Early College Folio

A Growth MindSTEM for Next Gen

Volume 3, Issue 1 | 2024

Early College Folio
Volume 3, Issue 1 | 2024

Enhancing Holistic Learning: Insights from the Women in Technology (WiT) Workshop Series

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Abstract

Online technical bootcamps serve as robust tools for imparting in-demand skills, with their efficacy dependent on successful completion and participant confidence. However, to optimize these programs, a one-size-fits-all approach is insufficient. Tailoring programs to the specific needs of participants is essential, particularly when reaching out to marginalized communities characterized by low confidence levels and confronting digital challenges like limited internet access, power instability, and security concerns.

This study introduces the Women in Technology (WiT) online training program, designed to empower women in the tech industry in Myanmar. Uniquely, this program integrates technical proficiency with communication, collaboration, and leadership skills, aiming to narrow the gender gap in technology. Through quantitative pre- and post-survey methods involving 38 WiT program participants, we explore the factors influencing training success and confidence improvement. Our findings reveal that participants' educational and professional backgrounds have minimal impact on performance improvement. Notably, a substantial, positive correlation (approximately 0.7) exists between soft skills and technical skills. This research underscores the program's significant support for women in tech, providing them with well-rounded, in-demand skills and bolstering their confidence for success in the industry.

Impressively, the program boasts high completion and attendance rates (84% completion, with 50% achieving attendance rates over 90%). These figures highlight the program's ability to motivate and support participants, even in regions facing disruptions such as security concerns and limited resources. Moreover, participants demonstrated a substantial improvement in their self-assessed scores in technical skills, doubling from their initial levels, showcasing the program's efficacy in empowering women in the tech sector. By providing a tailored and holistic approach, the WiT program proves instrumental in addressing the diverse challenges faced by women in the tech industry, making significant strides towards gender inclusivity and skill enhancement.

1 Introduction

The landscape of education has undergone a profound transformation in recent years, with online education taking center stage as a prominent mode of learning. This digital revolution has ushered in a new era of accessibility and flexibility, enabling individuals to pursue education regardless of geographic or temporal constraints. Within this evolving educational paradigm, online education workshops have emerged as vital instruments in enhancing educational opportunities and outcomes. Nevertheless, there exists an uncharted pathway towards holistic education, one that not only imparts knowledge but also nurtures personal and holistic development. This paper seeks to navigate this uncharted territory, embarking on a journey to explore the possibilities and challenges in transforming online education workshops into holistic educational experiences, focusing on a compelling case study.

Online education workshops have witnessed a surge in popularity, driven by their inherent accessibility, flexibility, and versatility in catering to diverse learning needs. These workshops span a wide spectrum of subjects, ranging from technical disciplines like coding and data analysis to soft skills such as communication and leadership. In particular, the domain of computer science has seen the rapid evolution of online technical bootcamps, which have become powerful tools for equipping individuals with the precise technical skills demanded by today's dynamic job market. Among these bootcamps, coding programs stand out for their comprehensive training in hands-on coding, programming, information technology, and cybersecurity skills.

The transformative impact of these technical bootcamps is indisputable, as they consistently demonstrate their ability to bridge the gap between education and employment. An illuminating example is drawn from the Gallup-2U Boot Camp Graduates Study Ray (2022), which surveyed 3,824 adults in the United States who graduated from 2U-powered bootcamp programs between 2016 and 2021. Remarkably, graduates, irrespective of their race, gender, age, or location, reported substantial salary increases post-graduation. This underscores the practical and job-oriented nature of the training they receive, emphasizing the tangible benefits of investing in one's technical education. However, amidst the advantages of online technical bootcamps, it's crucial to acknowledge the disparities in access created by digital technology and online learning. This discrepancy, favoring those with access, leaves others at a disadvantage, resulting in negative consequences such as disparities in opportunities and resources among different segments of society. This global issue is particularly pressing in developing countries like Myanmar.

Myanmar faces significant developmental challenges due to political complexities, including periods of military rule, contributing to enduring social and economic difficulties. The nation encounters challenges in digital readiness, ranking low in ASEAN across indicators like ICT development, e-government development, network readiness, and cybersecurity (Oxford Business Group (2020)). The global impact of the COVID-19 pandemic in early 2020 led to the closure of educational institutions worldwide, including Myanmar schools and universities. Responding proactively during the crisis, the National League for Democracy (NLD) government (2015–2021) formulated emergency strategies and sustainable interventions to ensure the continuous learning, safety, and well-being of students and education staff (*Myanmar COVID-19 National Response and Recovery Plan for the Education Sector* (2020)). Despite these measures, digital infrastructure limitations, disparities in digital device access and digital skills, motivation, and readiness to embrace technology persisted.

The existing disparities in digital access and inequality in Myanmar were significantly exacerbated by the 2021 coup d'état (Nanthakorn et al. (2023)). The country's educational infrastructure, including schools and universities, faced partial dismantling. Moreover, teachers and students encountered formidable challenges in returning to schools, driven by factors such as injuries, fear, or a collective decision to protest against the military government's education system. The repercussions were severe, with the military government reportedly dismissing approximately 30% of teachers (Bhatta et al. (2023)). This mass dismissal resulted in a substantial weakening of service delivery capacity within the public education system. The World Bank report also sheds light on a noteworthy shift in families' educational preferences, indicating a preference for non-state schools and online education.

This evolving educational landscape has generated a growing demand for online technical bootcamps, especially among young individuals encountering obstacles in pursuing formal education elsewhere. This demand is also prominent among young adults who have faced setbacks due to political and economic instability in the country. According to the World Bank report on workers wellbeing in Myanmar(Roy (2023)), Myanmar witnessed a decline in labor force participation and employment rates, dropping by 1.6 and 4.8 percentage points, respectively, between 2017 and 2022. The report also highlights gender disparities, indicating that compared to men, adult females are more likely to be out of the labor force, unemployed, and without education or training. Additionally, female workers with college or higher education levels experienced a decline in the employment rate during this period. The incidence of 'Not in Employment, Education, or Training' (NEET) increased by 9.4 percentage points among **college-educated women** during this time.

Our prior study on the challenges faced by women in the technology field in Myanmar (Thida et al. (2023)) also emphasized that 27% of participants lost their jobs due to company layoffs. The study shed light on the mental strain resulting from losing colleagues and friends who had already left the country, a lack of confidence in technical and soft skills, such as communication and leadership skills, and the absence of mentorship for career advice. Notably, a significant number of participants expressed a desire to seek employment overseas, citing reasons such as the prospect of a better quality of life (63%), higher employment opportunities (49%), a higher salary (49%), job security (33%), and safety concerns (30%). However, despite their aspirations, participants reported encountering several barriers when trying to secure employment overseas. The most significant challenges highlighted by participants included a lack of confidence in their technical skills and industrial experience, as well as limited networking opportunities.

In an effort to extend the benefits of online education to marginalized communities in Myanmar, the "Women-in-Tech (WiT) workshop series" has been designed to encompass both soft skills and technical expertise. The aim is to boost the confidence of Myanmar women working in technology sectors or seeking jobs in this field, addressing both the technical and interpersonal aspects. Furthermore, our objective is to evaluate the outcomes of the workshop series, contributing to the overarching goal of alleviating gender disparities within the tech industry. To facilitate this assessment, our study relies on *pre-survey*[1]and *post-survey*[2] data, complemented by learning assessment information through the workshop series. Our research aims to answer three key questions:

1. How does participating in a comprehensive workshop series affect individuals in Myanmar, considering the country's challenges like security concerns, limited internet, and intermittent electricity? We aim to assess attendance, completion rates, and perceived confidence improvement, accounting for disruptions caused by these challenges.

