SKILLS MISMATCH IN ENTRY-LEVEL PROGRAMMER POSITIONS: EMPLOYER EXPECTATIONS VS. OBSERVATIONS IN LALITPUR, NEPAL

Amrit Puri

Kathmandu University
School of Education
2021

LELAM-TVET4INCOME

Amrit Puri

Kathmandu University
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Nepal

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Kathmandu University School of Education, Hattiban, Kathmandu
Post Box – General Post Office 6250
Phone: +97715250524
https://soed.ku.edu.np/
admin@kusoed.edu.np

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Publication of this book is financially supported by the project Linking Education and Labor Market (LELAM), funded by the Swiss Agency for Development and Cooperation (SDC) and Swiss National Science Foundation (SNSF).
Despite an annual influx of programming graduates from Information Technology (IT)-focused educational institutions, software companies struggle with the persistent challenge of finding qualified candidates for entry-level programming roles. In this context of skill shortage, this study explored the crucial issue of skill mismatch of IT graduates, by assessing the employers’ expectations and observations vital for entry-level programming positions. This study employed a quantitative survey approach to delve into this skills mismatch issue. Professionals within 128 software development companies in Lalitpur were surveyed, all holding managerial positions and possessing programming experience. Utilizing a Likert scale questionnaire distributed through Google Forms, these industry experts rated their expectations and real-world observations concerning the specific skills requisite for entry-level programming positions.

The analysis of expectations of skills showed that learning attitude (personal), basic concepts of programming (technical), and organizational culture fit (interpersonal) were considered the most important skills. Personal or college projects and skills in version management and testing were considered equally important. The analysis of skill expectations versus observations uncovers noteworthy disparities, mostly observed in personal skills, with expectations significantly exceeding actual observations. Almost 50% of the skills were found to have high importance and high gaps, most of which were personal skills. The discrepancy was comparatively less in interpersonal and technical compared to personal skills. Perceptions regarding the alignment of knowledge, skills, and attitude (KSA) were mixed in which most of the respondents indicated moderate to strong alignment between expectations and observations for knowledge and skills, while weak alignment for attitudes. Statistical analysis confirmed significant mean differences between expected and observed skills across all skill categories, reaffirming the existence of a skills mismatch. Notably, employers overwhelmingly advocate
addressing these skill mismatches through training and development initiatives. These findings shed light on the multifaceted nature of the skills mismatch challenge in Lalitpur’s entry-level programming job market, emphasizing the need for targeted interventions to bridge this gap and foster alignment between employer expectations and the skills of recent graduates. Aligning curriculum with industry needs and designing skill development approaches is of utmost importance to enhance graduates’ workforce readiness, facilitating a smoother transition for entry-level programmer positions.

**Keywords:** skill mismatch, entry-level programming, software industry, skill expectations, workforce readiness
I am a Computer Engineering graduate who previously worked as a software engineer. I always wondered about the gap between the skills acquired by the graduates and the skills expected by the employers. Thus, I started on a research journey to understand this issue. This dissertation has been possible with the support of many, known and unknown, who have directly or indirectly guided me at various stages of proposal drafting, research design, data collection, writing, and proofreading.

First and foremost, I would like to express my sincere gratitude to the research committee of the School of Education, Kathmandu University for providing me the opportunity to embark on this significant research journey. Additionally, I am sincerely grateful to the University Grants Commission Nepal for awarding me a scholarship under the Formula Funding Scheme. This scholarship has been immensely valuable in supporting my academic journey and enabling me to pursue my studies effectively. Secondly, I extend my deepest and humble gratitude to my dissertation supervisor Mr. Anup Bhurtel, who has been of tremendous support throughout this journey. His valuable feedback and suggestions have been crucial to enrich the quality of my dissertation. His patience, expertise, and willingness to help have greatly contributed to my understanding of the subject matter and the research process.

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I would like to acknowledge and express my gratitude to all the respondents of my research who graciously agreed to participate and shared their valuable insights. Their contributions have provided me with a deeper understanding of the subject. I would like to express my sincere appreciation to those who took the time to talk with me. Their willingness to share their experiences and perspectives has been instrumental in my research and has provided valuable insights into the practical application of the course content. I would also like to thank my MTVET (2021) batchmates for their support throughout this journey. Their collaboration, encouragement, and assistance have been crucial in completing this research.

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<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>ANOVA</td>
<td>Analysis of Variance</td>
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<tr>
<td>API</td>
<td>Application Programming Interface</td>
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<tr>
<td>AWS</td>
<td>Amazon Web Services</td>
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<tr>
<td>BCIS</td>
<td>Bachelor of Computer Information Systems</td>
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<td>BCA</td>
<td>Bachelor in Computer Applications</td>
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<tr>
<td>BEd. ICT</td>
<td>Bachelor of Education in Information Communication Technology</td>
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<tr>
<td>BEIT</td>
<td>Bachelor of Engineering in Information Technology</td>
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<tr>
<td>BIM</td>
<td>Bachelor in Information Management</td>
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<tr>
<td>BSc. CSIT</td>
<td>Bachelors of Science in Computer Science and Information Technology</td>
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<tr>
<td>CEO</td>
<td>Chief Executive Officer</td>
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<tr>
<td>CI/CD</td>
<td>Continuous Integration and Continuous Delivery/Continuous Deployment</td>
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<tr>
<td>COO</td>
<td>Chief Operating Officer</td>
</tr>
<tr>
<td>COVID</td>
<td>Corona Virus Disease</td>
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<tr>
<td>CSS</td>
<td>Cascading Style Sheets</td>
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<tr>
<td>CTEVT</td>
<td>Council for Technical Education and Vocational Training</td>
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<tr>
<td>CTO</td>
<td>Chief Technical Officer</td>
</tr>
<tr>
<td>DCE</td>
<td>Diploma in Computer Engineering</td>
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<tr>
<td>DIT</td>
<td>Diploma in Information Technology</td>
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<tr>
<td>DOIND</td>
<td>Department of Industry</td>
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<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
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<tr>
<td>HCT</td>
<td>Human Capital Theory</td>
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<tr>
<td>HR</td>
<td>Human Resources</td>
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<tr>
<td>HSD</td>
<td>Honestly Significant Difference</td>
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<tr>
<td>HTML</td>
<td>Hypertext Markup Language</td>
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<tr>
<td>Abbreviation</td>
<td>Full Form</td>
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<tr>
<td>ICT</td>
<td>Information Communication Technology</td>
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<td>IDE</td>
<td>Integrated Development Environment</td>
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<td>IIDS</td>
<td>Institute for Integrated Development Studies</td>
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<tr>
<td>ILO</td>
<td>International Labor Organization</td>
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<tr>
<td>IS</td>
<td>Information System</td>
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<tr>
<td>IT</td>
<td>Information Technology</td>
</tr>
<tr>
<td>ITeS</td>
<td>Information Technology Enabled Services</td>
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<tr>
<td>KSA</td>
<td>Knowledge Skills Attitude</td>
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<td>MWDS</td>
<td>Mean Weighted Discrepancy Score</td>
</tr>
<tr>
<td>NSIC</td>
<td>Nepal Standard Industrial Classification</td>
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<tr>
<td>OCR</td>
<td>Office of Company Registrar</td>
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<tr>
<td>OJT</td>
<td>On-the-job training</td>
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<td>OOP</td>
<td>Object Oriented Programming</td>
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<tr>
<td>OS</td>
<td>Operating System</td>
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<tr>
<td>PHP</td>
<td>Hypertext Preprocessor</td>
</tr>
<tr>
<td>QA</td>
<td>Quality Assurance</td>
</tr>
<tr>
<td>RDS</td>
<td>Ranked Discrepancy Score</td>
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<tr>
<td>REST</td>
<td>Representational State Transfer</td>
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<td>SaaS</td>
<td>Software as a Service</td>
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<td>SD</td>
<td>Standard Deviation</td>
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<td>SDLC</td>
<td>Software Development Life Cycle</td>
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<tr>
<td>SEE</td>
<td>Secondary Education Examination</td>
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<td>SPSS</td>
<td>Statistical Package for Social Sciences</td>
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<tr>
<td>SQL</td>
<td>Structured Query Language</td>
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<tr>
<td>TVET</td>
<td>Technical Vocational Education and Training</td>
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<tr>
<td>UI</td>
<td>User Interface</td>
</tr>
<tr>
<td>UX</td>
<td>User Experience</td>
</tr>
<tr>
<td>VET</td>
<td>Vocational Education and Training</td>
</tr>
<tr>
<td>VP</td>
<td>Vice President</td>
</tr>
<tr>
<td>VPE</td>
<td>Vocational and Professional Education</td>
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CHAPTER I
INTRODUCTION

With technology becoming a crucial part of the modern world, becoming important more and more every day in personal and professional lives as well as the smooth functioning of other industries and governmental operations, horizontal and vertical growth happening in the software industry is inevitable and already observed. According to a report by Precedence Research (2023), the global software market is rapidly expanding driven by cloud computing, development of mobile and online apps, and remote employment. The market size is estimated to reach around USD 1,789.14 billion by 2032 at a compound annual growth rate of 11.74%. The Asia Pacific region had a 44% market share in 2022 and will experience even more surge according to the study. From a labor market perspective, this means a tremendous increase in the demand for employees in the software industry. Programmers or coders make up a big part of this workforce demand. As a consequence of this increasing demand, educational institutions must prepare a workforce ready for the job market, providing them with employable skills as required and necessary for the programming professions.

Computer Programming (also simply referred to as programming or coding) is the process of developing a computer program. It is generally understood to be software programming where the programmer develops software, applications, games, etc. using one or more programming languages (like Python, PHP, JAVA, etc.) using some framework (like Django, Laravel, Rails, etc.) for any platform (mobile, web, desktop, etc.). Every aspect of our lives depends on computer codes. Any kind of electronic device, be it a phone, computer, refrigerator, or bathroom shower, is programmable. The Internet of Things (IoT) technology has advanced in recent years and is adopted in mainstream use. IoT devices use artificial intelligence (AI) and machine learning to bring
intelligence and autonomy to systems and processes, such as self-driving cars, medical equipment, and home automation. Examples include smart TVs, Google Home, wearables, smart sensors in industries, etc. The number of businesses using IoT has doubled in the past decade and is projected to increase to 43 billion by 2023 (Dahlqvist et al., 2019). As AI continues to evolve with research and development, it is estimated that AI will increase the world’s economy by approximately 15% contributing over $15 trillion annually (Walsh, 2023). As a result of these technological advancements, programming jobs are in high demand and continue to grow. This is evident from a 2020 study by Evans Data that showed the worldwide developer’s population continued to grow by half a million in 2020, reaching a total of 24.5 million (Carey, 2021). USNews (2023) has ranked computer programming as number 11 in the best technology jobs in the US. According to USNews, computer programming is a lucrative career these days for a variety of reasons, including exciting and meaningful employment, low stress levels, balanced work-life, opportunities for improvement, getting promoted and earning better pay, upward mobility, and flexibility.

The demand for programming expertise is not confined to global tech hubs but extends to burgeoning IT sectors in countries like Nepal. According to a report by Lemma et al. (2017), the information, communications, and technology (ICT) sector had experienced the fastest growth with the strongest expansion prospects of a 21% increase in employment annually. Nepal’s IT sector has also experienced considerable progress in recent years, evident from the registration of numerous IT companies. According to a report published by the Institute for Integrated Development Studies (IIDS), the value of the IT service export market in Nepal was estimated to be around USD 515 million in 2022. This market was made up of 51,781 freelancers providing Information Technology Enabled Services (ITeS) and 106 companies providing IT export services, as well as 14,728 IT freelancers (IIDS, 2023). In 2022, the total value of IT service exports increased by 64.2%, making up 1.4% of Nepal’s GDP. The number of IT freelancers showed a 55.2% growth rate. According to the Industrial
Information System maintained by the Department of Industry (DOIND), for the fiscal year 2022/23, there are 112 companies registered in the ICT category, with a total proposed employment capacity of 6907 and a total capital of NRs. 8,929.82 million (DOIND, 2023). In the fiscal year 2022/2023 alone, 16 companies were registered in the Information Technology category, with a total proposed employment capacity of 889 and 11 companies in 2021/22 with a proposed capacity of 896. This growth trajectory is undeniable, and it inevitably translates into an escalating demand for skilled programmers.

