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Success Factors for Evaluating AI-Era Reskilling and Upskilling among IT Professionals: Evidence from Global Developer Survey Data

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Abstract
Artificial intelligence is shaking the field of software development by altering the manner in which IT professionals learn, embrace and use new tools in the workplace. This paper analyzes the success factors of AI-era reskilling and upskilling of IT professionals based on the data of global surveys of developers. The Stack Overflow Developer Survey 2025 was studied using a quantitative, explanatory, cross-sectional design. The operationalization of AI-career upskilling was the self-reported learning about AI-enabled tools needed in their jobs or that could help them professionally. Individual, professional, workplace, AI-readiness, and AI-adoption factors were explored using descriptive statistics, chi-square tests, Cramer V, and hierarchical binary logistic regression. The results indicate that AI-career upskilling exists, albeit it is disproportionately found in 40.04% of professional developers who reported job/career-oriented AI learning. The success of upskilling was significant among AI-agent users, who also exhibited more positive AI sentiment, higher AI trust, and greater AI-tool engagement compared to the entire professional sample. The bivariate and regression findings show that the main success factors are AI-tool adoption, frequent use of AI-agents, positive AI attitudes, and faith in AI ability to carry out the tasks better than the demographic, professional or workplace factors by themselves. The research contributes an evidence-based five-dimensional framework for evaluating AI-era reskilling and upskilling through contextual conditions and barriers, AI readiness, AI adoption, learning success, and work-benefit realization. The results provide viable advice to AI-oriented workforce development, specialized reskilling policies and professional learning within the rapidly evolving developer work settings.

Keywords: AI upskilling; reskilling; IT professionals; AI readiness; developer survey data.

1. INTRODUCTION

Artificial intelligence has become a trend in the revolution of modern work. It is now having far-reaching effects on routine automation to professional, cognition, and technologically technical activities involving judgements, problem-solving and domain knowledge. According to labour-market research, AI is transforming the types of work performed, the skills needed, and the interaction between human ability and work aided by machine Frank et al. (2019). Nevertheless, this change is not equal as AI exposure is distributed unequally among jobs, sectors, and task methods Felten et al. (2021). The heavy adoption of generative AI and large language models has worsened the professional change requirement since these technologies are now capable of writing, code writing, debugging, information and documentation retrieval, decision support, and analytics Eloundou et al. (2024). On a global scale, generative AI has led to the emergence of new concerns regarding the quality of jobs, redesigning tasks, and constant skill updating Gmyrek et al. (2023).

Information technology professionals are the ones that the implications are especially important. Not only users of digital tools, software developers and other IT workers are also key actors in designing, deploying, maintaining, and adapting AI-enabled systems. Code-generation tools, AI copilots, automated debugging systems, and AI agents that assist with software development efforts are becoming prominent in their work. An AI agent refers to an AI-enabled tool or system that assists IT professionals in performing work-related tasks with some degree of automation, task support, or autonomous assistance, such as coding assistance, debugging, workflow support, documentation support, or technical problem-solving. The results of research conducted in the workplace show that generative AI can enhance performance, provided that workers successfully implement these systems in the performance of tasks Brynjolfsson et al. (2025). Assistant AI also demonstrates that generative AI can improve productivity in the appropriate conditions of the tasks Noy and Zhang (2023). Software In the software development field, AI-based tools like GitHub Copilot have been associated with productivity and workflow optimization in developers Ziegler et al. (2024). These trends show that AI-era reskilling, upskilling is emerging as a key focus of employability, productivity, and career advancement in the field of IT.

In the AI era, reskilling and upskilling cannot be interpreted as the participation of formal training only. They are also connected with the ability to adopt new digital practices, comprehend AI outputs, responsible application of AI-related tools, and adjustment of work practices to evolving technological needs. The research on digital skills indicates that modern professionals need to have general skills, such as the ability to manage information, communicate, solve problems, and be strategic in the digital environment van Laar et al. (2017). Recent studies in adult digital skilling also confirm the fact that working professionals are forced to constantly increase and improve their competences because technologies and the needs of the work change Mendoza-Chan and Pee (2024). In this study, AI-career upskilling refers to self-reported learning of AI-enabled tools that are needed for job performance or useful for career development. It is treated as the learning-success dimension within the broader evaluation of AI-era reskilling and upskilling. This realization aligns with the findings that AI-based transformation of a workplace necessitates skill, work practice, and organizational support system changes Babashahi et al. (2024).

Although there is increasing emphasis on AI in professional work, there is a lack of empirical understanding of the variables that relate to successful AI-era upskilling in IT professionals. The current literature is mainly concerned with the overall impacts of AI on the labour-market, the productivity, or occupational exposure. The studies are significant, yet they fail to articulate the reasons behind the reported successful career learning of AI-related topics among certain IT professionals and not all. Nonetheless, only scanty empirical research clarifies the manner in which both AI preparedness and AI adoption mutually influence career-oriented AI learning among IT practitioners using extensive survey data in terms of developer numbers. This is a significant gap since being exposed to AI does not necessarily lead to successful upskilling. Professionals can vary in their readiness to adopt AI tools, confidence in AI-generated outputs, perceptions of AI complexity, their use of AI agents, and their workplace provision of support to technology-enabled learning.

Another issue is that AI-related upskilling is commonly discussed as one of the learning outcomes, whereas it should be viewed as a multidimensional process. An IT specialist could study the AI tools to gain professional advantage, be a frequent or infrequent user, have confidence or lack confidence in AI-generated products, feel that AI is useful or a danger, and be both more productive and experience implementation difficulties. Hence, AI-career upskilling should not be examined through background factors such as age, education, role, or experience alone. It should be evaluated through five connected dimensions: contextual conditions and barriers, AI readiness, AI adoption, learning success, and work-benefit realization. This wider perspective is essential since the success of AI-era upskilling is not only about the type of professionals, but also the manner in which they interact with AI technologies in their work. Contextual conditions and barriers include individual, professional, workplace, and AI-related constraints; AI readiness captures sentiment, trust, threat perception, and perceived complexity; AI adoption reflects AI-tool use, AI-agent use, and usage frequency; learning success represents AI-career upskilling; and work-benefit realization captures productivity, time-saving, learning, quality, and automation benefits.