2. What are the key factors influencing the success of training and the improvement observed in participants?

3. Does the enhancement of soft skills through online bootcamps exert a positive influence on the development of technical skills among the participants?

The next subsection will highlight the motivation and contributions of this research, followed by Section 2 that provides in-depth insights into our research methodology. Section 3 presents key data insights derived from the survey, followed by discussions of the implications of these findings and recommendations for a deeper understanding of the factors driving success in online technical training and the development of confidence among participants. Finally, Section 4 outlines the study's limitations, and Section 5 provides the concluding remarks.

1.1 Motivation and Contribution

Our study is motivated by the need to address gender disparities in the technology sector and mitigate the unique challenges that women face in technology-related

[1]Pre-Training Survey for Data Analytics Track: `https://forms.gle/kNwTU5HR3MyDad3x9` and Software Engineering Track `https://forms.gle/AgY4fqfUQYMo7qzB8`

[2]Post-Training Survey for Data Analytics Track: `https://forms.gle/KCMEdXFMDTcoPrV17` and Software Engineering Track `https://forms.gle/3sEb9UvSwkVsgUeF7`

fields in Myanmar. To achieve this, we are focusing on the development of training workshops and evaluating its effectiveness given the severe disruption in internet access, and electricity supply. Furthermore, we aim to explore the potential of holistic education within the context of online workshops, recognizing the necessity for a comprehensive approach that includes soft skills and personal growth.

Our paper makes substantial contributions in the following ways:

1. **Insights from a Specific Case Study**: Our research focuses on the Women in Technology (WiT) workshop series, a bootcamp-style program that integrates technical proficiency with soft skills development. This case study approach allows us to provide unique insights into the effectiveness of holistic education, particularly in addressing the specific challenges faced by women in the tech sector, especially in regions like Myanmar. By examining the WiT bootcamp, we aim to offer invaluable insights into enhancing completion rates in online technical training programs and the success of integrating soft-skill training in these workshops.

2. **Empirical Research with Primary Data**: Our comprehensive investigation draws upon primary data sources and employs rigorous quantitative pre- and post-survey methods. This research seeks to elucidate the specific factors that influence training success and participants' confidence enhancement. Our empirical approach yields data-driven insights that can optimize online technical training, ensuring our findings are firmly grounded in real-world experiences.

3. **Emphasis on the Importance of a Diverse Skill Set**: Our study underscores the critical significance of cultivating a diverse skill set, encompassing not only technical expertise but also essential soft skills. In today's multifaceted professional landscape, these soft skills empower individuals to excel by fostering effective communication, collaboration, and adaptability. We emphasize the value of this holistic skill set in terms of career success and personal development.

2 Research Methodology

2.1 Workshop Design and Structure

The methodology employed for the Women-in-Tech (WiT) workshop series is founded on a well-considered design and structure that aligns with the objectives of addressing gender disparities in technology-related fields and empowering female participants. The need for this workshop series arises from "Gender Equality in STEM workforce" by Thida et al. (2023), the study on persistent underrepresentation of female workers in STEM fields, particularly in computing roles. The workshops are designed to bridge this gap by offering tailored support and resources that resonate with the unique experiences, learning preferences, challenges, and aspirations of female participants.

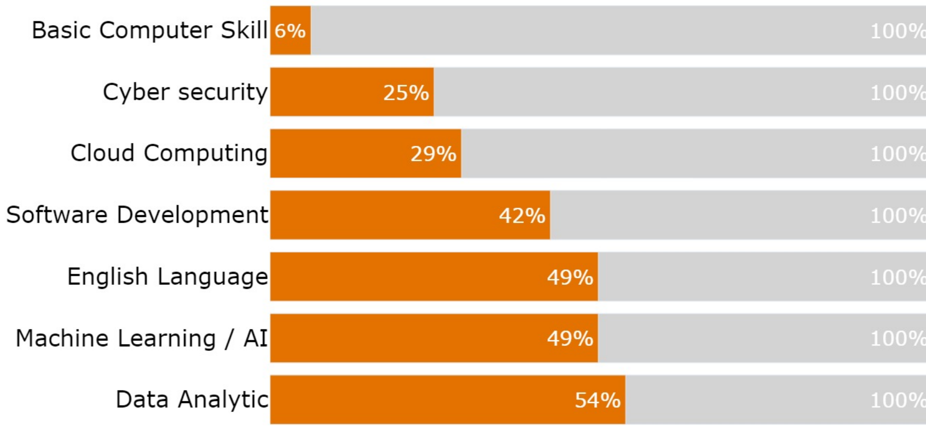

Figure 1: Interest in Technical Skills Development among Women in Myanmar's Tech Industry

2.1.1 Need Analysis

To gain a comprehensive understanding of the experiences and challenges faced by women in Myanmar's tech industry, a survey initiative was conducted from December 10 to December 24, 2022. A total of 93 women actively employed in various tech-related fields across Myanmar participated, and the detailed survey findings can be found in Thida et al. (2023). The results of this survey shed light on several critical aspects: motivations, barriers, and aspirations of women navigating Myanmar's tech job market, while underscoring the pressing need to address gender disparities in accessing job opportunities and professional networks.

The survey also highlights the evident gender disparities in accessing job opportunities and professional networks, which numerous respondents expressed concerns about. These findings emphasize the necessity to address these disparities urgently and to cultivate a robust network of women in the tech industry, as articulated in our program objectives, with the aim of providing mutual support and collaboration opportunities. Furthermore, the survey data highlights the pivotal role played by mentorship and support systems in the career advancement of women in tech. Many respondents cited mentorship as a critical factor in their professional growth. This finding informs our approach, recognizing the importance of integrating mentorship and support mechanisms into our workshop series.

These insights not only clarify the challenges and aspirations of women in Myanmar's tech industry but also serve as guiding principles for program design. One noteworthy survey finding is the strong motivation among women in the tech industry to acquire technical skills. Figure 1 illustrates this enthusiasm, with 54% of respondents expressing a strong desire for training in data analysis and 42% displaying keen interest in software development. This data highlights the participants' eagerness to enhance their skill sets and aligns perfectly with our objective to enhance participants' technical proficiency.

In summary, the survey findings serve as the foundation for our program's design, ensuring it is responsive to the needs, motivations, and challenges faced by women in Myanmar's tech industry. These insights emphasize the significance and urgency of our objectives, which include improving technical proficiency, addressing gender disparities, and providing mentorship and support. By interpreting and acting upon this data, we've designed a workshop series that aim to empower and equip women in the tech sector for success.

2.1.2 WiT Program Objectives

With a comprehensive understanding of the challenges and aspirations of women in Myanmar's tech industry, our program objectives directly address the needs and insights highlighted in our need analysis:

- To create a strong network of women in the tech industry, fostering collaboration and mutual support within the community. This network will serve as a valuable resource for participants throughout their careers.
- To improve participants' technical proficiency, enabling them to excel in their chosen career paths. The training will equip them with the practical skills and knowledge needed to succeed in the rapidly evolving tech landscape.
- To cultivate confidence among women in the tech industry, empowering them to take on challenges and seize opportunities. The program aims to develop not only technical skills but also the personal and professional attributes needed for success.

