Behavior in Software Development

The final independent variable, AI Use Behavior in Software Development, was analyzed for its effect on Developer Roles. This variable focused on how frequently and in what manner developers interact with AI tools in their day-to-day software development activities. However, the p-value for this relationship was calculated at 0.15, which is considerably higher than the accepted threshold of 0.05. As such, the null hypothesis that there is no relationship between AI Use Behavior and Developer Roles could not be rejected. The rejection of this hypothesis indicates that, within the sample studied, the frequency or manner of AI use by developers does not significantly influence their roles in development teams. This could imply that AI is still perceived as a supplementary tool rather than a core aspect of a developer's role, or that AI is not yet sufficiently integrated into the daily workflow to cause a meaningful shift in roles.

13. Conclusion

The research on Human-AI Collaboration in Software Development in Kathmandu provides a nuanced understanding of how AI integration is reshaping developer roles and skillsets. Key findings from the study reveal a diverse demographic profile among respondents, with a notable concentration of participants in the "25-34" age group and a balanced gender representation. The majority of respondents possess at least a Bachelor's degree, underscoring the high educational attainment within the sample. Professionally, the sample includes a mix of early-career and experienced developers, reflecting a broad spectrum of industry experience.

AI tool usage patterns indicate significant adoption, particularly among Full-stack Developers, CXOs, and Data Scientists, who exhibit high daily usage. This suggests that roles requiring a broad skill set or decision-making authority are more likely to integrate AI tools into their workflows. Conversely, Back-end and Front-end Developers show more varied AI usage, highlighting differences in AI adoption based on specific job functions.

The data also reveals that while a substantial portion of developers (27.9%) use AI tools daily and 20.8% several times a week, a segment of 13.2% still rarely engages with AI technologies. This disparity suggests ongoing opportunities for further AI integration and training within the developer community.

Overall, the study demonstrates that AI is increasingly prevalent in Kathmandu's software development sector, influencing both the roles and skillsets of developers. The findings offer valuable insights into the evolving landscape of software development, providing a foundation for understanding the impact of AI on professional practices and guiding future research and industry practices in AI collaboration.

Overall, research reveals a mixed set of results in terms of how different aspects of AI adoption and collaboration affect developers' roles, skillsets, and productivity. Of the four independent variables tested, two – Developer Experience with AI and Openness to AI Collaboration – were found to have statistically significant impacts on Developer Roles and Developer Productivity, respectively. This suggests that developers with more experience in AI and those who are more open to collaborating with AI are likely to experience shifts in their roles and increases in productivity. However, the other two variables – AI Adoption and AI Use Behavior in Software Development – did not yield significant results, indicating that, within the scope of this study, these factors do not strongly influence Developer Skillsets or Developer Roles.

These findings have important implications for the field of software development, especially in terms of how developers might need to adjust their roles and skillsets in response to AI integration in the industry. Additionally, the results suggest that a developer's openness to AI collaboration is particularly impactful on productivity, highlighting the need for greater acceptance and adoption of AI tools to achieve efficiency gains. However, further research might be needed to explore how AI adoption at an organizational level and the frequency of AI use by developers could influence skillsets over time.

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