This research is confined to AI-career upskilling of IT professionals based on worldwide developer survey data. The research question is whether the respondents report learning AI-enabled tools that they need to perform their job or are useful in their career. It will analyze individual, professional, workplace, AI-readiness, and AI-adoption predictors that might relate to this outcome. The study fails to test real-life AI proficiency by performance testing and fails to test a certain formal training programme. The results are seen as correlations, instead of causal impacts because the data is cross-sectional and self-reported. Such boundaries are suitable as the aim of the study is to determine the success factors and create an evidence-based model of assessing the AI-era reskilling and upskilling.

This research is meaningful to research and practice. It also advances the field of AI and work scholarship by refocusing efforts on professional learning and adaptation instead of automation and productivity. It expands the digital-skilling studies by operationalizing AI-career upskilling in quantifiable survey measurements. It is also useful to an organization, educator, workforce-development agency, and technology leaders as it must understand the circumstances in which IT professionals are more willing to report successful AI-related career learning. The originality of this research lies in combining global developer survey evidence with a five-dimensional evaluation framework that links contextual conditions and barriers, AI readiness, AI adoption, learning success, and work-benefit realization in one integrated model of AI-era professional development. The study does not explore AI adoption, AI trust, or digital skills in isolation, but instead relates these spheres in one model of AI-era professional development.

The study is guided by the following research objectives:

1.To assess the prevalence of AI-career upskilling among IT professionals using global developer survey data.

2.To identify the individual, professional, workplace, AI-readiness, and AI-adoption factors associated with AI-career upskilling success.

3.To develop an evidence-based five-dimensional framework for evaluating AI-era reskilling and upskilling among IT professionals.

2. Literature Review

The reskilling and upskilling in the age of AI starts with the general revolution in work with the automation and intelligent technologies. When the technology changes, Autor (2015) opined that the jobs are not simply lost but redistributed and the value of complementary human abilities is enhanced. This point is at the heart of the upskilling of the AI age since the major issue is not only the replacement of human labor by AI systems, but rather the ability of professionals to acquire the skills to work effectively with AI systems. This opinion was furthered by Jarrahi (2018) with the concept of human-AI symbiosis in which AI is most useful in helping people make judgements and not in completely eliminating expertise. Raisch and Krakowski (2021), on their side, have written about the automation-augmentation paradox, in which AI causes the role of a human in certain tasks to become less important, but requires more supervision, interpretation, and strategy formulation. Parker and Grote (2022) also demonstrated that automation and the use of algorithmic systems transform autonomy, task complexity, coordination, and the learning requirements. These studies combined with others imply that AI-era reskilling must be considered in terms of work-transformation problem, rather than the training problem.

Research on digital-skills offers a conceptual baseline to professional learning about AI. van Laar et al. (2018) have demonstrated that digital competence at workplace is multidimensional and comprises of information, communication, collaboration, creativity, problem-solving and strategic capabilities. These dimensions are pertinent since AI upskilling can not be achieved only through exposure to technical tools. Addressing the outcomes of AI-based use in the workplace, professionals also need to comprehend them, consider their reliability, and implement the results of AI-assisted work. Long and Magerko (2020) defined AI literacy as the skills to comprehend, apply, assess, and critically interact with AI systems. Similarly, Ng et al. (2021) postulated that in their argument on AI literacy, they included technical knowledge, ethical knowledge, and practice. These articles suggest that AI-career upskilling cannot be considered a tool training. It is to be comprehended as a more inclusive professional skill that entails learning, interpreting, adapting, and using AI responsibly.

Technology-adoption literature explains the reason why there exists a disparity in how active professionals are in using AI tools. Unified theory of acceptance and use of technology has performance, effort as well as social influence and facilitating conditions and behavioural intention as significant contributors to technology use Venkatesh et al. (2016). This logic is more complicated in AI cases due to autonomy, opaque, perceived intelligence, and evolving user expectations of AI systems. Venkatesh (2022) thus equated that AI implementation studies ought to consider such unique attributes. At the organizational level, Uren and Edwards (2023) revealed that the readiness of technology, organizational capability and implementation maturity determines the adoption of AI. At the employee-level, Chiu et al. (2021) have identified that pre-adoptive appraisal by workers dictates the interception of AI as an opportunity or a threat, and Choi (2021) has indicated that employee AI acceptance would be affected by the perceived usefulness, attitudes, and organizational conditions. These papers justify the idea that AI readiness and AI adoption should be included among the key success-factor areas of AI-career upskilling.

Trust and attitudes also contribute to meaningful use of AI-enabled systems by the professionals. Gkinko and Elbanna (2023) demonstrated that the trust in conversational AI is developed based on the workplace interaction, perceived reliability, and user experience. Glikson and Woolley (2020) discovered that AI based on the performance of the system, transparency, context of the tasks, and perception by the user. The General Attitudes towards Artificial Intelligence Scale was created by Schepman and Rodway (2020) and later validation research found it to be correlated with trust, distrust and individual differences Schepman and Rodway (2023). This literature justifies the use of AI sentiment, AI trust, perceived threat and perceived complexity as indicators of preparedness. It implies also that the success of AI upskilling can be determined both by the availability of tools, and the ability of professionals to responsibly use AI outputs.

The specific AI tools targeted at developers are relevant to the IT professionals directly. The study by Peng et al. (2023) revealed that GitHub Copilot had the potential to enhance the productivity of developers, meaning that AI-assisted coding tools have the potential to transform technical working practices. But the productivity of using AI generated code rests on how developers comprehend, test and incorporate these programs. Vaithilingam et al. (2022) demonstrated that the code-generation tools can result in a disconnect between expectation and experience particularly where usability, correctness and workflow integration issues may occur. These results are significant since the concept of AI-era upskilling among developers does not necessarily focus on the adoption of the tools. It also entails the process of learning to trust AI recommendations, the way to analyze the generated results, the way of integrating AI support into the process of software-development.