2.1.3 Career Track and Modules

To bridge the identified gaps and empower women in Myanmar's tech industry, the Women in Technology (WiT) workshop series takes a comprehensive approach. It offers training in two distinct career tracks: Data Analytics and Software Development (Web/App Development). This approach allows participants to choose a track aligned with their interests and career aspirations, ensuring a more focused and relevant learning experience.

While the WiT workshop series shares some similarities with bootcamps, it follows a format that differs from the traditional "bootcamp" model. Traditional bootcamps typically provide intense and condensed training over a short period. In contrast, our workshop series combines hands-on skills development with knowledge-based topics in data analytics and software development. Additionally, we dedicate 3 weeks to career planning, leadership and coaching, making it a more comprehensive program.

Table 1: Details of the workshops

Week	**Date**	**Data Analytics**	**Software Development (Web/App Development)**
Week1	3-May	What is Data Analytics?	Web Application Development Fundamental
Week2	10-May	Introduction to Natural Language Processing	Introduction to API Development
Week3	17-May	Basic Cyber Security training	Basic Cyber Security training
Week4	24-May	Career Planning	Career Planning
Week5	31-May	Tableau Handon workshop	Working with Open Source Projects
Week6	7-Jun	Mid-career job hunting	Mid-career job hunting
Week7	14-Jun	Working with python in your local machine	How to become a better coder / what is clean code?
Week8	21-Jun	Career Coaching	Career Coaching
Week9	28-Jun	Understanding Version Control	UX For software engineer
Week10	5-Jul	Leadership Skills	Leadership Skills
Week11	12-Jul	Playing with clouds platforms	Management in Software Project
Week12	19-Jul	Ask Me Anything Session	Ask Me Anything Session

Comprehensive Curriculum: Our curriculum is designed to equip participants with a well-rounded set of skills. In the Software Engineering Track, participants gained expertise in seven specific technical areas. Similarly, the Data Analytics Track provided participants with six essential technical knowledge and skills. These topics are thoughtfully integrated into our training program to ensure that participants receive practical and relevant education based on the results from the need analysis.

Program Duration and Format: The WiT workshop series spans over 12 weeks, comprising seven technical workshops and four soft skills training sessions, as detailed in Table 1.

2.1.4 WiT Workshop Participants

This program is specifically designed to benefit individuals in the early or mid-career phases in technology or those considering transformative career shifts, with a particular focus on **Myanmar women** who actively engaged in the “Challenges for Myanmar Women in Tech" survey.

Out of an initial pool of 254 applicants, 38 women with a background in tech were selected for participation - 20 women for the Data Analytics Track and 18 women for the Software Engineering Track. The following list outlines the key participant profiles, and for more detailed information, please refer to Thida (2022).

- **Age Range**: The age range of the participants spanned from 18 to 54 years. The majority of participants (42%) fell within the age bracket of 18-25 years, and an additional 42% fell within the age bracket of 26-35 years as shown in Figure 2.

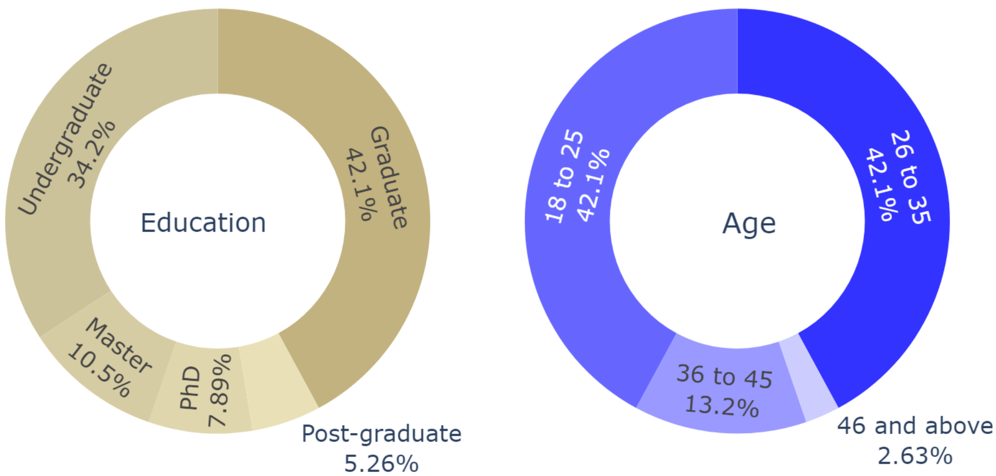

Figure 2: Age and Education Background of participants

- **Educational Background**: The participants exhibited a diverse range of educational backgrounds, with qualifications ranging from high school diplomas to PhDs. The largest subgroup among the participants held Bachelor's degrees, constituting 42% of the sample, followed closely by undergraduate students, who made up 34% of the participants (Figure 2). In addition, a substantial majority (87%) of our participants come from engineering and science backgrounds. Furthermore, over 85% of those who joined the Software Engineering Track have one to two years of prior coding experience.

- **Work Experience**: More than half of our participants have less than three years of work experience, with 20% having no prior work experience. Notably, 85% of the participants in the Data Analytics Track are not currently employed, whereas 40% of the Software Engineering Track participants are currently working.

Additionally, there were 11 dedicated volunteers who have generously contributed their time and expertise to support the administration of the program. These volunteers not only assist in program management but also actively engage as participants.

2.2 Data Collection

We collected data in four distinct sets:

1. **Participant Demographic Information**: This dataset includes participant demographic details, such as age, educational background, self-reported English language proficiency, academic and professional backgrounds, work experience, and job positions (if applicable). This dataset contains 9 attributes and 38 records.

Table 2: Details of the Skills Assessed in the Pre and Post Survey

Skill Category	Skill Name (Data Analytics Track)	Skill Name (Software Engineering Track)
General Knowledge	General Knowledge of Data Analytics	General Knowledge of Software Engineering
Tech Skill	Natural Language Processing Concept	Web Application
	Cybersecurity Concepts	API Development
	Version Control	Cybersecurity Concepts
	Hands-on Skills in Tableau	Open-Source Projects
	Hands-on Skills in Python	Coding Skill in Python
	Cloud Platforms Concept	UX Design Concepts
		Software Project Management
Soft Skill	Confidence for Career Advancing	Confidence for Career Advancing
	Confidence for Communication	Confidence for Communication
	Confidence for Leadership	Confidence for Leadership

2. **Pre-Training Survey Data**: This dataset, collected before the program's commencement, consists of participants' self-assessments of various aspects, including general knowledge, technical skills, soft skills, and career goals. The technical skills assessed differ between the Data Analytics Track (6 skills, as detailed in Table 2) and the Software Engineering Track (7 skills, as detailed in Table 2). Career goals and 3 soft skills are the same for both Data and Software Engineering Tracks. Participants rated themselves on a scale from zero (indicating no knowledge) to 10 (representing expertise). This dataset comprises 19 attributes (including skills and general knowledge) and consists of 35 records (participants). It's important to note that participation in the pre-survey was voluntary, and not all program participants chose to take part.

3. **Post-Training Survey Data**: After program completion, the post-training survey dataset captures participants' self-assessments of the same categories assessed in the pre-survey: general knowledge, technical skills, soft skills, and career goals. This dataset comprises 19 attributes and includes 33 records. Similar to the pre-survey, participation in the post-survey was voluntary.

4. **Attendance**: We also recorded data related to class attendance, which includes the student ID and the attendance records of 38 participants for 12 sessions.