Educational institutions in Nepal have proactively responded to this demand by offering a plethora of IT, programming, and computer science-related courses. 110 academic institutions in Nepal provide IT-related bachelor's and master's degree programs, according to IIDS (2023). Moreover, the popularity of programming as a profitable career path has increased the number of students enrolling in these courses. According to Basnet and Kim (2010), there is a significant need for graduates of Diploma in Computer Engineering (DCE), both inside and outside of Nepal, especially in the Gulf nations of Malaysia, Thailand, and India. However, their report surprisingly found that this demand was not because of their skill or the credibility of the DCE program but because these graduates weren’t conscious about hierarchy or status, and had lower salary expectations. Consequently, a myriad of entry-level job opportunities have arisen for fresh graduates in the IT sector, offering a promising path to career initiation. There exist numerous different jobs besides programming in IT companies. Among these jobs, Merojob (2021), which is one of the most popular online job portals in Nepal, has listed 14 most demanding jobs in the IT industry, 10 of which are entry-level jobs suitable for a fresh graduate.

Employers of small-scale and large-scale software companies often hire fresh graduates of IT and Computer Science related courses for entry-level positions and internships. Even companies that aren’t directly related to software development but require programmers to perform specific tasks are also the other pool of employers. For example: An E-commerce company might
require website’s development and maintenance, the usage of machine learning and artificial intelligence to predict consumer patterns, and such. All of these employers seek a certain set of entry-level skills related to programming that are ‘general’ to all kinds of roles that require software development. These skills encompass fundamental competencies in algorithms, data structures, programming concepts, design patterns, databases, proficiency in programming languages, and familiarity with essential tools like Git and Unix (Bartaula, 2023; Stamm, 2023). It is these foundational skills and knowledge that form the bedrock of entry-level positions, shaping the employment landscape for recent graduates entering the field of computer programming. Other non-technical skills like communication, learning aptitude, time management, adaptability, teamwork, etc. are equally sought out by employers of the software industry in Nepal (IIDS, 2023; Lemma et al., 2017; Sharma, 2023). However, entry-level applicants and employees lack skills in comparison to the industry demand (Bartaula, 2023; IIDS, 2023; SEEP Nepal, 2018). According to the survey by SEEP Nepal (2018), about 68% of employers face difficulty in hiring entry-level employees for software development and most of the applicants lack practical knowledge and project management skills. The increasing prominence of skills mismatches in the rapidly evolving job market, particularly within the tech industry, has spurred significant research interest. As the demand for highly specialized skills grows, understanding the dynamics of skills acquisition and alignment with employer expectations has become paramount in addressing workforce challenges and increasing the employability potential of IT graduates. The issue at the heart of this study is a disparity between the skills obtained during formal education and those demanded by employers of the software industry—a phenomenon herein referred to as the "skills mismatch.".

International Labor Organization (ILO, 2014) defines skills mismatch as an imbalance between skills required and possessed. There is no single definition of skill mismatch that is accepted universally. However, a skills mismatch can be understood as an equilibrium disruption between the skills possessed by individuals and those expected by employers or dictated by industry standards.
Focusing on the qualitative aspect as noted by Bulgarelli (2009), skill mismatch will be approached as an overarching term for the difference between what is expected and what is actually possessed. For example, in the field of computer programming, a graduate’s proficiency may fall short of the expectations held by IT industry employers, thereby highlighting a skills mismatch. In simpler terms, when the skills possessed by graduates do not align with the benchmark of required skills, a skills mismatch appears. The assumption is that the graduates are under-skilled and have some level of skills. The term ‘skill gap’ becomes apparent only if there is a complete absence or lack of skills (ILO, 2014).

Skills mismatch is costly. The skills mismatch phenomenon has far-reaching implications for both individuals and the workforce at large. According to Muo (2016), the inability to obtain decent jobs despite educational qualifications causes frustration in youths. The author further adds that the unemployment resulting from skills mismatch adversely affects the overall economic growth and GDP of the nation. Hoteit et al. (2020) reveal that skills mismatch often goes unnoticed by governments and businesses, with over 1.3 billion individuals globally working in roles that do not align with their qualifications or skills. According to their research, the economic repercussions are substantial, as skills mismatch resulted in an $8 trillion loss to the global economy in 2018, amounting to a 6% reduction in productivity. They further add that in a post-COVID-19 world, the projected loss by 2025 is, at best, about 8% annually and, at worst, an opportunity cost of 11% of GDP. The consequences of skills mismatch extend beyond economic costs, impacting factors such as productivity, innovation, and sustainable development, as countries with higher degrees of skills mismatch tend to score lower on global competitiveness and innovation indices. Within this context, the study of skills mismatches becomes important in understanding the intricacies of the contemporary software development and programming job market. As industries evolve and job requirements shift, the ability to identify and address skills mismatches becomes paramount for individuals, employers, and policymakers in the fields of labor, education, information, communication, and technology. It is this
exploration of skills mismatches, particularly within the realm of entry-level programming positions that forms the core focus of this research.

**Statement of Problem**

Despite the significant contribution of the software industry to the economic development of Nepal and the interest of Nepali educational institutions to produce the required ‘employable’ workforce for this industry, an imbalance of workforce has been observed. The graduates from the institutions aren’t ‘ready’ for the entry-level programming jobs offered by the software development companies. The skill mismatch situation has become an important issue in the current software industry.

Though 7085 out of 9000 graduates who enter the job market annually find job opportunities in the IT sector, Nepal’s IT industry still faces the challenge of an imbalance between the demand for IT experts and the supply of skilled graduates (“Nepal’s export”, 2023). Employers in software companies aren't finding suitable candidates for entry-level programming jobs even though thousands of students graduate from educational institutions every year with a programming major from educational institutions offering IT courses such as Bachelor in Engineering (Computer), Bachelor in Computer Science, Bachelor of Computer Information Systems (BCIS), Bachelor of Education in Information Communication Technology (BEd. ICT), Bachelor of Engineering in Information Technology (BEIT), Bachelor in Information Management (BIM), Bachelor of Science in Computer Science and Information Technology (BSc. CSIT), Bachelor in Computer Applications (BCA), Diploma in Computer Engineering (DCE), and Diploma in Information Technology (DIT) among others (CTEV, 2022; IIDS, 2023; Kathmandu University, 2023; Tribhuvan University, 2023; Pokhara University, 2023). A lot of the software companies in Nepal are looking to hire people as interns or junior programmers. But time and again, in seminars, conferences, and informal discussions, the companies’ team leads and managers are heard complaining about not finding suitable candidates. The employers argue that there is a weak link between curriculum and
employment, that students are not exposed to real-world issues, that internships are ineffective, and that the educational system is not practical (Bartaula, 2023; Basnet & Kim, 2010). Employers tend to agree on not finding someone with the ‘bare minimum’ skills required for an entry-level job. The issue, henceforth discussed, is that of a skill mismatch, a situation where the graduates don’t possess the skills expected for an entry-level programming position.

Graduates who complete their required course in the institution however enter into the world of work without sufficient knowledge and skills required for employment. Sometimes, these skills may be completely absent. Consequently, employers have to spend extra effort to groom their employees whereas students face a lot of challenges with their employment like spending extra time learning in a low-paid (sometimes unpaid) entry job or internship or working for a position below their educational qualification (under-education). And the graduate is inclined to possibly choose a job position completely different from their field of study. This situation has created some pertinent questions: is there a skill mismatch as expressed by employers on graduates? If it exists, what type of imbalances exist? This issue has been a significant area of inquiry for the researcher.

There has been extensive research work on the issue of skill mismatch, particularly related to IT skills. For example, Draus et al. (2022) and Radermarcher (2012) found that IT students were short of expectations in software development tools, knowledge of software testing, security, data modeling, version control, data science, teamwork, and communication skills among others. Contrarily, Lundberg et al. (2020) and Istiyowati et al. (2020) found that there was no ‘big difference’ in the competencies of IT graduates in accordance with the expectations of industry professionals and lecturers. However, there have been limited studies specific to the context of Nepal. Though considered important, it hasn’t been much explored. Basnet and Kim (2010) conducted a review of the Diploma in Computer Engineering program and found that 54.2% of graduates were found to be employed. However, they did not study the mismatch situation in
detail. Lemma et al. (2017) found that though the labor market is ‘relatively tight’ for skilled labor in ICT, the availability was ‘adequate’ at the entry-level. However, they didn’t investigate the issue in detail. Sharma (2023) studied graduates’ employability in the ICT sector and found that employers’ expectations of graduates’ employability are higher than those of graduating students. Although, the study provides a nuanced detail of the non-technical skills, since it was focused on the general ICT sector, the gap in technical capabilities and software skills required for entry-level programming roles aren’t probed in detail. A recent report published by the Institute for Integrated Development Studies, IIDS (2023) provides an analysis of the issue of ‘limited skills and competence’ of IT employees and found that 63% of IT companies believe entry-level employees to be below average. However, in their list of software competencies anticipated by the employers, they haven’t addressed the expectations for entry-level positions. Similarly, it has to be noted that the study done by IIDS was specific to the IT service export industry and hence the expectations are different than the expectations for entry-level workforce in the general software industry. Bartaula (2023) investigated the skill gap among IT employees in financial technology (fin-tech) companies at three levels: entry, mid and senior. The author found that the highest skill gap was found among the entry-level employees. Though programming and other related disciplines like web development, software development tools and mobile technology development were investigated, the employers rated only the overall perceived gap related to these disciplines and didn’t specifically rate the individual skills. In this sense, in the context of Nepal, it lacks a particular study of the dynamics of skill mismatch of individual skill requirements in entry-level programming jobs.

**Purpose of the Study**

The purpose of this study was to examine the mismatch between skills required by employers for entry-level programming jobs and the skills acquired by graduates of IT-related courses. The study focuses on gathering employers’ perceptions regarding the skill expectations and actual observations for entry-level
programming positions, thereby making a comparison of the discrepancies between expectations and observations.

**Research Questions**

The purpose of this study was to answer the following questions:

1. Is there a difference in skills possessed by the applicants for an entry-level programming job in accordance with the expectations of employers?

**Hypothesis**

In this study the following hypotheses were developed to elaborate and specify the research question.

- **H₀₁**: There is no significant difference in technical skills expected by employers of the software industry and skills possessed by IT graduates for entry-level programming positions ($\mu_{et} = \mu_{ot}$).
- **H₀₂**: There is no significant difference in personal skills expected by employers of the software industry and skills possessed by IT graduates for entry-level programming positions ($\mu_{ep} = \mu_{op}$).
- **H₀₃**: There is no significant difference in interpersonal skills expected by employers of the software industry and skills possessed by IT graduates for entry-level programming positions ($\mu_{ei} = \mu_{oi}$).

The alternative hypotheses are as follows:

- **Hₐ₁**: There is a significant difference in technical skills expected by employers of the software industry and skills possessed by IT graduates for entry-level programming positions ($\mu_{et} \neq \mu_{ot}$).
- **Hₐ₂**: There is a significant difference in personal skills expected by employers of the software industry and skills possessed by IT graduates for entry-level programming positions ($\mu_{ep} \neq \mu_{op}$).
- **Hₐ₃**: There is a significant difference in interpersonal skills expected by employers of the software industry and skills possessed by IT graduates for entry-level programming positions ($\mu_{ei} \neq \mu_{oi}$).