The existing research offers valuable information on the topics of AI-based work transformation, digital literacy, AI literacy, technology adoption, AI readiness, trust, and developer productivity. But these streams are still in pieces. The reason is that skill adaptation is required, and the contents that professionals need to learn are available in automation and work-design studies, whereas the digital-skills and AI-literacy studies. The adoption and readiness theories describe why certain professionals are more active in using AI, and a trust research describes the influence of the perception on the use of AI. The studies made by developers and tools reveal the reasons why these are of particular concern to software experts. However, there are minimal studies that combine these dimensions into one empirical model of assessing AI-career upskilling among IT professionals. The current work fills this gap with global survey data on developers, and correlates learning success with personal, professional, workplace, AI-preparedness, and AI-adoption variables. This way, it aligns AI-era reskilling and upskilling as a multidimensional process that is determined by preparedness, adoption, work benefits, and situational impediments.

3. Methodology

3.1 Research Design

To investigate the sources of success related to AI-era reskilling and upskilling among IT professionals, this research study has chosen a quantitative, explanatory, cross-sectional, and secondary-data research design. The study design was suitable since the research needed massive evidence on globally spread IT professionals and quantifiable correlations among AI-related learning and personal, career, work-related, AI-readiness and AI-adoption variables. Structured survey data permitted the selection of the responses to be converted into empirical variables that would be used in descriptive analysis, bivariate association testing, and in hierarchical logistic regression.

It was an explanatory study as it evaluated the ability of the various groups of predictors to enhance the insight into AI-career upskilling effectiveness. The analysis was structured based on a staged modelling framework where individual factors, professional characteristics, workplace context, AI readiness and AI adoption were analyzed in a sequential manner. Using this approach allowed assessing the explanatory value of AI-specific factors in addition to demographic, professional, and organizational factors. The data were cross-sectional and self-reported, thus the study did not make causal assertions. Interpretation of the findings was in terms of statistical association, likelihood and explanatory contribution as opposed to direct cause and effect.

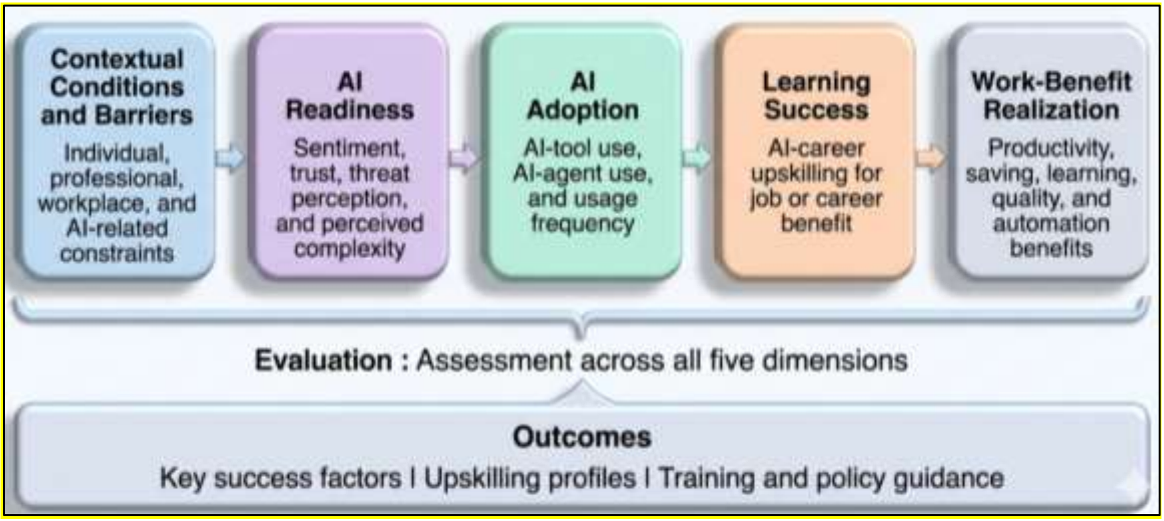

Figure 1. Overall Framework for Evaluating AI-Era Reskilling and Upskilling among IT Professionals.

3.2 Data Source and Data Collection

The data source of the study was the secondary data on the Stack Overflow Developer Survey, which was obtained via the official StackExchange Survey GitHub repository, StackExchange (2025). The repository contains the open source archive of Stack Overflow Developer Survey data and documentation, such as respondent-level data, schema data, and survey tools. The reason behind the choice of the 2025 survey materials is that they provide numerous data on professional characteristics of developers, their experiences with coding, work context, use of AI-tools, adoption of AI-agents, their attitude to AI and their learning behaviour. The analysis was supported by three elements of the survey archive. The output file was used as the primary respondent level data to be statistically analyzed. The schema file served as the data dictionary and was used to check the names of variables, response choices and meanings of questions. The conceptual relevancy of the survey items selected and the language in the survey questionnaire were validated by the survey questionnaire. Collectively, these files furnished the empirical and measurement foundations to investigate AI-era reskilling and upskilling of IT professionals. This study did not collect any primary data.

3.3 Population and Sampling

The target audience was global IT professionals with specific focus on professional developers. This group was suitable since the research will focus on the reskilling and upskilling in software creation and associated technical jobs in the AI era. The entire survey data had a total of 49,191 responses. Out of this data, the main sample during analysis was those respondents who described themselves as developers as their line of business. This resulted in the creation of a primary sample of professional developers of 37,467 respondents.

Following a process of filtering of valid outcomes responses, the primary sample of analysis included valid professional developer cases (34,757).
Additional validation was also taken to a wider sample of the coding-related IT professional. The wider sample incorporated the respondents who did not always have to be professional developers but indicated the coding as a part of their work or research. The general sample of IT professionals had 42,361 respondents prior to any final modelling filters. The core analysis of the sample was executed with the main one, and only the broader sample was selected to investigate whether the overall results did not change once the definition of IT professionals was expanded.