2.3 Data Preprocessing

Data preprocessing is a crucial step in this project, which involves the following key processes:

- **Handling Missing data**: Missing records for self-assessment scores in the pre and post survey dataset have been imputed using the median values. This imputation approach was chosen because the background knowledge and confidence levels of the participants exhibit reasonable similarity and diversity, aligning with the assumption that missing values are similar to typical values within the dataset. Furthermore, this method ensures the preservation of the overall distribution of the dataset, thus maintaining data integrity while effectively handling missing values.

Regarding text responses, specifically in the case of career goals, a different strategy was employed. For missing records in the pre-training data, it was assumed that individuals did not have any predefined career goals before commencing the training. Conversely, participants who did not provide post-training career goals were excluded from further analysis.

- **Feature Engineering**: In the case of attendance records, binary data indicating attendance or absence is transformed into more informative features. This transformation includes calculating the number of days attended and computing the attendance rate. These engineered features provide a more comprehensive view of participants' attendance behavior, facilitating more in-depth analysis and modeling.
- **Dataset Merging and Division**: The pre- and post-survey datasets are combined to evaluate the impact of the training program on boosting participants' confidence, aligning with the objectives of the WiT program. Subsequently, the new dataset is divided into two subsets: pre- and post-survey datasets for the Data Analytics Track and pre- and post-survey datasets for the Software Engineering Track.
- **Demographic Data Integration**: In a similar concept, the dataset containing participant demographic information is merged with the weekly attendance dataset to investigate the impact of demographic factors on class attendance patterns. This integration aims to provide insights into how these demographic factors may influence and help explain variations in class attendance among program participants.

Upon the completion of the above data preprocessing steps, we have three distinct datasets ready for analysis:

- The **pre- and post-survey datasets for the Data Analytics Track** consist of 29 records, comprising responses from 20 participants and 9 volunteers. It contains 22 attributes, including 2 for pre and post general knowledge, 12 for pre and post technical skills, 6 for pre and post soft skills, and 2 for pre and post career goals assessment.
- Similarly, **the pre- and post-survey datasets for the Software Engineering Track** include 17 records, with 16 participants and 1 volunteer. This dataset encompasses 24 attributes, including 2 attributes for pre and post general knowledge, 14 for pre and post technical skills, 6 for pre and post soft skills, and 2 for pre and post career goals assessment.

- The **demographic and attendance dataset**, which combines participant demographic information with attendance records. This combined dataset comprises a total of 38 records, each associated with 14 attributes. These attributes encompass a wide range of demographic information, such as age, gender, educational background, and class attendance rate.

2.4 Data Analysis

With the datasets collected and preprocessed as described above, we proceed to conduct a comprehensive data analysis. This section provides a comprehensive overview of our data analysis process, which encompasses various crucial components.

1. **Exploratory Data Analysis (EDA)**: We initiate the analysis by performing Exploratory Data Analysis (EDA) to gain insights into the characteristics of our datasets. This includes visualizations, summary statistics, and distribution analysis to identify patterns and trends within the data.

2. **Assessment of Training Impact**: We assess the impact of the training program on participants' self-assessment scores for technical and soft skills. This involves comparing self-assessment scores before and after the training to determine whether there were significant improvements.

3. **Content Analysis of Career Goals**: In the case of career goals, where qualitative responses were collected, we perform content analysis to extract meaningful insights and identify common themes and aspirations, and goals expressed by participants. In addition to understanding participants' career goals at the outset of the program, we compare these goals with the career aspirations expressed after completing the training. By analyzing changes in career goals, we aim to assess how the training program may have influenced participants' career aspirations and objectives.

4. **Correlation Analysis**: Building upon the preceding analyses, we systematically explore potential relationships between self-assessed soft skills, technical skills, and various demographic factors, including age, gender, and educational background. To achieve this, we employed a combination of statistical methods tailored to the nature of the data.

   First, we conduct Pearson correlation analysis to examine the relationships between the improvement in self-assessed technical and soft skills after training and a set of key numerical variables, including attendance rate, prior Excel assessment scores, and programming scores. This analysis allowed us to assess the strength and direction of associations between these factors and the improvement scores, providing valuable insights into whether attendance, prior excel knowledge, and programming proficiency were correlated with the observed enhancements in participants' self-assessed skills after completing the training program. Studying the linear correlation between improvement scores in technical and soft skills also helped us determine whether improvements in soft skills were correlated with enhancements in technical proficiency, ultimately probing on the overall impact of the integrated training program, which includes both technical and soft skills training.

Additionally, for the categorical demographic factors—age groups, gender, and educational backgrounds—we opt for analysis of variance (*ANOVA*). ANOVA was utilized to explore whether there were statistically significant differences in self-assessment scores among different categories within these demographic variables. By employing these complementary statistical techniques, we gained a detailed understanding of how demographic factors influenced participants' skill assessments and whether these assessments varied significantly across demographic categories.

The findings from this study hold considerable importance in evaluating the Women in Technology (WiT) program and offer valuable insights for future improvements. The statistically significant improvements in self-assessment scores and shifts in career goals underscore the program's effectiveness in empowering participants. The correlation analysis reveals demographic factors that impact participants' experiences, offering insights for targeted enhancements to better cater to the diverse needs of program participants. This, in turn, contributes to the broader mission of promoting gender diversity in technology.

3 Results and Discussion

In this section, we present the results of our data analysis, which encompass a comprehensive examination of various aspects of the Women in Technology (WiT) program.

3.1 Key Findings

- 84% of participants successfully completed the training, with 50% of them having attendance rates exceeding 90%.
- Participants gained confidence and were open to exploring different career opportunities. 11 participants without prior goals established clear career ambitions, with 8 aiming for overseas positions.
- Technical skills improved approximately two-fold (6 skills for data analytics, 7 for software engineering). Post-training scores show significant improvements, with some skills doubling or tripling their pre-training levels. Tableau, Python, and Version Control skills, for instance, increased nearly threefold, while software engineering skills improved 1.5 to 2 times, with open source and project management skills nearly tripling.

- Soft skills, encompassing leadership, communication, and confidence for advancing career, improved marginally by about 20%. In the Data Analytics Track, the most significant improvement is in leadership skills, but there's only a slight increase in confidence about career advancement. In contrast, participants in the Software Engineering Track have gained notable confidence in career advancement, with marginal improvements in communication and leadership skills.

- Age, field of study, and professional background in terms of seniority did not significantly affect performance improvement in technical and soft skills in the workshop, while English proficiency influenced the improvement of technical skills.

- Higher class attendance is positively associated with more substantial improvements in technical skills (Pearson correlation coefficient = 0.147), but there's no significant impact of attendance on the development of soft skills (Pearson correlation coefficient = -0.085) in the training program.

- The findings indicate a positive correlation (Pearson coefficient = 0.68) between enhanced soft skills and improved technical proficiency, highlighting the importance of soft skills development in the training program.

The above list provided a concise summary of the key findings, elucidating the critical aspects of participant performance and the influencing factors. In the following sub-sections, we will present and discuss the key insights derived from the Exploratory Data Analysis (EDA) and correlation analysis.

3.2 Exploratory Data Analysis (EDA)

The participants' profile is detailed in the program design and structure section (Section 2.1.4). Within this subsection, we present the statistical distribution of the class attendance rate and self-skill assessments conducted prior to and after the program's commencement.

3.2.1 Class Attendance Rate

Figure 3 presents the histogram illustrating the class attendance rate. Notably, nearly 50% of the participants, accounting for 18 out of 38 individuals, exhibited a remarkable attendance record, with attendance rates exceeding 90% across the training workshops. Another 13 students demonstrated consistent engagement, attending more than 50% of the training sessions.