**Significance of the Study**

Because the number of software companies is rapidly increasing, thus creating jobs in entry-level programming positions,
educational institutions have the opportunity to prepare a workforce ‘ready’ for the jobs. The alignment of skills with employer expectations is paramount for individual career success and economic development. The study is significant as it explores the mismatch issue and provides valuable insights into a critical issue that affects both recent graduates and the broader workforce. By focusing on the domain of computer programming, this research aims to uncover patterns of skills mismatches that may have far-reaching implications for educational institutions, employers, and policymakers.

Firstly, this study can inform curriculum developers, educators, teachers, and leaders in educational institutions, enabling them to better prepare graduates with the skills that employers are looking for. This will help the institutions to prioritize the skills and knowledge that need to be given much importance while delivering the curriculum. It can also inform the students on what they should focus on to become more employable and work-ready.

Secondly, for employers, a deeper understanding of skills mismatches can aid in refining recruitment and selection strategies. It can assist employers in identifying areas where additional training and development opportunities may be required. By aligning the skills expectations with the skills possessed by applicants, they can provide targeted training programs to bridge any skill gaps, leading to improved job performance and increased productivity. The employers can thus strategically be prepared beforehand on what skills are difficult to be provided by the educational institutions and need to be provided during on-the-job training.

Thirdly, these insights may be used by decision-makers to create policies that support skill development, close the skills gap, and stimulate economic growth. Policymakers may create tailored interventions to enhance school curricula, vocational training programs, and job placement methods by identifying the precise skills mismatches that impede labor productivity. Such measures might have far-reaching long-term effects, including the ability to encourage economic development, draw in investment, and gain a
competitive edge in the international market.

Furthermore, the findings of this study will also benefit the larger academic community and researchers working on similar subjects. The findings from this study might aid as a useful initial point for further research because skills mismatches and employability difficulties are still important concerns in a variety of industries.

Limitations of the Study

The study was strictly reliant on perception surveys of employers. It has been acknowledged that the participants' perceptions and interpretations of skills may vary, potentially influencing the accuracy of the gathered information. Thus, there was a degree of subjectivity and potential response bias. Despite efforts to design a robust survey instrument and ensure clarity in questioning, inherent subjectivity remains a consideration in data interpretation. While the findings present valuable insights into employers' perspectives, the study acknowledges the inherent limitations associated with perception-based data collection methods. By recognizing these limitations, this study intended to provide a transparent account of its scope and potential constraints.

Organization of the Dissertation

This dissertation consists of seven chapters. Chapter one introduces the study and discusses the background of the study. In chapter two, different literature on skill mismatch, causes and consequences of skill mismatch, and skills required in programming roles have been reviewed. Additionally, it presents an analysis of the requirements of Nepali employers and IT-related courses in Nepal and provides a framework for skills required in programming and the taxonomy of different skill categories. It also presents human capital theory combined with job-fit theory and expectation-performance model given by Bui and Porter (2014) as the theoretical framework of the study. Chapter three focuses on research methodology and research design. It explains the research flow, how the study was conducted, and how the data was collected and analyzed. Chapters four and five present quantitative analysis
of the demographic variables, employer’s perceptions regarding KSA match, and skill ratings. Chapter six provides insights into the major findings and discusses the findings alongside previous research on the major skill expectations and major skill gaps. Finally, a conclusion is provided in chapter seven with possible implications of the study.
CHAPTER II

LITERATURE REVIEW AND THEORETICAL/RESEARCH FRAMEWORK

This chapter discusses the past studies done on the skills mismatch in computer science, computer programming, or any sectors in general and the arguments made by these researchers. The focus is to understand how past studies have gathered the skills required in the workplace, how they have assessed the skills, what kind of skills they have assessed, and how they connect to the employability of the graduates, if any. Secondly, it presents some of the skills required in programming according to different literatures from a global perspective. Thirdly, the skill requirements are contextualized to Nepal by analyzing job postings. Based on this literature, a comparison of the curriculum of programming related courses is also presented.

Skills Mismatch Overview

Among the many objectives of education, one key objective is to instill skills in the students so that they can get a job after graduation. Students agree that having a higher education is a predictor of getting employment (Ali & Jalal, 2018). That means, vocational and educational institutions should equip students with ‘employability skills’. Yorke and Knight (2006) have defined employability skills as a “set of achievements, skills, understandings and personal attributes” that increases the chances of acquiring employment (p. 3). Other scholars agree with them in saying that employability skills are the generic skills, attitudes, and behaviors that are desired by employers, and they are competencies required to get a job. Different scholars have divided employability into key elements. Some examples of these elements based on various scholars are basic work and academic skills, personal
qualities or traits, core skills, and process skills, high-order thinking skills, social skills, etc. (Supriatna et al., 2019). Na (2019) provides a three-dimensional model of understanding skills viz. type, level, and content. Various frameworks exist to define the skill type, the most common being core skills and specific skills related to the industry/job. Core skills are not associated with work and are grouped as basic or foundational skills (literacy, numeracy, etc.) and transferable or transversal skills (personal and interpersonal skills like problem-solving, communication, critical thinking, collaboration, etc.) (Na, 2019; Palmer, 2017). Skill level can be broadly based on an individual's educational qualification, job performance, or skill proficiency necessary to perform a job task. Skill content refers to the knowledge, skills, attitude, tools, procedures, work processes, etc. required to perform a task, job, or occupation (Na, 2019). For this study, skill level will be understood as the level of proficiency of soft skills and job-specific technical skills required or expected for an entry-level programming position.

Skill mismatch is a very complex phenomenon, and can be understood as a disparity between skill supply and demand, either in terms of quantity or quality (Bulgarelli, 2009). Na (2019) also notes that skill mismatch can be categorized as qualitative or quantitative. A qualitative skill mismatch occurs when there is a mismatch in the kind of skills that an individual possesses compared to what is needed. On the other hand, a workforce mismatch, or a mismatch between the supply and demand of labor, is a quantitative mismatch. The study focused on the qualitative skill mismatch. So, in general terms, we can understand the ‘skills mismatch’ as some kind of difference in skills; a difference of one set of skills from another reference set of skills. The reference here is the set of skills demanded or required by the employers or the labor market (Arayssi et al., 2023). Against these required skills, we compare the available set of skills. International Labor Organization (ILO, 2014) notes skills mismatch as an ‘encompassing term’ that covers a variety of situations where there is an imbalance between skills required and possessed. ILO (2014) provides seven such types which are presented in Table 1.
Table 1 Frequently Discussed Types of Skills Mismatches

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>Skill shortage (surplus)</td>
<td>Demand (supply) of people with a skill is more than the supply (demand) of people with that skill</td>
</tr>
<tr>
<td>Skill gap</td>
<td>Level of skill differs from what is needed to do the job well</td>
</tr>
<tr>
<td>Vertical mismatch</td>
<td>The level of education is less or more than required for the job</td>
</tr>
<tr>
<td>Horizontal mismatch</td>
<td>The type/field of education is different than what is required for the job</td>
</tr>
<tr>
<td>Over-education (under-education)</td>
<td>Employees have more or fewer years of education than what is needed for the position.</td>
</tr>
<tr>
<td>Over-qualification (under-qualification)</td>
<td>Employees are more or less qualified than what is needed for the position.</td>
</tr>
<tr>
<td>Skills obsolescence</td>
<td>Skills for a profession are no longer needed, or they have gotten worse over time.</td>
</tr>
</tbody>
</table>

Source: ILO (2014)

Scholars have used ‘skills gap’ and ‘skills mismatch’ interchangeably and sometimes synonymously. According to the definition of ILO, the skills gap is defined as the ‘lack of necessary skills’ i.e., a complete absence of required skills. So, it can be categorized as a type of skills mismatch. For this study, the assumption is that graduates of the IT and computer science related programs have some skills but not sufficient to the benchmark requirement. Thus, this is the case of under-skilling within the realm of skills mismatch. Some researchers argue that skill gaps and under-skilling are synonymous. For example, according to McGuinness et al. (2017), it is just a matter of who the question is directed at. In general, skill gaps are often quantified by gathering data on employer’s perceived skill inadequacies of employees. When identical questions are aimed at employees, this is typically comparable to under-skilling; the question style is likely to change, however. For this study, the skill mismatch thus becomes the difference between skill sets in programming acquired by the graduate of programming-related programs and skill sets required by the employers in companies involved in some level of software development that hire software programmers. A framework for this skill mismatch concept is presented in Figure 1.
As shown in the framework in Figure 1, students enroll in educational institutions that offer IT related courses with programming majors. Students acquire skills, knowledge, and attitudes during the period of study. Upon graduation, the students are assumed to have a set of skills. On the other hand, software companies are looking to hire entry-level software programmers from a pool of fresh graduates. The companies require graduates to have some set of skills. The presence or lack of discrepancy between skills acquired and skills required will help understand if there is a skills match or mismatch. We will note that there is a skill gap if the graduates have no skills compared to the benchmark of required skills.
Causes and Consequences of Skills Mismatch

Skills mismatch is undoubtedly a crucial issue from both the perspective of education and the workforce. Since skills mismatch has much broader effects on individuals, and organizations as well as on a bigger scale affecting the economy of the country, it has attracted substantial attention for the research in addressing the issue. Scholars note that the causes of the skills mismatch differ according to the type of economy (formal or informal) and the type of country (lower income, middle income, or high income). Jiang and Guo (2022) argue that, unlike interest-mismatch workers, the skill-mismatch (and demand-mismatch) occurs due to structural reasons. Palmer (2017) notes information asymmetries and inadequacies, low education base of people, unequal access to training, underdeveloped markets for skills, lack of attention from public training providers to the needs, and constraints to training as some of the causes of skills mismatch in the informal economy. He adds globalization, technological changes, and urbanization to the list. According to ILO (2014), skills mismatch in Europe is attributed to various factors, including incomplete and imbalanced data, unresponsive educational and training systems, ineffective job placement services, and a lack of post-schooling training opportunities. Na (2019) suggests multiple ‘contextual factors’ including education, economic structure, population, technological changes, etc. contribute to the skill mismatch. As a result, the causes can be viewed from the perspectives of both skill supply and demand. On the skill side, Na (2019) agrees with Palmer and ILO that lack of labor market information, lack of labor mobility, and inefficient education and training systems are the causes. On the supply side, some of the causes could be wages, internal organizational problems, industry-specific challenges, lack of job stability, fear of job obsolescence, etc. For the purpose of this study, we are more interested in the skill demand side. However, the study doesn’t dig deeper into the reasons for the skill mismatches.

Palmer (2017) explored the idea of informality (informal employment) as the cause of skill mismatch and found a positive correlation between the proportion of young individuals engaged in informal employment and the degree of qualification mismatch.
According to a study by Kupets (2019), lower-income countries including Nepal, Benin, Cambodia, and others had a high prevalence of both informal employment and qualification mismatch. However, despite these challenges, they tend to exhibit relatively low levels of youth unemployment. In these nations, a significant proportion of less-educated young individuals are engaged in informal sector occupations. Simultaneously, many young workers find themselves in jobs that do not align with their education and training, primarily being underqualified. The widespread prevalence of informal employment, coupled with this issue of underqualification, serves as a substitute for unemployment, making youth unemployment less of a pressing concern in the majority of these countries.