3.4 Variable Measurement and Operationalization

AI-career up skilling success was the dependent variable. It was based on the question in the questionnaire which inquired regarding whether the surveyed participants had acquired skills on how to use AI-enabled tools necessary/helpful in the work they do; or useful in their career. The respondents who have chosen this answer were coded as successful in AI-career upskilling.
This operationalization directly corresponded to the title since it reflected job-related and career-oriented AI learning. The independent variables were categorized into five domains of analysis, namely, individual factors, professional characteristics, workplace context, AI readiness, and AI adoption. The main constructs and their focus of measurement are summarized in Table 1.

Table 1. Measurement and Operationalization of Key Constructs

Construct	Measurement Focus
AI-career upskilling success	Learning AI-enabled tools for job or career benefit
Individual factors	Age, education level, country, coding experience, professional work experience
Professional characteristics	Employment status, developer role, industry, contributor or manager role
Workplace context	Organization size, remote work arrangement, job satisfaction, work-tool count
AI readiness	AI sentiment, AI trust, AI threat perception, perceived AI complexity
AI adoption	AI-tool use, AI usage frequency, AI-agent use, AI-agent usage frequency
Work-benefit realization	Productivity, learning, quality improvement, automation, time saving
Contextual barriers	AI frustration, integration difficulty, accuracy concerns, privacy concerns

This operational framework transformed the general notion of success factors into empirical empirical constructs. It also enabled the goal of AI-age upskilling to be measured as a multidimensional process that was influenced by the background features, professional positioning, working circumstances, AI preparation, AI implementation, and the perceived work outcomes.

3.5 Data Preparation and Cleaning

Data preparation was done through the process of identifying the variables of interest, checking their meaning with the schema and survey instrument and preparing the data accordingly. Categorical variables were checked and put into uniform standard, a level that will make responses similar. Variables based on experience were transformed into numerical formats where necessary. New indicators were developed, to depict AI-career upskilling success, AI preparedness, AI adoption, AI-agent engagement, and work-related AI benefits. Missing data were managed in an open manner.
Categorical missing values were excluded by explicitly leaving them as missing categories in the appropriate categories and, therefore, non-response patterns were not automatically eliminated in the analysis. The numeric variables were handled in terms of median imputation which was backed by the missingness indicators where necessary. Ahead of the logistic regression, categorical predictors were dummy-coded and odds ratios interpreted based on respective categories of reference. This method maintained the size of the analytical sample and the patterns of missing responses could still be observed in the modelling.

3.6 Data Analysis Techniques

A multi-stage statistical analysis approach was employed in the research. To start with, the prevalence of AI-career upskilling success among IT professionals was analyzed by the use of descriptive statistics. AI readiness, AI-tool adoption, AI-agent adoption, work-benefit realization and contextual barriers were also profiled using frequencies and percentages. This step determined the level of empirical evidence of job-related and career-related AI learning in the chosen sample of the professional population.

Second, bivariate association was implemented based on chi-square tests and Cramer V. Chi-square tests to identify the significant association of categorical predictors with AI-career upskilling success. The relative strength of association was compared with the groups of predictors using Cramer V. Third, hierarchical binary logistic regression was used due to binary dependent variable. Predictors were keyed in, in blocks: individual factors, professional characteristics, workplace context, AI readiness, and AI adoption. The contribution to the final explanatory contribution of the blocks of predictors was compared by using McFadden pseudo R2. Adjusted odds ratios and model-fit indicators were used to make the interpretation of the regression outcomes, and the focus was on the association, as opposed to causality.

3.7 Analytical Framework and Evaluation Method

The study used a five-dimensional analytical framework to evaluate AI-era reskilling and upskilling among IT professionals. The framework was aligned with the conceptual model and organized around five dimensions: contextual conditions and barriers, AI readiness, AI adoption, learning success, and work-benefit realization. Table 2 is the framework of the study.

Table 2. Analytical Framework for Evaluating AI-Era Reskilling and Upskilling

Framework Dimension	Measurement Focus
Learning success	AI-career upskilling success
AI readiness	AI sentiment, AI trust, AI threat perception, perceived AI complexity
AI adoption	AI-tool use, AI-agent use, usage frequency
Work-benefit realization	Productivity, learning, quality improvement, automation, time saving
Contextual conditions and barriers	Individual, professional, workplace, and AI-related constraints

Evaluation was treated as a process of assessment across the five dimensions rather than as a separate final outcome. Descriptive statistics were used to examine the prevalence and profile of AI-career upskilling. Chi-square tests and Cramer's V were used to compare bivariate associations. Hierarchical binary logistic regression was used to estimate the explanatory contribution of each predictor block and identify adjusted success factors. McFadden pseudo R^2 was used to compare model improvement, while adjusted odds ratios were used to interpret the direction and strength of predictors.

3.8 Ethical Considerations

The study used publicly available and anonymized secondary data. There was no personal contact with respondents and no primary data was gathered. The analysis did not strive to establish individual identities and the connection of answers to personal identities. The dataset was used only as academic purposes, referencing to the official source of data, the anonymity of responders was ensured, and the analytical process was also reported in a transparent way, which ensured the maintenance of ethical responsibility. Causal overclaiming was also avoided by the study since the data were self-reported and cross-sectional. These measures helped in keeping the research ethically related when utilizing a big-scale general dataset.

4. Results

4.1 AI-Career Upskilling Prevalence

The success of AI-career upskilling was assessed by the respondents themselves, who reported learning about AI-enabled tools they should know to do their job or to benefit their careers. The results of the sample of the professional developer are shown in Figure 2 and reported in the Table 3. The success rate of AI-career upskilling was reported in 40.04% among 34,757 cases of valid professional developers whereas it was not mentioned in 59.96% cases of valid professional developers. This suggests that AI-related upskilling is already happening among a significant percentage of IT professionals, albeit with an uneven distribution throughout the developer force.