However, it is worth noting that approximately 16% of the participants, a total of 6 students, initially engaged in only 20% of the training sessions but eventually chose to discontinue their participation in the program. This results in an 84% successful completion rate.

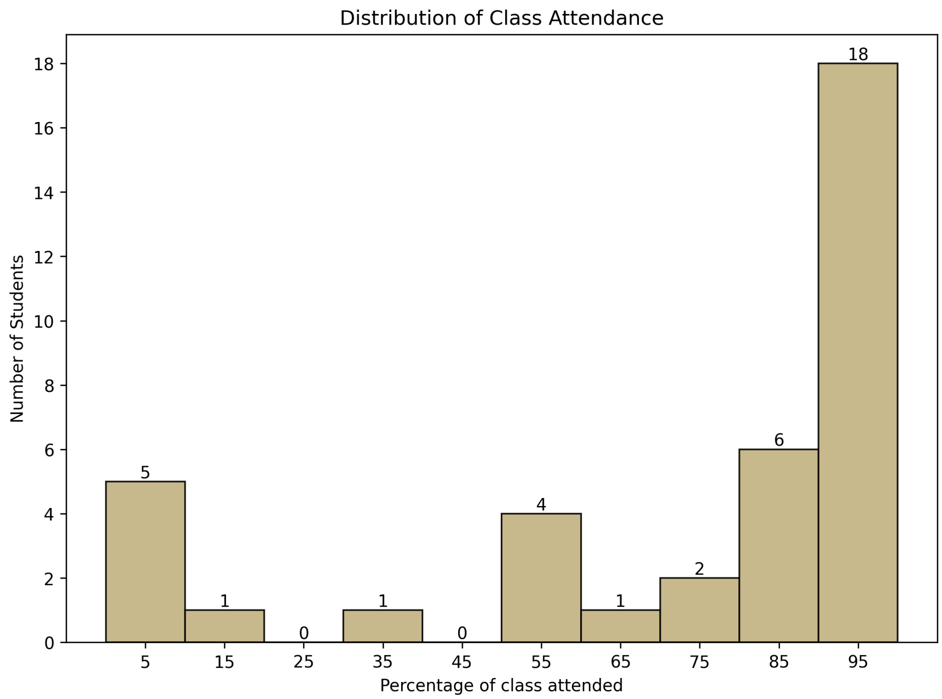

Figure 3: Distribution of the class attendance rate

3.2.2 Before Training: Pre-assessment Scores

Figure 4 illustrates the distribution of pre self-assessment scores for participants in both the Data Analytics Track and Software Engineering Track.

In the Data Analytics Track, participants reported higher average self-assessment scores in soft skills, with a median score of 5.5, in contrast to notably lower scores in technical skills, with a median score below 2. Additionally, a smaller interquartile range (IQR) of less than 1 suggests a more consistent, albeit lower, level of technical proficiency among Data Analytics Track participants before the training.

Conversely, participants in the Software Engineering Track displayed a different pattern. They reported relatively similar median scores in both technical (median score of 2.88) and soft skills (median score of 4.3). However, wider IQRs were observed for both technical and soft skills assessments, indicating a greater diversity in skill levels among Software Engineering Track participants prior to the training.

In summary, this comparison highlights the distinct skill profiles of participants in the Data Analytics Track and Software Engineering Track before the training. Data Analytics Track participants exhibited higher self-assessment scores in soft skills but lower scores in technical skills. In contrast, Software Engineering Track participants displayed a more balanced but diverse skill set in both domains.

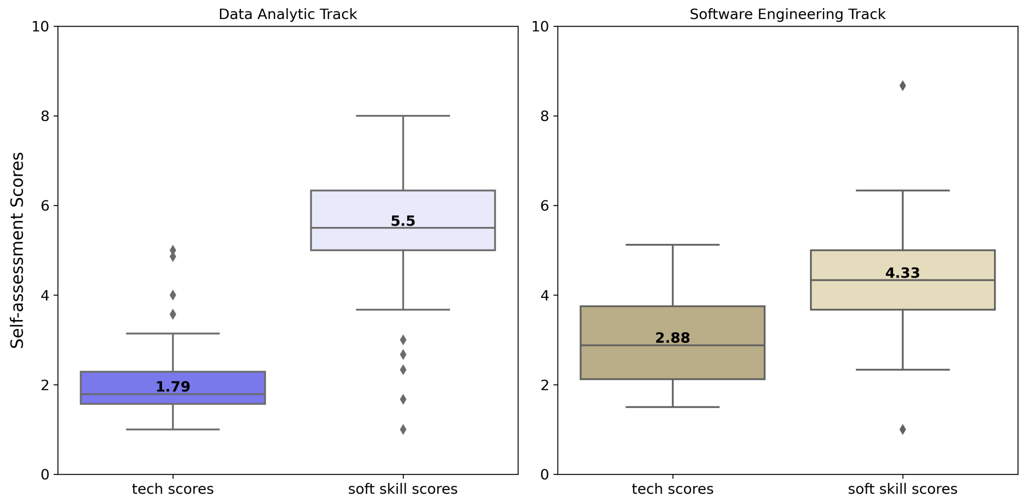

Figure 4: Distribution of the Pre-assessment scores in technical and soft skills

3.2.3 After Training: Post-assessment Scores

Figure 5 provides a visual representation of the post self-assessment score distributions for participants in both the Data Analytics and Software Engineering Tracks. Notably, both tracks demonstrated notable improvements in their assessment scores following the training program.

In the Data Analytics Track, participants experienced an increase in their median scores to 5.3 for technical skills and an impressive 6.5 for soft skills. Conversely, in the Software Engineering Track, median scores reached 5.25 for technical skills and 5.67 for soft skills, indicating substantial progress in both domains.

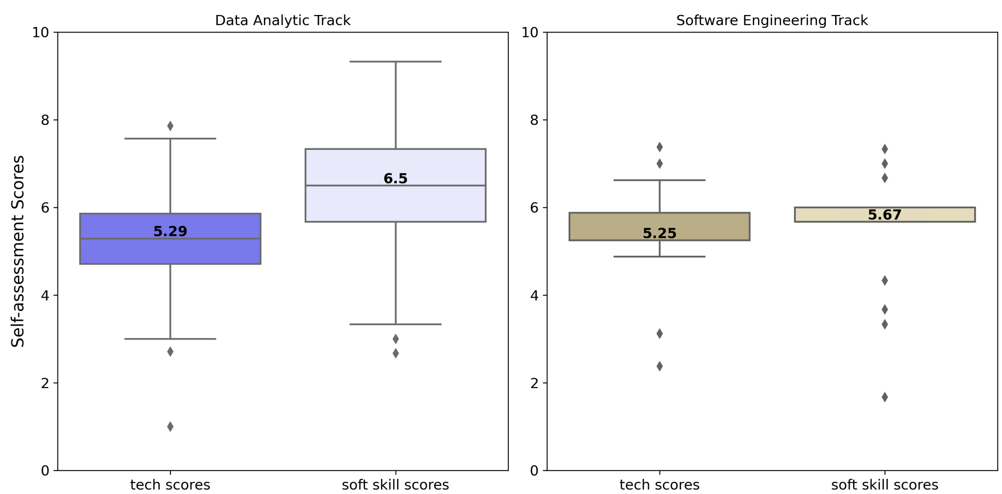

Figure 5: Distribution of the Post-assessment scores in Technical and Soft Skills

Of particular interest is the observation of wider Interquartile Ranges (IQRs) exceeding 2 in the Data Analytics Track. This suggests a more extensive range of skill levels among participants after completing the training program. In contrast, the Software Engineering Track displayed narrower IQRs, less than 1, for both technical and soft skills, signifying a more consistent and uniform improvement in these skills among participants.