Na (2019) finds that the consequences of skill mismatch are visible at different levels; individual (wage, job satisfaction, etc.), organizational (productivity, turnover, retention, etc.), and macroeconomic (unemployment, GDP growth, etc.). In a study of skills gaps in the fin-tech industry in Nepal, Bartaula (2023) found that at an individual level, it has an impact on a person's ability to grow personally, get a promotion, earn better, maintain a work-life balance, and be mentally well. On a company level, the effects were a decrease in productivity, increased operation costs, a decrease in profitability, and the need to outsource jobs. Rathelot et al. (2023) found that the negative effect of skill mismatch in early careers is large and persistent, specifically on wages. According to Arayssi et al. (2023), the Middle East and North Africa (MENA) area has substantial young unemployment due to skill mismatch, affecting employees’ income, job satisfaction, and career development while lowering the company’s productivity as well. Additionally, Jiang & Guo (2022) found that skill mismatch is linked to decreased chances of employment stability, promotion, and job satisfaction. The authors add that the effect is considerably stronger in demographic groups that include women, immigrants, and ethnic minorities. Sun et al. (2023) in their study of the effects of skill mismatch in China revealed the ‘crowding effect’ of skill mismatch where skilled labor ends up searching for low-skilled jobs thereby increasing unemployment for unskilled labor and causing a negative welfare
effect for the overall labor force. Palmer (2017) agrees that skill mismatch has an impact on the growth of the national economy as well as the productivity, profitability, and turnover of businesses. However, Palmer further claims that the effects are considerably weaker in low-income countries like Nepal, as mentioned earlier, where the consequence is not unemployment but underqualification. However, over-educated workers (working in jobs that require less of their possessed skills) tend to have lower wages, wage penalties, and less job satisfaction. Palmer further argues that skill mismatch may result in trends of companies recruiting low-skilled immigrant workers (who don’t require social security, contract, etc.), hiring talents from other companies by raising salaries, investing (or not) in training and development, individuals switching jobs or entering informal self-employment, etc. According to him, the other major consequence of skill mismatch is the “creation of a low-skills equilibrium” due to low investment in skills and low demand for skills. Employers may no longer be aware of experiencing skill shortages, which results in individuals having reduced motivations to pursue education beyond what is directly required by the job market.

**Skill Mismatch in Programming Jobs**

As the broader landscape of skill mismatch gains attention, delving into its issue within programming jobs becomes crucial, shedding light on the specific challenges faced by the rapidly evolving IT industry. Wang & Bromall (2018) found small gaps in logic, medium gaps in programming syntax and the highest gap in security for entry-level programming jobs. According to a meta-analysis of 13 countries by Garousi et al. (2019), the highest gaps were found in configuration management, software engineering processes, architecture and design as well as in testing. The study also notes that communication, teamwork, and leadership were the most important soft skills including culture fit, attitude, curiosity, etc. Numerous studies have found that soft skills (termed differently by different researchers) are of the highest priority for entry-level positions in IT programming-related positions. However, soft skills like communication, problem-solving, and
There has been very little research on the scope of skills mismatch or skill gap in Nepal. The recent report by IIDS (2023) indicates the skill demands of employers in Nepal for entry-level programming positions for the IT service export industry have clear priorities for specific software competencies like web development, User Interface/User Experience (UI/UX), Python, Structured Query Language (SQL), DevOps, and automation testing. Similarly,
soft skills are equally important like communication, teamwork, time management, and problem-solving. However, the study found that 63% of employers felt that entry-level employees were below average. Professionalism and limited skills were the major hurdles for IT companies according to the study. Sharma (2023) found that most of the employers weren’t satisfied with the work of fresh graduates, firstly due to their lack of practical skills and secondly due to their inadequate technical skills. Most employers found graduates’ core skills to be low while personality attributes and organizational adaptability skills to be medium. Further analysis of employability showed that for both the core skills and personality attributes, employers viewed graduates’ skills to be present but not ‘consolidated to reflect at work’. For the organizational adaptability skills, employers viewed it as emergent but not yet present (p. 111). Bartaula (2023) found that entry-level employees in the fin-tech sector had the greatest skill gap when compared to mid and senior-level employees. Most of the employers reported that the entry-level employees weren’t able to perform at the ‘required level’. According to the study, more than 90% of employers agreed that entry-level employees in programming had a very high gap or considerable gap in hard skills like SQL, database, Python, and PHP among others required to work at full proficiency as demanded by the job.

**Skills Required in Entry-level Programmer Positions**

Specific technical skills and knowledge required in programming jobs differ based on the programming language, the framework, the nature of the company, and others. However, certain skills are general that apply to entry-level programming. This study focuses primarily on these types of general technical skills because these are expected to be provided by educational institutions and to be acquired by graduates. Other programming language-specific skills and workplace or domain-specific skills are usually learned as on-the-job training or through experience in the workplace itself.

In the ever-evolving world of programming and information technology (IT), staying relevant and effective demands a
multifaceted skill set. Technical proficiency is the cornerstone of any successful IT career. Technical skills that are most required after by the employers of the software industry include operating systems, basics of programming, programming language, data structures, software development life cycle, object-oriented programming, algorithms, design patterns, version control and management, SQL, web programming, (Cummings & Janicki, 2020; Florea & Stray, 2019; Janicki et al., 2014; Lee & Han, 2008; Montandon et al., 2021; Noll & Wilkins, 2002; Tesch et al., 2008; Tomic et al., 2019; Weber et al., 2001; Woratschek & Lenox, 2014). These skills are essential for addressing the intricate challenges in the realm of programming and IT. Stamm (2023) found that employers rated ‘computer science fundamentals’ as the most important skill among 53 other qualifications, for entry-level positions which was also noted by Draus et al. (2022). Debugging skills and the ability to apply software engineering practices were other important technical skills according to the study. Among the 20 listed skills as important in their study, Cummings and Janicki (2020) found the importance of data structures, object-oriented programming, design patterns, and version management. They also found that requirements gathering was an important skill as well, but mostly necessary for someone who would work as a business analyst in the IT sector. Regarding languages, they found it important to integrate web programming and open-source programming into the curriculum. Scaffidi (2018) found that employers consider databases, source code management, testing, agile methods, user interface design, and testing among the important technical skills while collaboration, communication, and learning attitude as the most important soft skills. Aasheim et al. (2015) found that IT firms mostly seek programming languages and methodologies of systems development in entry-level positions. Younis (2022) categorizes the most important skills expected from new software engineering (SE) graduates into three areas: SE practices (e.g., requirements, design, software life cycle, project management), CS concepts (data structures, programming, databases, security, networking) and software tools (configuration management, development, tools). Blanchfield (2023) notes that
when teaching programming, it is important to include technical skills like software project development, GitHub (for practicing software systems development like Scrum), databases, and code debugging. Similarly working in teams is the most important non-technical skill to be emphasized. Draus et al. (2022) found that graduates must have a solid foundation in programming basics, logic, configuring the environment, testing, and debugging. Montandon (2021) found that the most demanded hard skill was related to programming languages. At the time of their investigation, Surakka (2007) observed that object-oriented programming has grown in importance. They found discrete mathematics and logic to be some other necessary skills of a developer in the software industry. Calculus, one of the parts taught in mathematics, is widely taught in computer-related degrees. However, Lethbridge (1999) found that in practice, only a small amount of it is necessary for software engineers. It might be necessary to communicate with other mathematics-related scientists and engineers, which isn’t in the scope of an entry-level hire. Burton and Bruhn (2003) postulate that there is a stronger connection between programming and mathematics in terms of the usage of symbols, syntax, grammar, representation, functions, etc. and thus basic concepts of mathematics that are used in programming are necessary to be taught in related courses.

First and foremost, data structures form the scaffolding upon which efficient data management is built. Profound knowledge of data structures equips professionals to organize, manipulate, and retrieve data efficiently and proficiency in programming languages specific to the job at hand is crucial for any programmer to have. Furthermore, skills like effective software design and pattern utilization, project requirements analysis, software architecture design, and writing scalable, reliable, and adaptable codes, are crucial (Cummings and Janicki, 2020; Lee and Han, 2008; Lethbridge, 1999). Competency in development methodologies is pivotal i.e., familiarity with Software Development Life Cycle (SDLC) methodologies, because it governs the software development process, providing a systematic framework for planning, creating, testing, and deploying software solutions for
effective project management and software engineering (Hamid & Ikram 2023; Janicki et al., 2014; Lethbridge, 1999). Apart from these ‘general’ skills, Smith and Ali (2014), in their analysis of trends of jobs in computer programming, found that there is a strong requirement for people with Structured Query Language (SQL) knowledge. SQL is still a very relevant skill and of high importance in the software industry in the coming years as noted by Cummings and Janicki (2020). Skill in database modeling and design is equally important as it forms the backbone of development, either on the web, mobile, or desktop.

Beyond technical expertise, interpersonal and management skills play a pivotal role in an IT professional’s success. McMurtrey et al. (2008) found that soft skills were the most important for entry-level IT professionals. Patacsil and Tablatin (2017) found that teamwork and communication were the most demanded soft skills among others. The other top-rated requirements were problem-solving, lifelong learning, curiosity, self-learning, English language proficiency, attitude, adaptability, and creativity (Bringula et al., 2016; Istiyowati et al., 2020; Jebreen & Nabot, 2021; Lundberg et al., 2020). In a study of job ads for software testers in Pakistan, Hamid & Ikram (2023) found that software companies want to hire fresh graduates with both technical. The findings of Younis (2022) concur with the authors. Communication skills and problem-solving skills were found to be very important (Montandon, 2021). Effective communication and collaboration are important aspects of a successful and productive team. IT professionals must convey complex technical concepts clearly and work harmoniously with colleagues. Stamm (2023) found that out of the 10 top important skills that employers agreed on, 8 were non-technical skills. ‘Positive attitude’ had the highest agreement of 67%. The author argues that graduates who have learned professional skills have a higher chance of being hired into their first job than those who focus only on technical areas. Project management, estimation, risk management, and quality assurance are essential competencies in IT roles (Lee and Han, 2008; Tesch et al., 2008). Proficiency in these areas ensures that projects are delivered on time and within scope. Understanding business processes and operations is increasingly
important in IT. IT professionals must align their technical efforts with broader business goals and strategies (Tesch et al., 2008). A comprehensive understanding of business operations and objectives is paramount. It enhances an IT professional's ability to contribute meaningfully to organizational success. As technology is changing at a rapid rate, employees in the IT sector must exhibit adaptability and a commitment to continuous learning (Tang et al., 2001). Staying current with technological trends and understanding their implications for competitive advantage is critical. Proficiency in systems analysis, design, and development methodologies is essential for addressing evolving business needs.

It has been noted from a comparative review of findings of the past and recent literature that some of the technical skills have become obsolete over the years (Florea & Stray, 2019; Lee & Han, 2008; Noll & Wilkins, 2002; Tesch et al., 2008). According to Tesch et al. (2008), changing technologies and changing business environment add pressures to update skill requirements and curriculums. Skills like networking, graphical user interface, hardware maintenance, procedural programming, systems design, etc. that were considered important in the late 90s are no longer relevant. And, if they are relevant, they are not considered entry-level requirements. On the other hand, skills like SQL, design patterns, version management and test-driven development, knowledge of cloud platforms, web and mobile development languages, development frameworks, database modeling, big data, user experience design, and user interface design, have emerged as highly required. Similarly, in the past business function skills like business problem analysis, and integrating existing and new business applications were considered important but now they aren't, at least for entry-level positions.

The literature review has shed light on a wide spectrum of skills that are imperative for success in the dynamic realm of programming and information technology. These competencies have been categorized into distinct domains, including technical proficiency, interpersonal and management skills, business knowledge, and adaptability. Technical proficiency encompasses data structures, skills in specific programming languages, software
design and analysis, design patterns, requirement analysis, and software architecture, as well as familiarity with development methodologies like SDLC, structured and object-oriented programming, and design patterns. Furthermore, interpersonal skills, management competencies, and a deep understanding of business processes constitute vital elements for effective IT professionals. Additionally, a solid grasp of advanced information systems applications is crucial. Finally, the ability to adapt to evolving technologies and manage systems development effectively forms the cornerstone of IT success. This multifaceted skill set, as uncovered in the literature, equips IT professionals to excel and navigate the ever-changing landscape of programming and information technology.