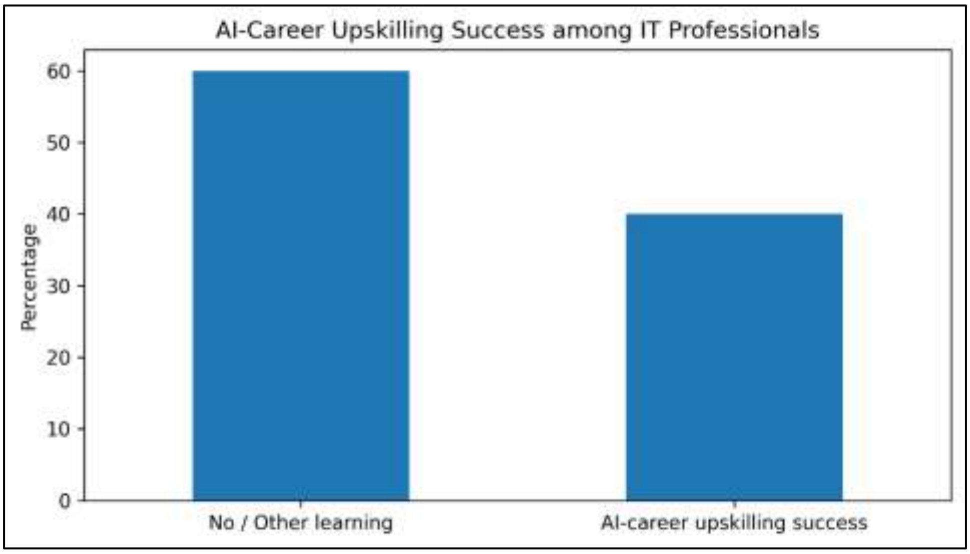

Figure 2. AI-Career Upskilling Success among IT Professionals

Table 3. Distribution of AI-Career Upskilling Success among IT Professionals

Category	Frequency (n)	Percentage (%)
No / Other learning	20,842	59.96
AI-career upskilling success	13,915	40.04

This results in the fact that the empirical theoretical basis of investigation of why AI-career upskilling differs between IT professionals is established.

4.2 AI Readiness, Adoption, Benefits, and Barriers

Table 4 demonstrates the descriptive profile of AI preparedness, AI adoption, perceived benefits, and obstacles between the sample of professionals and AI-agent users.

Table 4. Descriptive Profile of AI Readiness, Adoption, Benefits, and Barriers

Indicator	Professional Sample (%)	AI-Agent Users (%)
AI-career upskilling success	40.04	57.71
AI favourable sentiment	42.24	80.32
AI trust	22.25	45.93
AI tool user	56.14	97.53
Daily AI tool user	35.21	73.78
Daily AI-agent user	9.85	46.76
Productivity benefit	27.29	90.54
Time-saving benefit	26.91	89.61
Learning benefit	26.92	89.64
Quality benefit	26.98	89.73
Accuracy barrier	59.97	87.93
Integration barrier	59.12	86.99
Learning-effort barrier	58.96	86.77
Privacy barrier	59.24	86.61

The table indicates a pattern of description. The users of AI-agents recorded more upskilling success, better favourable AI sentiment, better AI trust and more intense AI-tool use compared to the full professional sample. The success rate in AI-career upskilling amounted to 57.71 in them, as opposed to 40.04 in the professional sample.

This implies that the more the individuals interact with the AI technologies, the more career-oriented AI learning. The trend of the benefit indicators is also strong. Perceived productivity, time saving, learning, and quality benefits were all near 90 among the users of AI-agent. Nevertheless, it also exhibited a high barrier, particularly, accuracy, integration, learning effort and privacy. That means that perceived work value and implementation challenges are linked with advanced AI engagement.

4.3 Bivariate Success Factors

The bivariate analysis investigated the strongest associated predictors of AI-career upskilling success. Figure 3 ranks the strongest bivariate associations based on Cramer V as Table 4 reports the corresponding Cramer's

V coefficients, it is the relative strength of association between categorical variables and does not indicate causality.

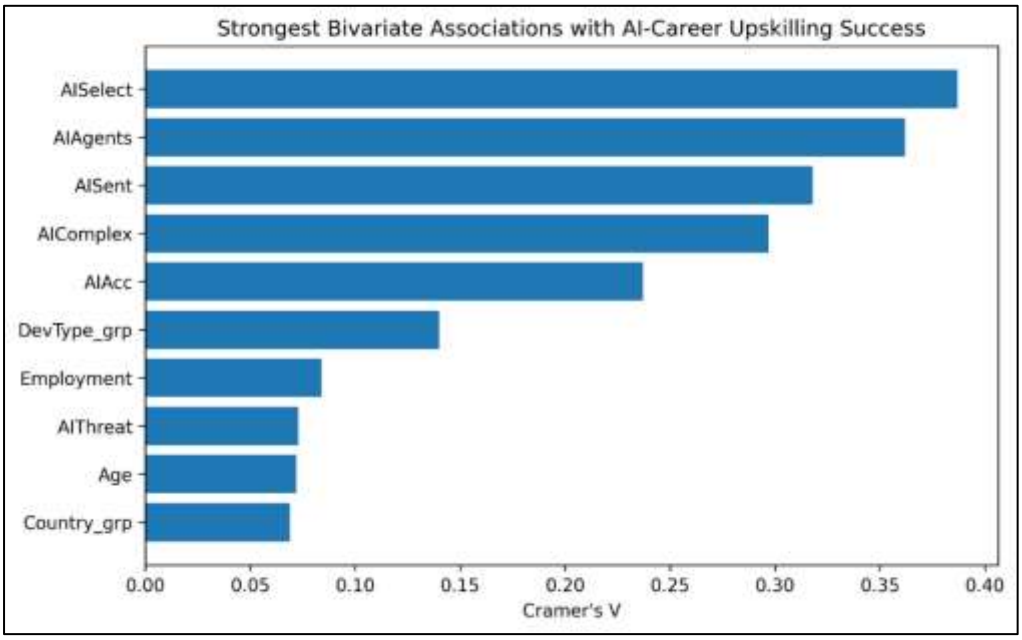

Figure 3. Strength of Bivariate Associations with AI-Career Upskilling Success

The highest level of association was identified with AI-tool adoption reporting Cramer V = 0.387 and then there was AI-agent adoption Cramer V = 0.362. There were also more associations between AI sentiment, AI complexity perception, and AI trust. Contrary, developer role, employed, age, country, size of organisation, and working remotely exhibited less strong associations. These findings show that AI-specific variables are significantly more correlated with success of upskilling AI-career than the background or workplace traits.