These findings provide a detailed understanding of the skill development progress within each track and offer valuable insights into the impact of the training program on participants' skill sets. In the following sub-section, we will present the results of a thorough comparison of self-assessment scores for each specific skill before and after the training.

3.3 Assessment of Training Impact

Figure 6 compares the average self-assessment scores, measured on a scale of 1 to 10, for 7 skills (1 general and 6 technical skills) within the Data Analytics Track before and after training. The details of the 7 skills are listed in Table 2.

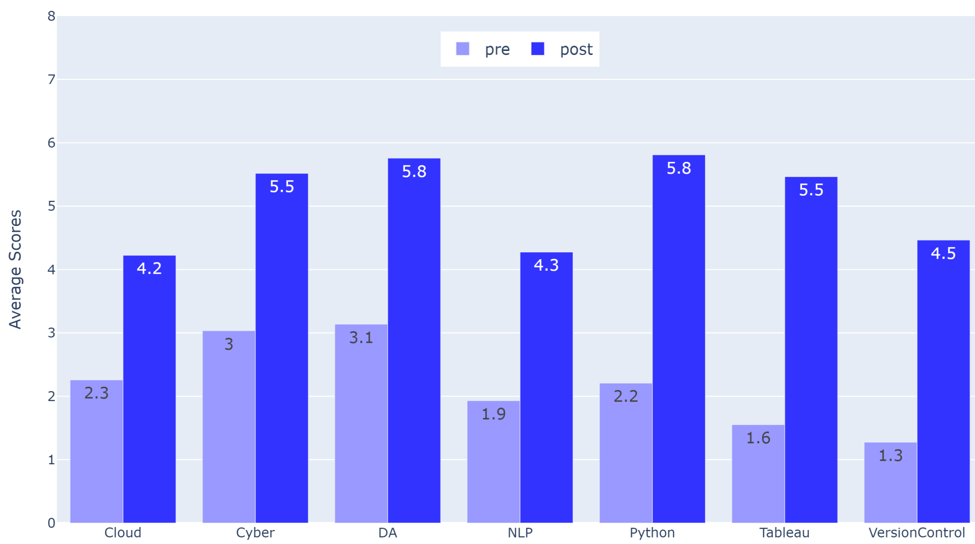

Figure 6: Comparisons of Pre and Post self-assessment scores in technical skills (Data Analytics)

The self-assessed post-training scores exhibit substantial and noteworthy improvements, frequently showing a remarkable doubling or even tripling of the pre-training scores. This is particularly significant in skills like Tableau, Python, and Version Control, where post-training scores surge to nearly three times the levels recorded prior to the training. This striking increase in post-training scores compared to the pre-training scores serves as a compelling indicator of the training program's effectiveness in facilitating tangible progress in participants' self-perception and skill development.

Similarly, the Software Engineering Track exhibits a comparable trend as shown in Figure 7, showcasing improvements of approximately 1.5 to 2 times the pre-training scores across 8 technical skills (as detailed in Table 2). The most

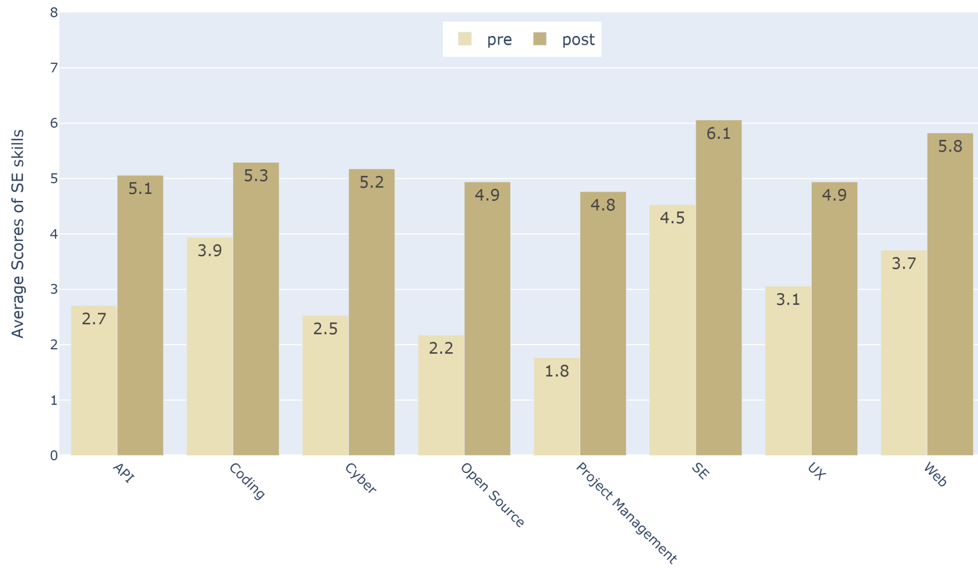

Figure 7: Comparisons of Pre and Post self-assessment scores in technical skills (Software Engineering)

notable advancements are observed in open source and project management skills, with post-training scores nearly tripling the pre-training scores.

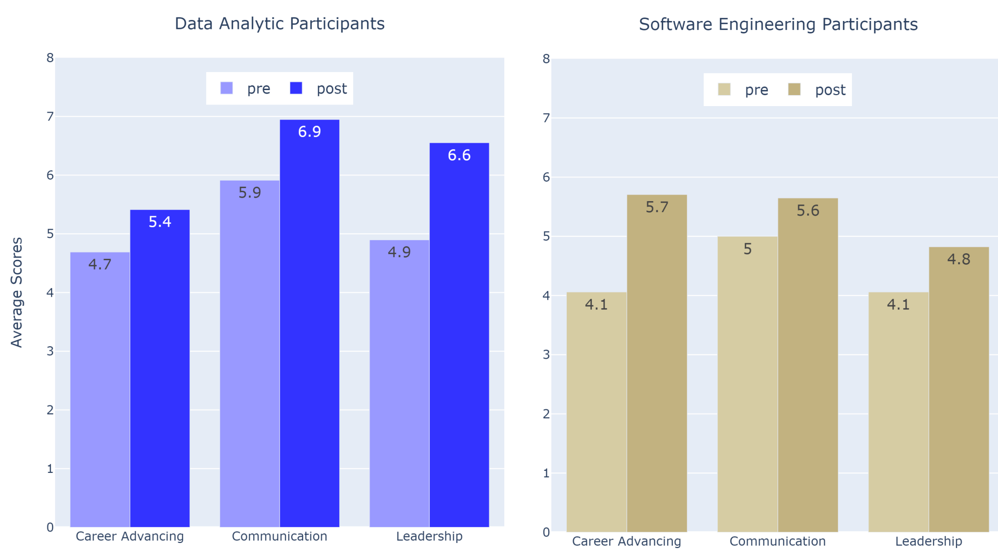

Figure 8: Comparisons of Pre and Post self-assessment scores in soft skills

The post-training self-assessment scores indicate substantial progress in technical competencies, but the same level of advancement is not evident in soft skills, as shown in Figure 8. Within the Data Analytics Track, participants exhibit the most significant enhancement in leadership skills, while the increase in confidence regarding career advancement remains comparatively modest. On the contrary, participants in the Software Engineering Track have notably bolstered their confidence in career advancement, but have seen only marginal improvements in communication and leadership skills.