**Categorization of Skills Required in IT**

Within the realm of skills, the categorization has long been a focal point of investigation and consideration. Various researchers have notably categorized these skills into two primary domains: hard skills and soft skills, the former is synonymous with technical skills and the latter encompasses non-technical proficiencies (Makasiranondh et al., 2011). It is a field rife with nomenclature diversity, including terms like soft skills, people skills, interpersonal skills, transferable skills, transversal skills, and general skills among others. Researchers have found that soft skills have considerably higher importance for employers when compared to programming-specific technical skills (Lee & Han, 2008; Noll & Wilkins, 2002; Stamm, 2023; Tesch et al., 2006). Extensive research in the field of IT and related professions has yielded a consensus on the fundamental categories of skills deemed essential for individuals embarking on careers in this domain. These categories encompass technical proficiencies, which are further delineated into general technical skills, providing a foundational understanding of computing, and domain-specific expertise, tailoring knowledge to specialized fields. In parallel, there is a pronounced emphasis on soft skills, often classified as transverse, non-technical, or behavioral competencies. Within soft skills, there is a noteworthy distinction between personal attributes and interpersonal abilities. Moreover, researchers have
underscored the significance of business functional skills, which equip professionals with the acumen to navigate the intricate intersection of technology and organizational needs.

In their study of gaps perceived by educators of Information Systems (IS), Tang et al. (2001) regrouped the knowledge/skills into four categories: “IS Technology Knowledge/Skills, Organization and Society Knowledge/Skills, Interpersonal Knowledge/Skills and Personal Traits” (p. 77). Similarly, Fang et al. (2005) classified the broad spectrum of critical IS requirements into four categories: “core IS knowledge (managerial and technical), knowledge about organizational/industrial entities, interpersonal skills, and personal skills” (p. 60). Aasheim et al. (2015) adapted the categorization as “technical skills, managerial knowledge/skills, personal skills/traits, and interpersonal skills/traits” with the addition of the “work experience and grade point average” in hiring entry-level IT employees in their study of requirements for IT graduates (p. 51). In the study of employability in the ICT sector in Nepal, Sharma (2023) considered six dimensions viz. personal attributes, 21st-century skills, workplace learning, soft skills, management skills, and technical skills, and categorized them into core skills, personal attributes, and organizational adaptability skills. IIDS (2023) classified expectations of IT companies in Nepal into software competencies and soft skills for their study. In a study of employers’ requirements from software testers, Florea & Stray (2019) used the following framework where the authors merged personal and interpersonal skills into one while introducing ‘domain-specific’ skills and ‘educational attainment’ into the expectations of employers (Figure 2).
Figure 2 Software Industry’s Requirements for Software Testers

Source: Florea and Stray (2023)

This study uses the skill categories and framework presented in Figure 2 to contextualize them to the scenario of Nepal and build a framework to present the skill expectations of employers in Nepal for entry-level programming positions. Before that, a brief context of Nepal is discussed below.

**Skill Demands of Employers in Nepal for Entry-Level Programming Positions**

According to the IIDS (2023), the skill demands of employers in Nepal for entry-level programming positions are marked by a clear prioritization of specific software competencies. These competencies, ranked in order of importance, include User Interface/User Experience (UI/UX), Structured Query Language (SQL), Python, full-stack web development, DevOps, and automation testing. However, it has to be noted that the study done by IIDS was specific to the IT service export industry and hence the expectations are bound to be considerably higher, unlike the expectations for an entry-level workforce. Additionally, soft skills
play a crucial role in employability, with communication, teamwork, time management, and problem-solving being highly valued attributes. Creativity and innovation are also regarded as significant qualities within the industry. Proficiency in the English language is notably emphasized due to the interaction with global clients. However, the report highlights challenges, such as limited competencies among the Nepali IT workforce and issues related to professionalism. For freelancers, a majority turn to online learning for upskilling, technological updates, and training activities. Furthermore, a substantial portion of IT companies perceive entry-level employees as needing improvement in both skills and competence, with a consensus that a 6-month training program could enhance their proficiency. Bartaula (2023) found that employers expected skills in React, Node.js, Python, JAVA, JavaScript, SQL, MongoDB, Oracle, Visual Studio, Git, Agile, SCRUM, JIRA, etc. for jobs in programming, mobile technology, and web development. Rather than skills, these are specific languages and tools used in programming. However, the author doesn’t clarify this notion. Sharma (2023) explored graduate employability in the ICT sector of Nepal in three areas viz. core skills, personality attributes, and organizational adaptivity skills. The study found that graduates were expected to have a higher level of core skills such as technical capabilities, software skills, learning aptitude, acumen, time management, basic hardware skills, analytical skills, etc. Similarly, personality attributes like confidence, self-discipline, and organizational skills like project management, communication, collaboration, and documentation were equally important. These findings underscore the multifaceted skill requirements faced by employers in Nepal's IT sector, emphasizing the need for a diverse skill set among entry-level programming professionals. Employers argue that curricula need to be updated as per market needs and give emphasis to hands-on practical teaching like on-the-job training (OJT) (Bartaula, 2023).

Merojob (2021) has listed the most demanding jobs in the IT industry including roles like web developer, web designer, PHP developer, Angular developer, React developer, and so on. All of
these roles hold future career prospects for a fresh graduate or an applicant looking to join an entry-level programming position. The specific skill sets required for each of these positions might differ. For example, a React developer position would require expertise in JavaScript specifically in React.js, the position for a JAVA developer would demand skill in “developing applications using Java EE platforms”. So, such specific skill sets might not be expected from an applicant for an entry-level position. However, within the realm of these roles (and many others), other ‘general’ skills are expected no matter what the future specialization might be for the applicant. For example: skills in HTML, CSS, Git, SQL, database, web services, object-oriented programming, etc. are ‘generally expected’ by employers. Apart from these technical skills, other ‘soft’ skills are also expected like teamwork, analytical skills, reasoning, ownership, etc.

Analysis of Job Postings in Online Job Portals

To better understand the skills sought by Nepali employers in this sector, a collection of 25 job postings from five different online job portals Kantipur Job, Kumari Job, Jobjee, Jobs Sniper, Merojob (retrieved from January 1 to January 15, 2023) were retrieved and analyzed. This analysis aims to provide insights into the skill requirements, qualifications, and other specifications employers look for when hiring entry-level programmers.

From the analyzed job postings, several key patterns and trends emerge:

1. Educational Requirements: Candidates having at least a bachelor's degree in computer science, engineering, or a similar discipline are preferred by most employers. Some job advertisements do, however, also take applicants with equivalent experience into account.

2. Experience: While these positions are generally not required for entry-level roles, it's common to see requirements for a minimum of 1 to 2 years of experience in specific programming languages or technologies.

3. Programming Languages: The primary programming languages in demand include Java, JavaScript, Python, C#,
and PHP. Proficiency in these languages is often a core requirement.

4. Web Technologies: Knowledge of web technologies such as HTML, CSS, and JavaScript, including modern libraries and frameworks (React.js, Vue.js, Angular), is commonly expected.

5. Database Knowledge: Familiarity with relational databases (e.g., MySQL, PostgreSQL) and SQL is valued. Experience in database design and optimization is a plus.

6. Version Control: Proficiency in version control tools like Git is often required.

7. Web Development Frameworks: For web development positions, employers seek candidates with experience in popular frameworks like Laravel (PHP), Spring Boot (Java), or Django (Python).

8. API Development: Many job postings emphasize knowledge of developing and integrating RESTful APIs.

9. Tools and Technologies: Knowledge of tools like Docker, and Linux, and familiarity with DevOps practices are becoming increasingly important.

10. Testing and Quality Assurance: For QA positions, employers look for skills in designing test cases, automation testing using tools like Selenium, and experience with bug tracking systems.

11. Mobile Development: For iOS and Android developer roles, employers seek experience with Objective-C/Swift and mobile app development lifecycle understanding.

12. Additional Skills: Additional skills such as familiarity with AWS, Docker, Kubernetes, and CI/CD pipelines are advantageous.

13. Projects: Demonstrated project experience, whether through academic requirements or personal initiatives, is highly valued by employers. Additionally, showcasing project demonstrations can significantly enhance a candidate's appeal.

In conclusion, the software industry in Nepal is in search of entry-level programmers with a strong foundation in programming
languages, web development, and relevant technologies. While a formal education is preferred, equivalent experience is often considered. Candidates who possess a combination of programming skills, an understanding of web technologies, and proficiency in using essential tools and frameworks are well-positioned to meet the demands of these entry-level positions. From the analysis of online job ads for entry-level positions as discussed above, it was observed that these postings require some ‘domain-specific’ skill sets and are directed mostly to applicants with some years of experience. This study further scrutinizes this list to focus more on entry-level general skills.

**Non-technical Requirements.** Additionally, in all of the job postings analyzed, the expectations regarding non-technical skills were clearly mentioned. A generalized list of non-technical requirements for entry-level positions is given below.

1. Communication Skills: Strong verbal and written communication skills to collaborate effectively within a team and convey ideas clearly.
2. Problem-Solving Abilities: Demonstration of problem-solving skills and a proactive nature to learning new concepts and technologies.
3. Team Player: Work collaboratively in a team space, share knowledge, and contribute to group projects.
4. Technical Curiosity: A passion for technology and a desire to explore and experiment with different tools and technologies.
5. Adaptability: Willingness to adapt to changing project requirements and learn new skills on the job.
6. Attention to Detail: Strong attention to detail to ensure accuracy in coding and project execution.
7. Time Management: Good skills in managing time, meeting project deadlines, and efficiently prioritizing tasks.
8. Learning attitude: Enthusiasm for learning and a strong desire to grow and develop as a professional.
9. Professionalism: Demonstrated professionalism and a commitment to upholding the company's values and standards.
From the above deconstructed list, it is explainable that most of the requirements are non-technical, commonly called ‘soft’ skills. It has to be noted that these requirements provide a broad framework for entry-level positions and can vary depending on the specific role and industry. Employers may have additional expectations based on their organizational needs, but the above list serves as a good starting point for entry-level job seekers.

To further understand the skill requirements for the ‘actual’ entry-level positions and validate the findings from the literature, the discussion was conducted with five experts from different software companies in Lalitpur with different experiences and roles in the company. The discussions were informal and carried out using a semi-structured questionnaire (see Appendix A). Based on these personal conversations with the industry experts, the findings of requirements were grouped into four major categories; Technical Skills, Soft Skills, Experiences, and Projects. Projects (whether they are personal ‘pet’ projects, semester works done as part of course fulfillment, or projects on the job) form the core of the requirements for these experts as ‘hands-on’ experience with making something using programming is a crucial learning strategy. On the other hand, educational qualifications and certifications serve as the base for initial screening though not absolutely mandated. These requirements have been presented in Figure 3 where projects are at the center.
Figure 3 Requirements of IT Employers in Nepal for Entry-Level Programming Positions

Source: Analysis of online job postings and discussion with experts

**Programming-Related Courses in Nepal**

Various educational institutions in Nepal offer programming-related courses that aim to produce graduates with the potential to be hired for entry-level programming jobs in software development companies. Some of these courses include Bachelors in Engineering (Computer), Bachelors in Computer Science, BSc. Computer Science and Information Technology, BSc. Information Technology, BSc. Computing, BSc. Software Engineering, BSc. Network Engineering, BSc. Ethical Hacking and Cybersecurity, BSc. In Computer Science & Software Engineering, BSc (Hons) in Mobile Application Development, BSc. Information Communication Technology Bachelors in Computer Applications, Bachelor of Computer Information Systems, Bachelors in Information Management, Bachelors in Information Technology, Bed. Information Communication Technology, Diploma in Computer Engineering, Diploma in Information Technology, etc. In
the report titled “Unleashing IT: Advancing Nepal’s digital economy - Expanding jobs and exports” by the IIDS in July 2023, it is highlighted that Nepal currently boasts 110 institutions offering programs related to IT at both bachelor’s and master’s levels. These programs encompass a range of disciplines, including a Bachelor’s in Information Technology, Computer Science, Cyber Security, and Digital Forensics, and Master in e-Governance and Information Technology Management, among others (IIDS, 2023). It is undeniable that educational institutions in Nepal have a lot of choices to offer in terms of courses related to IT. ‘IT’ itself is a vast and vague scope that encompasses a lot of things. For this study, we understand IT courses to be those courses that have space for exploration and learning of one or more programming languages in their curriculum, henceforth understood as ‘programming-related courses’.