4.4 Hierarchical Logistic Regression

A hierarchic binary logistic regression was employed to assess the ability of various predictor blocks to enhance the understanding of the success of AI-career upskilling. The staged enhancement in the pseudo R2 of McFadden is depicted in Figure 4 in the sequential model.

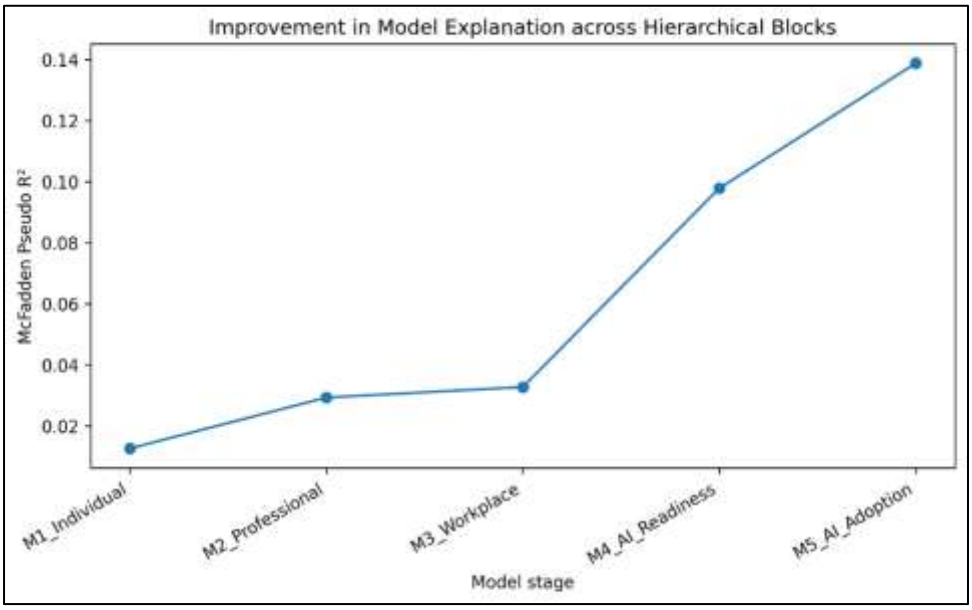

Figure 4. Improvement in Explanatory Power across Hierarchical Logistic Regression Models

Table 5. Hierarchical Logistic Regression Model Improvement

Model Stage	Predictor Block Added	McFadden Pseudo R^2
M1_Individual	Individual factors	0.0126
M2_Professional	Individual + professional factors	0.0293

M3_Workplace	Individual + professional + workplace factors	0.0327
M4_AI_Readiness	Individual + professional + workplace + AI-readiness factors	0.0978
M5_AI_Adoption	Individual + professional + workplace + AI-readiness + AI-adoption factors	0.1387

The model was refined with adding individual, professional and workplace factors. The pseudo R2 of McFadden rose to 0.0126 in the individual-factor model, and to 0.0293 when professional factors were incorporated, and to 0.0327 when workplace context was taken into consideration as shown in Table 5. The biggest increase was noted when the AI-readiness variables were incorporated and the pseudo R2 rose to 0.0978.
The last model that incorporated the AI-adoption factors got to 0.1387. The pseudo R2 improvement on McFadden suggests that the explanatory contribution of AI readiness and AI adoption contributed the most to the model. This trend indicates that AI-specific factors account for a significantly more variance in AI-career upskilling success than do demographic, professional, or workplace factors.

4.5 Key Adjusted Predictors of AI-Career Upskilling Success

Having established the significance of added to the xenization value of AI-readiness and AI-adoption variables, the final logistic regression model was tested using adjusted odds ratios. The most important predictors of AI-career upskilling success are presented in the Figure 5. There is a definite trend in the adjusted results. Lack of AI tools and no intention to use them were the factors with the lowest odds of a successful AI-career upskilling among the respondents who did not use AI tools.

Table 6. Adjusted Odds Ratios for AI-Career Upskilling Success

Predictor	Adjusted Odds-Ratio	95% CI Lower	95% CI Upper	p-value	Significance
Daily AI-agent use	1.4651	1.2623	1.7005	0.0000005	***
Weekly AI-agent use	1.3727	1.1735	1.6057	0.000075	***
AI only in copilot/autocomplete mode	1.2856	1.1075	1.4923	0.000960	***
AI very well at complex tasks	1.2441	1.0496	1.4745	0.0118	*
Very favourable AI sentiment	1.1548	1.0719	1.2441	0.000153	***
Daily AI-tool use	1.1433	0.8513	1.5354	0.3734	Not significant
Monthly/infrequent AI-agent use	1.1237	0.9549	1.3223	0.1604	Not significant
Perceives AI as job threat	1.0888	0.9954	1.1910	0.0629	Not significant
Very unfavourable AI sentiment	0.9781	0.8070	1.1856	0.8216	Not significant
Indifferent AI sentiment	0.9205	0.8428	1.0053	0.0655	Not significant
AI very poor at complex tasks	0.9151	0.8322	1.0062	0.0668	Not significant
Does not perceive AI as job threat	0.9047	0.8455	0.9681	0.0037	**
Unfavourable AI sentiment	0.8658	0.7596	0.9868	0.0308	*
Weekly AI-tool use	0.7926	0.5874	1.0695	0.1284	Not significant
No AI-agent use, plans to use	0.7726	0.6672	0.8946	0.000561	***
Does not use/know AI for complex tasks	0.6732	0.5881	0.7706	0.000000009	***
No AI-agent use, no plan	0.5210	0.4505	0.6026	0.0000000000 000000016	***
Monthly/infrequent AI-tool use	0.4333	0.3195	0.5877	0.000000074	***
No AI-tool use, plans soon	0.2495	0.1782	0.3492	0.0000000000 000006	***
No AI-tool use, no plan	0.1420	0.1010	0.1996	0.0000000000	***

				00000000000 0000000268	

Note. Odds ratios above 1 indicate higher odds of AI-career upskilling success, while odds ratios below 1 indicate lower odds. Significance levels: p < .05 (), p < .01 (), p < .001 ().