The data not only showcases the growth in participants' self-assessment but also underscores the program's ability to empower individuals to reevaluate and enhance their proficiency. It signifies that participants, after undergoing the training, perceive themselves as significantly more capable in these specific skills than they did before. This shift in self-perception has implications for their overall confidence and performance in their respective roles and career aspirations.

3.4 Content Analysis of Career Goals

The previous study in Thida et al. (2023) revealed that 72% of participants expressed a desire to find the overseas job in pursuit of better life conditions, increased employment opportunities, higher pay, and improved safety amid local instability. In consideration of these findings, we conducted a survey among WiT workshop trainees to understand their career goals before and after the training.

Participants were presented with five predefined options: 1) advancing within my current company, 2) switching to a new company or industry, 3) starting my own business or freelancing, 4) getting an overseas job in the same industry, and 5) getting an overseas job in a new industry. Additionally, participants had the freedom to choose not to answer if they did not have any specific goal. This approach allowed us to capture a comprehensive picture of their aspirations and discern any shifts in career goals resulting from the workshop's influence.

Figure 9 illustrates the transformation of career goals among our participants following the training program. This analysis sheds light on how the participants' aspirations evolved as a direct outcome of the training.

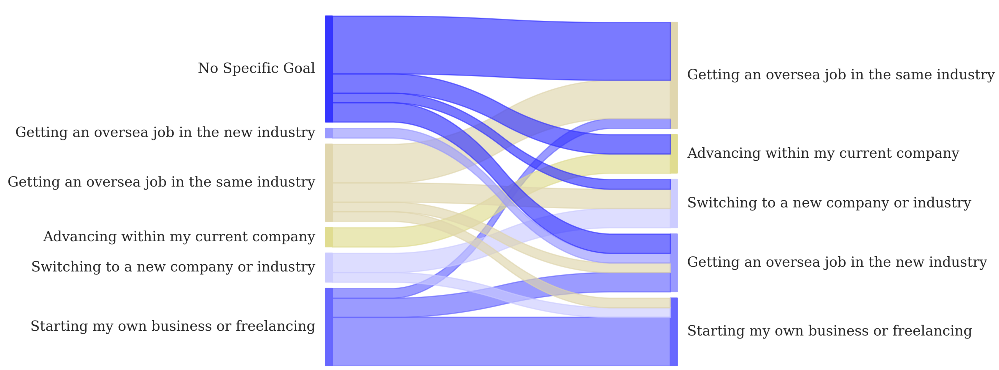

Figure 9: Transformation of career goals among the participants

Before the training, eight participants had expressed a shared goal of pursuing overseas jobs within the same industry. Remarkably, half of these participants (4 out of 8) maintained their initial goal. However, one participant opted to shift their career focus towards establishing a freelancing venture, showcasing the adaptability fostered by the training. Additionally, three participants displayed newfound confidence and a willingness to explore different industry sectors or companies, indicating the broadened horizons imparted by the program.

Another eight participants who had expressed interest in starting their own businesses or freelancing before the training emerged with diverse goals. While five of them maintained their original goals, three of them became confident enough to explore overseas job opportunities.

Notably, eleven participants who had entered the training without specific career objectives emerged with clear and ambitious goals. They now aspire to advance their careers within their current company (2), secure overseas employment opportunities (8), or transition to a new company or industry (1), underscoring the positive impact of the training in igniting their career ambitions.

The shifts in participants' career goals highlights the program's effectiveness in empowering individuals to reevaluate and adapt their aspirations, resulting in a more diversified and goal-oriented cohort.

3.5 Correlation Analysis

In this section, we present the results of the correlation analysis of our training program's various components to gain valuable insights into the factors influencing participants' skill development.

3.5.1 Age Group vs. Performance

The bar graph in Figure 10 displays the average scores across different age groups. This visual presentation highlights the similarity in scores among different age groups for both technical and soft skills, with one exception being the older age group, specifically those aged 46 and above. This underscores the absence of a significant correlation between age and the improvement scores in both technical and soft skills.

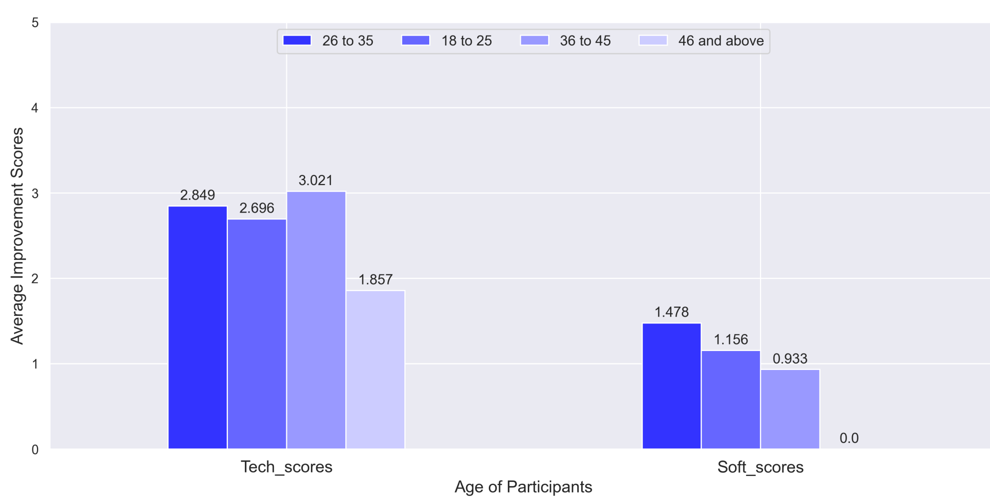

Figure 10: Average Improvement Scores across different age groups

3.5.2 Education Background vs. Performance

Table 3 displays the outcomes of an ANOVA (Analysis of Variance) test, investigating the link between education background (Bachelor, Master, or PhD), English language proficiency (Pre-intermediate, Intermediate, Advanced), field of study (Science, Engineering, or others), and improvement scores in both technical and soft skills. In ANOVA, the F-value helps determine if improvement scores differ significantly among groups. The p-values indicate the likelihood that these results occurred purely by chance. Small p-values suggest a potential real difference, while large p-values may indicate random differences.

Table 3: F-value and p-value resulted from ANOVA Test

	F-value (Tech)	p-value (Tech)	F-value (Soft)	p-value (Soft)
Edu Background	0.5	0.736	0.107	0.979
English Proficiency	3.861	0.031	0.938	0.402
Field of Study	0.646	0.591	2.011	0.132

A higher F-value and a small associated p-value suggest a meaningful difference between groups. However, examining Table 3, all F-values are relatively small, and the p-values are large – for education background (F-value, 0.5, p-value, 0.736) and field of study (F-value, 0.646, p-value, 0.591). This suggests that there are not significant differences between people with various education backgrounds or fields of study. In simpler terms, it means improvement scores do not appear to be influenced significantly by a person's education background or field of study.

While the statistical results for English proficiency (F-value, 3.861, p-value, 0.03) suggest a possible connection with technical skill scores across proficiency levels (basic, intermediate, advanced), it's important to consider that the advanced group consists of only one candidate. This raises concerns about the reliability of the findings. Due to the limited size of the advanced group, the actual impact remains uncertain. To establish the validity of these results, additional research with a larger and more diverse sample is necessary.