Analysis of Programming Related Courses Offered in Nepal

As previously mentioned, there are a lot of programming-related courses taught in Nepal through institutions affiliated with various universities; national and international. To better understand and explore what students are being taught (or not taught) in the institutions, a comparative analysis of course structure and curricula of eight different courses from different universities was conducted; BSc CSIT (Tribhuvan University, 2022), BCIS (Pokhara University, 2013), Bachelor in Engineering (Kathmandu University, 2023), Bachelor in Computer Engineering (Tribhuvan University, 2023), BSIT Mobile App Development affiliated to Westcliff University, California (Kings College, 2023), BSc Hons Computing affiliated to London Metropolitan University (Lord Buddha Education Foundation [LBEF], 2023), Diploma in Computer Engineering (CTEVT, 2022), Diploma in Information Technology (CTEVT, 2022). Specifically, subjects that directly involved programming-related topics and that aligned with findings from conversations with employers (Figure 3) were considered.

The curricula of two CTEVT (Council for Technical Education and Vocational Training) programs, Diploma in Computer Engineering and Diploma in Information Technology,
intend to produce middle-level technical professionals in the field of computer and IT. The curriculum mentions that this program is designed to produce ‘technicians’ with “knowledge and skills” required by the IT-related industries and organizations in Nepal (CTEVT, 2022). The B.Sc. CSIT curricula claim that their graduates have career opportunities at different government and non-government, public as well as and public organizations, telecommunication industries, networking providers, software companies, etc. in the roles of a software developer, web developer, project manager, and network administrator among others.

The objectives and job prospects of the courses outlined in the curricula vary in alignment with industry demands. Programs like BSc CSIT and Bachelor in Computer Engineering from Tribhuvan University and BCIS from Pokhara University offer comprehensive coverage of technical skills like programming, database management, and software development, aligning well with the industry’s expectations. These courses provide a strong foundation for entry-level programmers. In contrast, courses like BSc Hons Computing from London Metropolitan University and BSIT Mobile App Development from Westcliff University, California, may have a more specialized focus, preparing students for roles in mobile app development and aligning with current technological trends.

When comparing the provided curriculum for different courses to employers’ expectations, it’s evident that the alignment varies across programs. While most courses cover fundamental aspects such as basic computer literacy, programming concepts, and operating systems, the depth and focus can differ significantly. Some programs, like BSc CSIT and BCIS, are likely to extensively cover topics such as data structures, object-oriented programming, and database-related subjects, while others may have less emphasis. Furthermore, the inclusion of specific skills like version management tools, testing, and test-driven development, and recent trends in software development may depend on the program’s specific focus. Soft skills development, including communication, critical and creative thinking, problem-solving, and learning attitude, may be part of the curriculum but might vary
in intensity. Additional skills like hardware troubleshooting, computer networking, and project management tools could be more prevalent in engineering-focused programs.

Upon conducting a comparative analysis of these eight courses based on the categories of Technical Skills, Soft Skills, and Portfolio, the following observations have been made.

**Technical Skills**

These courses offer varying levels of technical skill development. BSc CSIT at Tribhuvan University provides a comprehensive curriculum covering programming, languages, databases, and tools, offering a robust technical foundation. BCIS from Pokhara University delivers a solid grounding in programming and databases. Kathmandu University’s Bachelor in Engineering, though including computer science, may emphasize engineering concepts over technical skills. The Bachelor in Computer Engineering (Tribhuvan University) focuses on computer engineering with coverage of programming and electronics. BSIT Mobile App Development (Westcliff University) specializes in mobile app tech. BSc Hons Computing (London Metropolitan University) offers a broad computing curriculum. Diplomas in Computer Engineering and Information Technology (CTEVT) likely emphasize practical tech skills, covering programming, databases, and IT basics.

**Soft Skills**

Soft skills are not usually explicitly covered in course curricula but are developed through interaction and experiences during the program. However, some of the programs include non-technical courses like Communication English, Business and Technical Communication, and Technical Communication. These courses are present in almost all of the analyzed programs. Other courses that provide soft skills include Organization Management, Entrepreneurship, Engineering Professional Practice, Academic Communication, Speech, Debate, and Ethics, Psychology, Motivation, & Decision Making, Professional Issues, Ethics, and Computer Law, among others. However, it must be noted that these are mostly theory-based classes and might lack actual skill
development. It has also been noted from previous studies that the development and growth of soft skills also depend on the student’s attitude and efforts. Similarly, group projects, guest lectures and workshops are part of the courses that can be helpful in soft skills development.

**Portfolio**

In this category, two aspects have been found; projects and software development cycle. The quality and quantity of projects can vary among these courses. Generally, programs that emphasize practical application and project-based learning (e.g., BSc CSIT, BCIS, BSIT Mobile App Development) are likely to provide more hands-on experience. Courses that cover the software development cycle in-depth, including requirements gathering, design, implementation, testing, and maintenance, are valuable for understanding real-world software development processes. Overall, these two make up the ‘experience’ without the on-the-job experiences by involving students in ‘job-like’ situations and processes. Similarly, some institutions also mandate internships as a part of course fulfillment that provides work-based learning and helps in building up the student’s portfolio. On the other hand, most of the degrees contain courses in English like Communication English and Business and Technical Communication that can help students write a good cover letter and design a CV/Resume to showcase their skills portfolio.

**Learning About New Technological Trends**

Most of the programs offered electives that were aligned with the emerging trends. Electives like Artificial Intelligence, Cryptography, Cybersecurity, Big Data, and Machine learning were available in most of the courses. However, the onus of learning falls under the students themselves as well. It can be equally argued that due to the rapid changes that happen in the context of software development, educational institutions might not keep updating and upgrading the curriculum parallely. However, a good university and industry relationship can ease this process of updating the curriculum (Sharma, 2023). Educational institutions can foster of learning culture through workshops, seminars, and hackathons.
where the students are encouraged to participate and learn about the newest trends.

**Conceptual Framework of Skills Required in Programming**

Building upon the categorizations and frameworks uncovered from previous studies and insights from the conversations with IT employers of Nepal, this study presents a conceptual framework of requirements for entry-level programming positions, drawing adaptation from the works of Aasheim et al. (2015) and Florea and Stray (2019). This framework in Figure 4 serves as a foundational structure for the forthcoming analysis, enabling a comprehensive evaluation of the alignment between curriculum offerings and industry expectations in the context of entry-level programmer positions.

**Figure 4 Framework for Skills Requirement in Entry-Level Programming Positions**
Figure 4 above proposes a conceptual framework of employers’ expectations for entry-level programming positions. The expectations are divided into expectations of skills and portfolio. For the purpose of this study, the expectations of skills are focused more. Based on the literature review, the skills have been grouped into technical skills and non-technical (soft) skills. Non-technical skills have been further divided into personal and interpersonal skills. Holtzman et al. (2021) found that employers preferred to see a portfolio of the applicants during the hiring process as the portfolio helps the recruiters see the presence of a lack of applicant’s skills required for the position. Portfolios provide a thorough insight into an applicant’s skills and experience (Castell, 2023). The expectations of a good CV/cover letter, projects, project demos, and previous experiences are grouped into ‘Portfolio’ in the questionnaire. The domain-specific skills can be organization and job-dependent. Such specific skills aren’t considered for this study which focused more on the general skill requirements.

Furthermore, this study adopts the questionnaire used by Tesch et al. (2008) in their study of perceptions and expectations of employers for IS skills in tandem with the insights gathered from the analysis of online job postings and conversations with industry experts (from November 15, 2022 to January 15, 2023) to create a taxonomy of the technical, personal, interpersonal and portfolio requirements in entry-level programmer positions in the context of Nepal (Figure 5 and 6).
Figure 5 above presents a taxonomy of the individual skills within the technical skills category. The technical sub-categories are computer basics, hardware, programming, programming tools, and technology. There are altogether 22 skills under the technical category. The major focus of expectations is on the programming and programming-related tools which is obvious as the study is about entry-level programming positions.

Similarly, Figure 6 presents a taxonomy of the non-technical (soft) skills category further divided into personal and interpersonal skills.
According to Figure 6, there are 14 skills in the personal category and 5 skills in the interpersonal category. As noted, the major focus is on personal skills. Since the expectations are for entry-level roles, there are less interpersonal expectations. And the expectations of educational qualifications, projects, and previous experiences along with the skill in CV writing are grouped as portfolio expectations.

**Theoretical Framework**

When designing research projects, determining an appropriate theoretical framework is crucial since it enables the researcher to conceptualize the study from a wider perspective (i.e., the field of existing knowledge). The study uses the Human Capital Theory as the theoretical framework and combines it with the job-fit theory to propose a framework for the purpose of this study. Additionally, the expectation-performance model given by Bui and Porter (2014) is used to further explore the dynamic of employability.
Human Capital Theory

According to Human Capital Theory (HCT), a worker's market value ideally theoretically should rise in proportion to the quantity of education they get since it assumes human capital improves with further education. Carneiro et al. (2010) posit that the HCT is a prevalent paradigm in the economic aspects of education which suggests that “education and training are investments that make individuals genuinely more productive” (p. 255). Thus, according to this theory, a productive employee will also have a higher salary and be more employable. This attainment of human capital by a student is often measured by the acquisition of a formal degree, assessed through different standardized tests and the number of credits. As students (future employees) build up their human capital by investing in education and acquiring more knowledge, expertise, and effectiveness for a job, their worth in the market should rise. However, according to Schmidt and Hunter (1998), it is erroneous to assume that obtaining a formal degree entails having the necessary skills for the position.

Policymakers around the world, who are primarily dedicated to investing in ‘human capital’, generally agree without question that funding education and training is a good idea. Carneiro et al. (2010) note that Vocational Education and Training (VET) has been particularly used as a “means of achieving higher economic growth and national prosperity while also achieving equity goals” (p. 255). Many scholars agree that a ‘formal’ background in education is considered one of the significant determinants of human capital because investment in education should, in theory, result in higher employability and productivity. Building human capital, therefore, means investing in people’s skills and knowledge (Robinson & Garton, 2008). Education and training are key investments that could be made in this matter. Almendarez (2011) discusses how education could be compared to an ‘economic good’ because it provides the consumer (e.g., students) a path to develop human resources necessary for economic and social mobility. Moreover, a study by Psacharopoulos and Patrinos (2018) found that returns are higher in low-income countries, suggesting that investment in education is
particularly beneficial in these contexts. Several other studies push forward the idea that education in any form, formal or informal, vocational training, institutional degrees, etc. can be used as a tool for building human capital by producing a skilled workforce thus increasing national and global prosperity (Carneiro et al., 2010; Robinson & Garton, 2008).

Anderson (2008) argues that vocational and professional education (VPE) is a primary source of trained and certified labor, and it promotes economic growth by increasing the availability of human capital needed by industry. Although human capital theory has evolved over time, the central rationale for investment in education (including TVET) has remained the same, that educated and skilled workforce leads to economic growth. It can be understood from a human capital theory perspective that there could be a possible linear relationship between skills, employment, and economic growth. From a supply-driven viewpoint, employment and growth are certain to occur as long as the skilled labor supply is strong. However, this doesn’t seem to be the current scenario in the case of IT graduates who aren’t getting job opportunities. If we look at the demand-driven perspective, we can assume that if there is a demand for certain skills in the market, educational institutions should produce a workforce with such skills for increased employment opportunities and thus economic growth. Though there is a high demand for programmers in the software industry, the graduates are failing to be employed.