As shown in Figure 5 and Table 6, daily AI-agent use showed the strongest positive association with AI-career upskilling success, followed by weekly AI-agent use and the use of AI exclusively in copilot or autocomplete mode. Respondents who reported that AI performs very well on complex tasks and those with very favourable AI sentiment also had higher odds of reporting AI-career upskilling success. These findings indicate that frequent AI-agent engagement, positive AI sentiment, and confidence in AI capability are important predictors of AI-career upskilling.

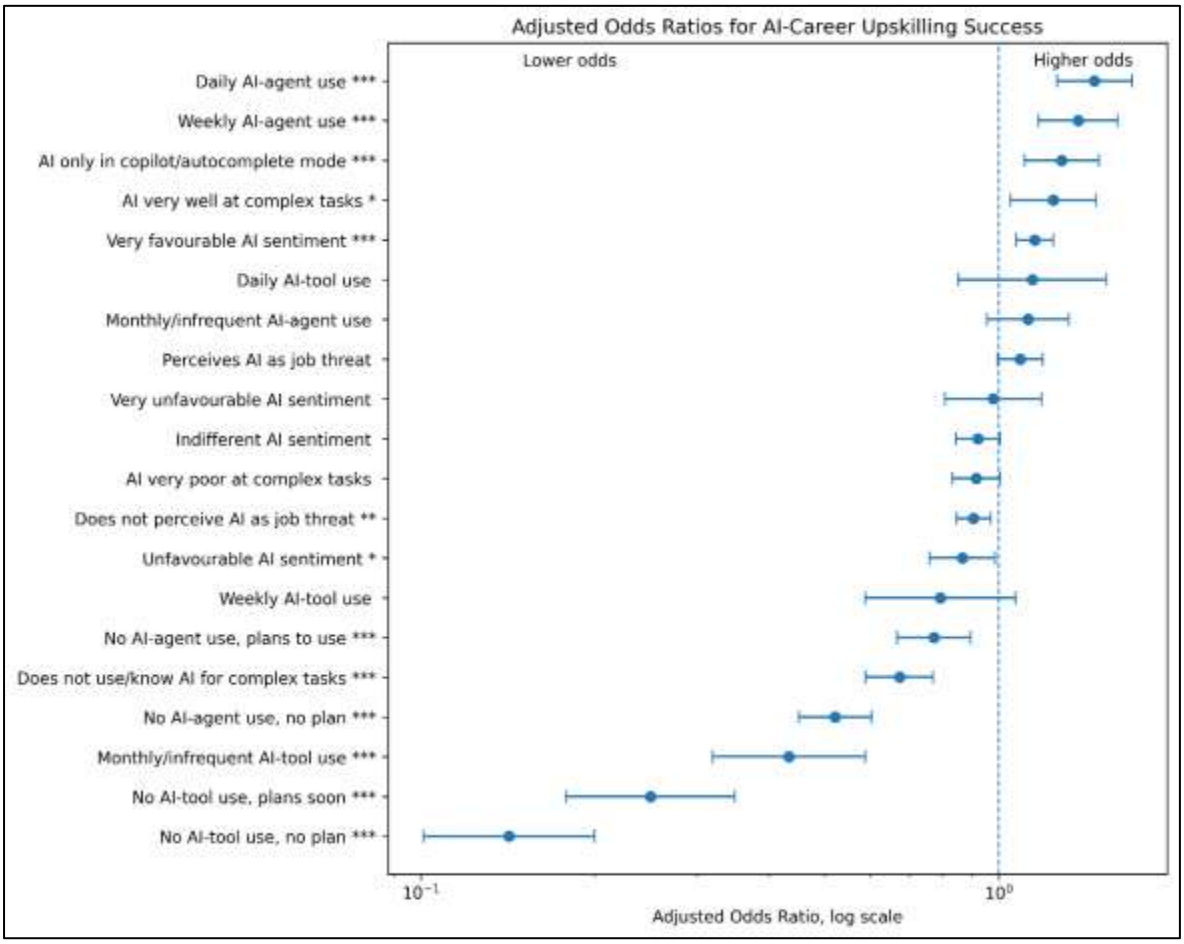

Figure 5. Adjusted Odds Ratios for Key Predictors of AI-Career Upskilling Success

In contrast, those respondents who were not using AI tools and had no desire to use them were less likely to report successful AI-career upskilling. Conversely, using AI-agents at work on a daily/weekly basis were linked with increased success. The importance of AI readiness was also a factor to consider since the very favourable AI sentiment and confidence in AI capabilities to complete complex jobs was linked to the higher chances of AI-career upskilling success. Combined, these results define AI preparedness and AI adoption as the most potent empirical areas related to AI-career upskilling success.

5. Discussion

The results show that AI-career upskilling in IT professionals is becoming one of the important yet disparate outcomes of professional development. The prevalence outcome demonstrates that a significant proportion of professional developers had job- or career-oriented AI learning, but the others did not. This implies that the upskilling of AI era is not dispersing across the workforce of developers equally. The trend aligns with the existing indications that AI is reshaping jobs in an unequal manner, both in terms of work, tasks, and industries (Frank et al., 2019; Felten et al., 2021). Thus, AI-career upskilling is to be viewed as a differentiated process that is influenced by both the individual involvement and AI-related conditions of work. One of the implications of the findings is that the readiness of AI and the adoption of AI are not marginal variables. They play a key role in elucidating why there are IT professionals who report successful AI-career upskilling.

AI preparedness is important as professionals who have positive attitudes towards AI, who have confidence in

AI output and believe AI can assist with complex tasks will tend to adopt AI tools as learning tools than as an external threat. The importance of AI adoption is that with repeated exposure to AI tools and AI agents, there would be a developed familiarity with AI, confidence, and practical learning opportunities. That is why AI-agent users demonstrated better upskilling success, greater trust, more positive sentiment and AI-tool use in comparison to the entire professional sample. This interpretation is supported by the results of bivariate and regression.
The adoption of an AI-tool, frequent use of an AI-agent, positive attitudes towards AI, and trust in an AI-agent ability to perform certain tasks were found to be more effective success factors than demographic, professional and workplace attributes. This aligns with the technology-adoption theory where perceived usefulness, behavioural intention, and facilitating conditions have been highlighted as determinants of technology use (Venkatesh et al., 2016; Venkatesh, 2022). It is also consistent with the literature on the AI trust, which reveals that the level of trust, perceived reliability, and situation of the task affect how users interact with AI systems (Gkinko & Elbanna, 2023; Glikson & Woolley, 2020). These readiness and adoption aspects in this research seem to be viable facilitators of AI-career learning.