3.5.3 Professional Background vs. Performance

Similar observations can be made concerning the influence of professional background on the enhancement of both technical and soft skills. An Analysis of Variance (ANOVA) test was employed to investigate this relationship, and the findings are summarized in Table 4. This table provides results of the ANOVA analysis, which aimed to explore the connection between professional background, quantified in terms of work experience in years and seniority levels, and the improvement scores in both technical and soft skills.

Table 4: F-value and p-value resulted from ANOVA Test

	F-value (Tech)	p-value (Tech)	F-value (Soft)	p-value (Soft)
Years of Working (In Group)	0.304	0.873	0.937	0.456
Postion (Senior or Junior)	0.215	0.885	0.677	0.573

The p-values provided in Table 4 are relatively high, surpassing 0.5. Consequently, based on the ANOVA analysis, there is insufficient evidence to assert that professional background significantly influences participant performance during training. To summarize, the ANOVA analysis suggests that professional background, measured by work experience and seniority levels, does not appear to be a significant factor in determining the improvement of technical and soft skills during the training program.

3.5.4 Prior Knowledge vs. Performance

Table 5 provides valuable insights relating the prior knowledge to the performance. This table lists the Pearson correlation coefficients that shows the relationships between improvement in self-assessed technical and soft skills and other numerical data, including prior Excel knowledge scores, prior programming scores, and attendance rates. Additionally, the table also highlights the linear correlation between technical and soft skills.

Table 5: Pearson Correlation Coefficients

	Avg. Technical Scores	**Avg. Soft Skill Scores**
Prior Excel	-0.172	-0.268
Prior Programming	0.024	0.012
Attendance Rate	0.147	-0.085
Technical scores	1	0.684
Soft skill scores	0.684	1

Notably, the data shows that higher prior Excel proficiency is linked to a slight reduction in the improvement of both technical (-0.172) and soft skills (-0.268). This suggests that participants with better Excel skills before the training may experience slightly less growth in both skill areas for Data Analytics Track. In contrast, prior programming knowledge does not appear to have a significant effect on Software Engineering Track participants' performance during the training program.

3.5.5 Class Attendance vs. Performance

Table 5 also provides insights into the relationship between class attendance and participant performance, a critical aspect of the online training program. A positive correlation, quantified by a Pearson correlation coefficient of 0.147 (as detailed in Table 5), is observed between class attendance and improvements in technical skills. In simpler terms, higher attendance rates are linked to more significant enhancements in technical skills among participants. However, it is interesting that there is not a statistically significant impact of class attendance on the development of soft skills, indicated by a Pearson correlation coefficient of -0.085. In other words, participants' attendance rates do not significantly affect the improvement of their soft skills during the training program.

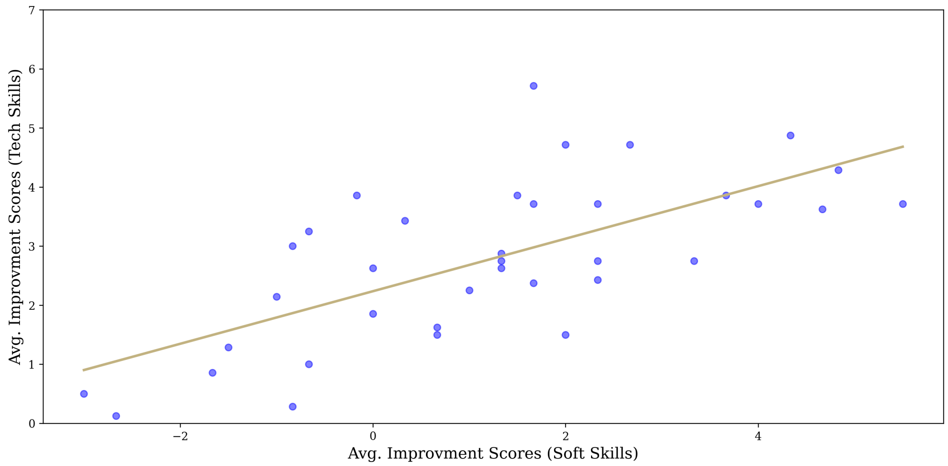

Figure 11: Soft Skills Enhancement on Technical Proficiency

3.5.6 Effects of Soft Skills Enhancement on Technical Proficiency

Figure 11 illustrates the linear relationship between the improvement scores in technical skills and soft skills. This graphical representation provides a clear insight into how changes in one skill set correspond to changes in the other. The pattern evinces that improvements in soft skills are significantly associated with enhancements in technical proficiency. The visual trend in the data points suggests a positive correlation between the two skill domains. This correlation is quantified by the Pearson correlation coefficient, which is calculated as 0.68.

The value indicates a moderately strong positive correlation. In practical terms, this means that as participants' soft skills improved, there was a corresponding increase in their technical proficiency scores. This finding underscores the significance of Soft Skills Enhancement in our training program, as it appears to go hand-in-hand with improvements in technical competence.

4 Limitation

It is important to acknowledge the limitations inherent in this study. Firstly, the findings are based on data collected from a relatively modest sample size of 38 participants, which may limit the extent to which the results can be generalized to the broader population of Myanmar. Secondly, the study heavily relied on self-reported data, particularly through self-assessments used to gauge participants' confidence levels. However, it is essential to bear in mind that these findings hinge on the subjective nature of self-reflection, which reflects participants' personal perceptions rather than objective measurements of knowledge and skills. These limitations emphasize the importance of approaching the study's outcomes with caution and a clear understanding of its scope and methodology.

5 Conclusion

In conclusion, this case study provides valuable insights into the Women in Technology (WiT) program's impact on participants' self-assessment scores and career aspirations, illustrating the effectiveness of training programs in the computer science field. The high completion and attendance rates (84% completion, 50% with attendance rates over 90%) demonstrate the program's ability to motivate and support participants, even in regions with disruptions like security concerns and limited resources. Moreover, the substantial improvement in participants' self-assessed scores in technical skills, doubling from their initial levels, highlights the program's positive influence on participants' self-assurance, particularly crucial in challenging regions. Additionally, the correlation analysis reveals that demographic factors such as age, field of study, and professional background do not significantly impact skill improvement, while higher attendance correlates with improved technical skills. A strong positive correlation (0.68) between enhanced soft skills and improved technical proficiency underscores the importance of developing soft skills in training.

As the technology industry becomes increasingly essential in our lives, these findings hold significance for program organizers, policymakers, educators, and individuals pursuing skill development and career advancement. This study emphasizes the potential of online training programs to bridge skill gaps, promote career growth, and contribute to a more inclusive and equitable technology sector, with far-reaching implications for society.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Acknowledgement

The authors would like to acknowledge all participants, speakers, volunteers and organizations supporting this research. Thank you, Women in AI (Myanmar Chapter), for the support on designing and facilitating the workshops.

Data Availability

Our research findings are published as a data visualization dashboard, which is publicly available here at `https://mmdt.istarvz.com/our_project/`. The dashboards are created by the WiT participants. The data that support the findings of this study are available from the corresponding author upon reasonable request.

Myo Thida, originally from Myanmar, is an educator and computer scientist with over 15 years of experience in the fields of computer and data science. She has been actively engaged in teaching and conducting research in areas such as data science for social causes, computer vision, and machine learning. Myo has published over 10 scientific papers and articles in international conferences and high-impact journals. Myo earned her Ph.D. in Computer Vision from Kingston University, UK, in 2013, following her B.Eng. and M.Eng. degrees in electrical and electronic engineering from Nanyang Technological University (NTU), Singapore, in 2005 and 2008 respectively. Currently, she serves as an assistant professor of Computer Science at Bard College at Simon's Rock.

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