Investing in a degree in a computer science-related program can be a significant financial commitment in the context of Nepal as well. The cost of such a degree can vary widely depending on the institution types (public versus private or online versus in-person), and the type of degree (national versus international or Bachelor’s versus Diploma versus Master’s). For instance, you may spend between five to ten lakhs for a four-year national Bachelor’s degree from a private college in Nepal (CTEVT, 2021; Duwal, 2021; Kathmandu University, 2022; LBEF, 2023; Patan Multiple Campus, 2023). On the other hand, running a Bachelor’s or Diploma course is equally a huge investment on the institutions’ part. There is another type of investment in addition to the ‘monetary’ one.
There’s an investment of time and effort; investment from both sides. The other crucial component of this investment of time, money, and effort is the accumulation of human capital, which includes the knowledge, skills, and experience that a student gains during their education. In the context of computer science, this could involve gaining job-specific technical skills like learning programming languages, understanding algorithms and data structures, gaining experience with software development practices, and more. It could include gaining transversal soft skills like problem-solving, collaboration, learning attitude, and others. Hoteit et al. (2020) claim that “skills mismatch” should be the topmost priority of every country’s ‘human capital development agenda’. Accordingly, we can analyze this situation from a human capital theory perspective to understand that the investment in producing human capital through the courses offering programming-related syllabi hasn’t been effective in producing the requisite skills in its graduates.

**Job-Fit Theory**

As discussed earlier, HCT posits that an individual increases their employability by gathering human capital with the investment in education and training. But the investment doesn’t necessarily produce an employable workforce. Metilda and Neena (2016) used the ‘job-fit’ theory to conduct an employability analysis of which of the components of job-fit are appropriate and crucial for the recruitment of freshers. The authors used an encompassing term of P-E (person to environment) fit to signify the overall concept of job fit theory and list down five components within the P-E fit viz. P-J (person to job), P-P (person to person), P-G (person to group), P-O (person to organization) and P-V (person to vocation). For the purpose of this study, P-J, P-P, P-G, and P-O fit will be considered which are crucial in making the individual ‘ready’ for the job. P-J fit is the degree to which a person's knowledge, skills, and abilities (KSA) align with the needs of the job or the demands/desires of the employers (Metilda & Neena, 2016; Sekiguchi, 2004). P-P and P-G fit is the match between the individual with another individual or group of individuals within the organization. And, P-O fit is the compatibility of the individual with the organization’s mission,
vision, values, culture, structure, attributes among others. Applying the job-fit theory and these four components to the concept of human capital theory, a framework has been proposed which is presented in Figure 7.

**Figure 7 Employability Framework based on Human Capital Theory and Job Fit Theory**

![Employability Framework Diagram](image)

*Note: Other factors that influence employability like social capital, labor market factors, national and international policies, demographic factors, etc. aren’t considered in this framework.*

As illustrated in Figure 7, the investments in education and training develop the human capital (skills, competencies, work experience) thus improving the individual’s ‘job fit’. Upon increasing the compatibility of the individual’s fit on the job, personal, group, and organizational levels, they become more employable. For the purpose of this study, the skill discrepancy will
be calculated. Thus, the categorization of skills is of interest to the study. Thus, here the P-J fit involves the technical skills (e.g., basic concepts of programming, data modeling, etc.) and personal attributes (e.g., critical thinking, learning attitude, ownership, etc.) required by the employers to perform on the job. Similarly, P-P, P-G, and P-G constitute the interpersonal skills for this study like collaboration, and organizational culture fit among others.

However, the job fit isn’t so straightforward. Creating the match involves three stakeholders viz. students, educational institutions (educators), and employers. Bui and Porter (2014) provided a framework for the analysis expectation-performance gap observed in the job which will be used to further elaborate on the job-fit dynamic.

**Expectation-Performance Gap Structure**

The expectation-performance gap structure given by Bui and Porter (2014) has employers at two extreme ends. On one end is the employers’ desire for skills and on the other end is the employers’ perception of skills possession in applicants. The discrepancy between these two ends (desires versus observations) gives us the expectation-performance gap.

**Figure 8 Structure of Expectation-performance Gap**
Source: Bui and Porter (2014)
It can be noted from Figure 8 that within these two ends lie three types of gaps that constitute the expectation-performance gap viz. expectations gap, constraints gap, and performance gap. The disparity between what companies and educators believe graduates should possess to be prepared for the workforce is known as the expectations gap. Constraints gaps are the factors that limit the students’ learning. These constraints are either personal (students’ perception of the course and the profession, their motivation, and their KSA) or institutional (lack of teaching resources and facilities, institutional systems, etc.). Furthermore, the performance gap refers to the discrepancy between employers' real expectations of graduates and educators' expectations for the level of skills that graduates should possess. The performance gap is the consequence of the ineffectiveness of educational institutions (teaching methods, lack of problem-solving instructional style, instructor’s skills and enthusiasm, etc.) (Bui & Porter, 2014). This framework provides a comprehensive dynamic of the job-fit and how the discrepancy of expectation and performance occurs. For the purpose of this study, the focus will be only on the expectation-performance gap i.e., the difference between employers’ expectations and observations. However, it is of crucial importance to note that other factors affect the overall gap. Analyzing the skills gap will inform further studies into the expectation gap, constraints gap, and performance gap.

Chapter Summary

In this chapter, the literature review of the studies relevant to the topic was presented. Firstly, it discussed the overview of the skill mismatch. Then it presented how different studies have found about the skills required in entry-level programmer positions and the different categorizations of these skills. It also discussed the skill demands specific to the context of Nepal based on an analysis of job postings. An analysis of existing programming-related courses in Nepal was presented to discuss them along with the literature review. Additionally, a conceptual framework of skill expectations in entry-level programming positions was presented along with the taxonomy of three skill categories. Human capital theory combined
with job-fit theory was used to propose a theoretical framework for the purpose of this study. The expectation-performance gap structure further probed the dynamic of this employability framework.
CHAPTER III
RESEARCH METHODOLOGY

This chapter discusses the research methodology, specific methods, and techniques that were used to identify, gather, process, and analyze information in this study. This chapter discusses in brief the post-positivist research paradigm, which guides the quantitative approach and methods adopted for the study. It also discusses the rationale for the selection of surveys as the data collection method. Similarly, it presents the study area, the method of sampling, and sample size calculation along with the data collection tools and procedures as well as the data analysis tool. Lastly, it mentions some ethical considerations that have been considered during the process of this study.

Research Design

This study was guided by the post-positivist research paradigm whose ontological belief is on one verifiable reality that there is a mismatch in skills possessed by graduates and skills required by the employers but “accepts that theories, background, knowledge and values of the researcher can influence what is observed” and believes that ideal “objectivity cannot be achieved but is approachable” (Kawulich, 2012, p. 9). Thus, it has been acknowledged that our perspectives, as researchers, can influence the study, and the study remains cognizant of this throughout. It informs the approach to investigating the mismatch in skills, allowing us to consider multiple viewpoints and account for potential researcher biases. Thus, a quantitative survey method was employed in this study which aligns with the post-positivist paradigm. By collecting structured, numerical data from a wide range of employers in the software industry, the study aims to create a comprehensive and objective understanding of the skills gap, however, remaining mindful that the process of data collection and interpretation can be influenced by both our perspectives and
the respondents' perspectives. This acknowledgment of subjectivity underscores the importance of triangulating the findings with multiple data sources and employing rigorous statistical analyses to mitigate bias and enhance the objectivity of this research. A systematic sequence of key steps was followed for this research as shown in Figure 9.

**Figure 9 Research Design Flow**

As shown in Figure 9, the research started with a comprehensive literature review, where existing research and insights into skills expectations and observations were examined followed by the compilation of a list of required skills in different skill categories, essential for entry-level programming roles. Then employers of the software industry in Nepal were consulted to gain industry-specific perspectives. Similarly, online job advertisements
were analyzed to further improve the list of required skills. Following the insights from the literature and experts, using the questionnaire used by Tesch et al. (2008) as the aid, a survey questionnaire was designed that was used as the data collection tool. Before the main data collection, a pilot survey involving employers was conducted, offering a preliminary assessment of the research instruments’ effectiveness. It helped refine and tailor the questionnaire for the final survey. The data collection phase involved the rating of expectations of skills and the rating of observations of skills by the participating employers. These datasets, Dataset 1 and Dataset 2, serve as the raw data for the subsequent statistical analysis, where quantitative methods are employed to investigate skill mismatches.

Following this, the initial findings prompted a revision of the questionnaire, refining its structure and content, the question items, and variables. For example: Choices for the ‘nature of organization’ were added based on inputs from the pilot study. The question “What percentage of the employees working in your organization in a programming-related role have only up to Diploma or Secondary level education?” was reframed as “Among the employees working in a programming related role, what percentage have bachelor's level of education or higher?” as it was found that percentage of employees with a Diploma level education was very low. Similarly, the ordering skills in the technical category were restructured to make it more relevant. Additional questions regarding the actions taken by employers to mitigate the skill gap were added to get a perspective into what employers have been already trying from their side. Subsequently, a final survey was conducted to acquire a comprehensive dataset for in-depth analysis. The data was analyzed using a paired samples \( t \)-test to derive conclusions and accept or reject the hypothesis.

**Study Area**

The study was conducted in the Lalitpur district of Nepal which hosts the second-highest number of ICT-based companies in operation (DOIND, 2023; OCR, 2023). For the quantitative survey of employers, the respondents were the IT companies in Lalitpur.
that had programming experience and were currently in a role to hire new recruits; Chief Executive Officers, Chief Technical Officers, senior developers, tech leads, team leads, managers, etc. To assist in the construction of the skills required for entry-level programming positions and validate the questionnaire, experts in the software industry in the Lalitpur and Kathmandu districts were consulted.

Population and Sampling

According to the Department of Industry’s (DOIND) industrial information system, there were 112 industries registered under the ‘Information Communication Technology (ICT)’ category in Nepal and 27 in Lalitpur district with either local investment, foreign investment, or joint investment. However, there are considerably more companies registered in this sector (IIDS, 2023). Therefore, a further list of software development companies registered in the Office of Company Registrar (2023) in the Lalitpur district under NSIC code 7220 (activities of software development and providing computer software consulting services) was obtained from Nepal. Then, the following procedure was used to find the population for the study.

In the first step, the obtained list from OCR was screened based on publicly available information (e.g., website, Facebook page). The criteria for screening were: a) the companies were directly involved in software development and b) the companies hired entry-level programming employees. In the second step, the number of companies meeting the screening criteria was determined. It was found that only 323 companies were directly involved in some kind of software development activities. In the third step, all the companies meeting the screening criteria were contacted to assess their eligibility. It was found that 8% did not apply to this research survey, 17% did not exist or were not in operation and 11% were unreachable. In the final step, the accessible population for the study was determined which was 207.

The sample size was calculated using an offline instrument developed by Bukhari (2021) that uses the Krejcie and Morgan formula (1970) to calculate the sample for a population of a finite size. After inputting the values into the formula, the sample size for
this research was calculated to be 128 at a 95% confidence level, a 0.05 margin of error, and a 0.68 population proportion (obtained from the pilot study).

$$\text{Sample Size} = \frac{z^2 \times p(1-p)}{e^2} \times \frac{1}{1+\left(\frac{z^2 \times p(1-p)}{e^2N}\right)}$$

where,

e = Margin of error = 0.05 at Confidence level ($\alpha$) = 95%
N = Population size = 207
z = Z-score = 1.96
p = Sample proportion = 0.68

The sample size was adjusted to 140 to account for the non-response. Applying the random sampling method using a spreadsheet-based formula, the names of 140 sample companies were drawn from the population list. The respondents for the survey were the employees in these sample companies of Lalitpur that had programming experience and were currently in a role to hire new recruits (Example: Chief Executive Officers, Chief Technical Officers, senior developers, tech leads, team leads, managers, etc.).