Table 7. Comparison of Prior Studies with the Proposed Study

Study	Approach	Outcomes
van Laar et al. (2018)	Developed and validated a digital-skills instrument for working professionals.	Demonstrated that workplace digital competence is multidimensional and includes information, communication, collaboration, problem-solving, and strategic skills.
Long and Magerko (2020)	Conceptualized AI literacy through competencies and design considerations.	Established that AI capability requires understanding, evaluating, and using AI systems, not only operating technical tools.
Venkatesh (2022)	Proposed an AI-adoption research agenda grounded in UTAUT.	Highlighted the importance of perceived usefulness, effort, trust, autonomy, and user expectations in AI adoption.
Glikson and Woolley (2020)	Reviewed empirical research on human trust in AI.	Showed that trust in AI depends on system performance, transparency, task context, and user perception.
Ziegler et al. (2024)	Examined the impact of GitHub Copilot on developer productivity.	Found that AI-assisted coding tools can improve developer workflow and productivity, making AI upskilling highly relevant for software professionals.
Proposed study	Uses global developer survey data to examine AI-career upskilling through descriptive analysis, bivariate association, and hierarchical logistic regression.	Develops an evidence-based framework showing that AI readiness and AI adoption are central success factors for evaluating AI-era reskilling and upskilling among IT professionals.

van Laar et al. (2018) created and tested a digital-skills tool among working professionals. Illustrated how workplace digital competence is multidimensional and encompassing information, communication, collaboration, problem solving and strategic skills. Long and Magerko (2020) defined AI literacy in terms of competencies and design aspects. Developed that AI capability entails understanding, assessing, and applying AI systems, rather than using technical tools. Venkatesh (2022), put forward an AI-adoption research agenda based on UTAUT. Emphasized the significance of perceived usefulness, effort, trust, autonomy, and user expectations in adopting AI. Glikson and Woolley (2020) surveied the human trust in AI empirical studies.
Demonstrated that the confidence in AI is contingent on the performance of the system, its transparency, situation of the tasks, and how users perceive it. Ziegler et al. (2024) analyzed how GitHub Copilot affects developer productivity. Concluded that AI-assisted coding aid could enhance the process and productivity of developers, and AI upskilling is thus very important when it comes to software professionals. Proposed study Relying on the global developer survey data, this study proposes to study AI-career upskilling using descriptive statistics, bivariate correlation, and hierarchical logistic regression. Teaches an evidence-based framework demonstrating that AI preparedness and AI adoption are key success factors when considering AI-era reskilling and upskilling among IT professionals.
The theoretical and practical implications of the study are provided. Theoretically, it expands the digital-skilling and AI-adoption studies by applying AI-career upskilling as a multidimensional outcome, instead of a one-time training event. It links the success of learning to AI preparedness, AI adoption, perceived work benefits, and contextual barriers. This integration will contribute to filling the gaps in the literature on digital skills, AI literacy, trust, technology acceptance, and developer productivity. In practice, the results indicate that AI upskilling should not be modeled at organizations as a technical teaching of a general type. Programmes

focused on teaching AI literacy, practical use of AI-tools, calibration of trust, and responsible use, and support in managing barriers like accuracy issues, integration challenges, privacy threats, and learning burden, should be effective. There are limitations of the study.

The cross-sectional design implies that the results are an indication of an association, but not a causal relationship. Second, the self-reported AI-career learning is the basis of the outcome and does not assess the actual AI proficiency by directly measuring the performance. Third, the research is based on survey variables that are already available, and this restricts the measurement of training quality, motivation in learning organizations and the long term career outcome. Fourth, the dataset is global, but country-level, sector-level, and organizational variations are not completely studied. Longitudinal designs should be employed in future research to study the progression of AI-career upskilling over time.

Mixed-method research can also indicate why certain professionals relate more productively with AI tools when compared to others. More studies ought to be done to compare developers in terms of roles, industry, regions and experience levels. Upcoming research must also experiment on whether AI-career upskilling can be translated into quantifiable results like productivity, employability, career mobility and long-term flexibility in AI mediated workplaces.

6. Conclusion

This paper discussed the success variables of AI-era reskilling and upskilling among IT professionals based on the global data on developer surveys. The results reveal that AI-career upskilling exists, albeit disproportionately with 40.04% of professional developers disclosing job- or career-oriented AI learning. This means that learning involving AI has become a critical part of the professional growth, but it has not yet spread even throughout the IT workforce. The analysis revealed that the most significant areas related to the success of AI-career upskilling are AI readiness and AI adoption. The use of AI tools, AI involvement, positive attitudes towards AI, or trust in AI and belief in its capacity to perform complex tasks were all more favored associated with upskilling success than demographic or professional or work-related factors alone. Such results prove that the effective upskilling of the AI-era is not only based on professional experience, but also on the perceptions, trust, and usage of IT professionals to AI technologies at work.

The study contributes an evidence-based five-dimensional framework for evaluating AI-era reskilling and upskilling through contextual conditions and barriers, AI readiness, AI adoption, learning success, and work-benefit realization. This framework can assist researchers, organizations, and workforce-development planners to evaluate AI-related professional learning more systematically. Future efforts ought to enhance AI literacy, promote responsible use of AI-tools, enhance the calibration of trust, and minimize obstacles associated with accuracy, integration, privacy, and learning cost. Longitudinal and mixed-method studies should be conducted in the future to study the dynamics of AI-career upskilling over time and its impact on productivity, employability, and career advancement. The paper thus places AI-era upskilling as a multidimensional professional-learning process that is informed by preparation, adoption, work benefits perceptions, and contextual obstacles.

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