**Data Collection Procedure**

This study used the Bui and Porter (2014) expectation-performance structure to conduct an evaluation of the skills mismatch issue. This analysis is quantitative in nature and readily adopts a closed-ended questionnaire strategy for the evaluation. The study focused on only the expectation-performance gap and not the other three gaps as posited by Bui and Porter (2014). So, the two ends of the structure viz. employers’ desires (expectations) and employers’ perceptions of applicant performance (observations) were of interest in designing the survey. A questionnaire survey using a five-point Likert scale was used as the data collection tool for the purpose of this study where the employers would rate their skill expectations and observations on a scale of 1 to 5; 1 being not expected/observed and 5 being significantly expected/observed (see Appendix A). In their examination of employers’ expectations and observations conducted by Tesch et al. (2008), the authors used a survey questionnaire with a five-point Likert scale where
participants were presented with pairs of questions related to entry-level IS skills and asked to assess the expected level of skills required for entry-level positions within their organizations and later were asked to evaluate the actual level of skills observed in entry-level employees within their organizations. Similarly, to analyze the skills mismatch for business graduates, Abbasi et al. (2018) used a survey questionnaire with bank officers who ranked the importance of 12 employability skills in the sector and then rated the employability of business graduates who were working under them. This study used a similar version of the methodology applied by Tesch et al. (2008) and Abbasi et al. (2018).

The survey questionnaire consists of two main sections: Demographic information and Skills rating. For the second part of the questionnaire, firstly, for each skill given, the respondents were asked to rate the expected level of skill required for entry-level programmer positions within their organizations based on their recent hiring experiences. Secondly, for each skill, the respondents were asked to evaluate the actual level of skill observed. Tables 2 and 3 present the five-point Likert scale used for both the expectations and observations rating.

**Table 2 Likert Scale for Employer’s Expectations Rating Survey**

<table>
<thead>
<tr>
<th>Scale</th>
<th>Level of importance</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Not required</td>
<td>Not necessary: Not required to perform tasks at our company</td>
</tr>
<tr>
<td>2</td>
<td>Slightly required</td>
<td>Could have: Optionally to perform tasks at our company</td>
</tr>
<tr>
<td>3</td>
<td>Moderately required</td>
<td>Good to have: Not mandatory. Extra skills that might be useful on the job.</td>
</tr>
<tr>
<td>4</td>
<td>Highly required</td>
<td>Should have: Mandatory. Average skill level is accepted. It is of crucial importance and will have to learn before joining the job.</td>
</tr>
<tr>
<td>5</td>
<td>Significantly required</td>
<td>Must have: Mandatory. High skill level expected, won't hire if not present.</td>
</tr>
</tbody>
</table>
Table 3  Likert Scale for Employer’s Observations Rating Survey

<table>
<thead>
<tr>
<th>Scale</th>
<th>Level of importance</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Not observed</td>
<td>The applicant didn’t exhibit anything</td>
</tr>
<tr>
<td>2</td>
<td>Slightly observed</td>
<td>The applicant possessed (or exhibited) a very low understanding, skill, knowledge, and attitude but couldn’t use it at all.</td>
</tr>
<tr>
<td>3</td>
<td>Moderately observed</td>
<td>The applicant possessed (or exhibited) an understanding, skill, knowledge, and attitude, and could use it to some extent on the job when necessary.</td>
</tr>
<tr>
<td>4</td>
<td>Highly observed</td>
<td>The applicant possessed (or exhibited) a good understanding, skill, knowledge, and attitude, and could use it effectively to carry out tasks on the job.</td>
</tr>
<tr>
<td>5</td>
<td>Significantly observed</td>
<td>The applicant possessed (or exhibited) an expert understanding, skill, knowledge, and attitude, and could use it effectively to carry out tasks on the job and beyond.</td>
</tr>
</tbody>
</table>

For the meanings of the values in the five-point scale, Tesch et al. (2008) mentioned 1 as ‘skill expertise not expected/observed’, 2 as ‘limited skill expected/observed’, 3 as ‘introductory skill expected/observed’, 4 as ‘reasonable skill expected/observed’ and 5 as ‘significant skill expertise expected/observed’. A similar adapted level of importance and meaning was considered for each scale value. Each skill acted as the variable of the study. The skills were further grouped based on the conceptual framework adapted for the purpose of this study (Figure 4). The two pairs of skill ratings served as the major dataset for the analysis of this study. Similarly, the respondents were two other questions regarding perceptions of knowledge, skills and attitude (KSA) match and the actions to mitigate the skills gap. For both of these questions, respondents were asked to indicate their agreement with each proposed action, ranging from "Strongly Agree" to "Strongly Disagree," with an option for "Not Applicable."

A pilot survey was conducted using these questionnaires to understand the difficulty of the questionnaire, and the effectiveness of each question to see if it is measuring what it is intended to measure and to analyze if any additional changes are required. The
A pilot survey was conducted from March to April 2023. Based on the feedback from the pilot survey, the new information and knowledge thus gathered, suggestions from the supervisor and survey participants, and consultations with the experts of the software industry, a final questionnaire was prepared. The survey questionnaire was administered using Google Forms. Emails of the prospective respondents who would fit the respondent profile (who is or has been in a managerial position and has experience working in a programmer position) were collected by calling the companies in the sample list. Then the respondents were emailed which contained a piece of brief information about the research, the research objectives, the research question, and an online link to the survey. The email also mentioned how the research findings would be helpful for the participating organizations. Finally, it was emphasized that their participation would be kept strictly confidential, with no affiliations to their company names disclosed in the final write-up. Also, an official letter from the university was attached for their reference. The data collection was carried out from July to September 2023.

**Data Analysis & Interpretation**

First, the data collected through Google Forms was cleaned up and checked for any irregularities. Some of the questions had an option to provide subjective answers (for example: nature of the organization) if the provided list was sufficient for the respondent. The answers to such questions were analyzed and new categories were created as necessary. No new data variables needed to be added. Then the data were analyzed using Statistical Package for Social Sciences (SPSS) version 25, a desktop software for statistical calculations. Illustrative and descriptive statistics are used to present and summarize demographics as well as skills related data. For this, tools like frequency table, mean, median, and standard deviation were used. Similarly, inferential statistics were used to generalize for the population. The two sets of data ratings of skills by the employers (expectations and observations) were analyzed to check if there is a significant mean difference between expectations of skills versus their observations. Paired sample \( t \)-test has been
used for the purpose of this inferential analysis.

To analyze the discrepancy and conduct the discrepancy categorization of the skills, Borich’s Mean Weighted Discrepancy Score (MWDS) was one option. Robinson and Garton (2008) used the MWDS method to prioritize employability skills, based on graduates’ perceptions. They also suggest creating prioritization of employability skills in four categories based on MWDS (greater than 0.80, between 0.50 to 0.79, between 0.30 to 0.49, and less than 0.30). The MWDS is calculated by deducting the importance rating from the competence rating to find each graduate’s discrepancy score for each employability skill. The average importance rating for the associated employability skill is multiplied by each discrepancy score to get a weighted discrepancy score. Lastly, the weighted discrepancy scores for each ability are added up, and the total is divided by the total number of respondents to determine the MWDS. However, Narine and Harder (2021) contend that Borich’s model presents two issues: a) the reliance on item means for importance influences the weighted discrepancy score, and b) the MWDS for individual competencies lacks a readily understandable and standardized range. Thus, they suggest using the Ranked Discrepancy Score Model (RDSM) as an alternative to the MWDS method. The RDSM is suitable only if “(a) cross-sectional data is gathered from a sample or census of a target population at one point in time, (b) data for each variable or item is paired on two ordinal scales with an equivalent number of response anchors, and (c) the objective is to assess discrepancies between two clearly identified states or conditions for each item.” (p. 98). All three conditions were satisfied for this study and hence the RDS model was used for discrepancy calculation as well as the prioritization of skill expectations. The resulting Ranked Discrepancy Score (RDS) is a standard score that falls within the -100 to 100 range. The RDS centers around an equilibrium point of 0, where negative scores indicate a significant gap, while positive scores suggest the absence of a gap or need (Narine & Harder, 2021). The four categories devised by Robinson and Garton (2008) can be adapted as a) Category I with an RDS greater than -80 (i.e., the highest gap) b) Category II with an RDS from -50 to -79 (i.e., a more moderate gap)
c) Category III with a RDS from -30 to -49 (i.e., a low gap) d) Category IV with an RDS less than -30 (i.e., a negligible gap). In this way, the RDS model has been used to find which skills have significant gaps and sort them from highest to lowest.

**Reliability and Validity**

Reliability refers to the consistency and repeatability of results over time. Firstly, a pilot survey was done with a few employers to ensure the reliability of the questions, and to know which questions were difficult to comprehend or which questions were ambiguous. To ensure the reliability of the data, internal consistency techniques were used. According to Sullivan and Artino (2013), experts recommend utilizing the Cronbach alpha, Kappa, or factor analysis approach to demonstrate sufficient intercorrelation among the scale's components and that the grouped items assess the underlying variable. The internal consistency of how closely connected a set of items is to one another as a group was measured using Cronbach’s alpha.

**Table 4 Cronbach’s Alpha of Different Skill Categories’ Ratings**

<table>
<thead>
<tr>
<th>SN</th>
<th>Skill ratings</th>
<th>No. of items</th>
<th>Cronbach’s alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Expectations</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Technical</td>
<td>22</td>
<td>0.927</td>
</tr>
<tr>
<td>2</td>
<td>Personal</td>
<td>14</td>
<td>0.893</td>
</tr>
<tr>
<td>3</td>
<td>Interpersonal</td>
<td>5</td>
<td>0.801</td>
</tr>
<tr>
<td>4</td>
<td>Portfolio</td>
<td>4</td>
<td>0.749</td>
</tr>
<tr>
<td></td>
<td><strong>Observations</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Technical</td>
<td>22</td>
<td>0.948</td>
</tr>
<tr>
<td>2</td>
<td>Personal</td>
<td>14</td>
<td>0.960</td>
</tr>
<tr>
<td>3</td>
<td>Interpersonal</td>
<td>5</td>
<td>0.908</td>
</tr>
<tr>
<td>4</td>
<td>Portfolio</td>
<td>4</td>
<td>0.880</td>
</tr>
</tbody>
</table>

Table 4 presents Cronbach’s Alpha coefficients for different skill categories related to factors influencing career choice. Cronbach’s Alpha measures internal consistency, with higher values indicating stronger consistency among the items in a category. The categories include "Expectations" (with subcategories: Technical, Personal, Interpersonal, and Portfolio) and "Observations" (with similar subcategories). The Cronbach's Alpha values for most categories are high, indicating strong
internal consistency among the items. "Expectations: Personal" and "Observations: Personal" have particularly high values (0.893 and 0.960, respectively). "Expectations: Portfolio" has a slightly lower value (0.749) but is still considered acceptable. Other variables demonstrate high internal consistency as well. These results suggest that the survey items within these categories reliably measure the skills associated.

The extent to which an assessment measures what it is intended to measure is referred to as validity (Ruch, 1924, as cited in Newton, 2012). To maintain the validity of this study, utmost care was taken while designing the survey questionnaire that was used to rate the expected and observed skills of the applicants for entry-level programmer positions. To make sure all the skills required by the employers were being assessed, a few experts from the software industry were involved in designing the questionnaire itself. Questionnaires of other similar studies were reviewed in the design process. No unnecessary questions were kept in the survey to ensure content validity. Feedback from the respondents was integrated to update the survey accordingly. This was done to maintain the content validity. Since it was an online survey, while administering the questionnaire, by default the questions were read exactly as it is written in the questionnaire. To maintain the external validity, respondents were selected using random sampling and the population being studied has been clearly defined, which are the employers from the organizations/companies involved in software development related activities, who are/were in a managerial/hiring position and have programming experience. Also, it was ensured that there were enough participants and that they were representative of the population.

**Ethical Considerations**

This study was started only after getting final approval from the research supervisor and research committee of the School of Education, Kathmandu University. All of the research ethics guidelines promulgated by the university were strictly followed. An approved and signed document from the university mentioning the objectives of the study was prepared beforehand (see Appendix
B). The signed document was presented at the OCR and DOIND while collecting a list of companies. It was also provided to the respondents as an attachment to the emails. Cacciattolo (2015) posits that it is crucial to adhere to a professional code of conduct, prioritizing the safety of all participants involved during the data collection process. Thus, respondents were well informed about the purposes, objectives of the study, and confidentiality of their participation. Wiles et al. (2008) suggest refraining from sharing information supplied by an individual with others and presenting research findings in a manner that prevents the identification of individuals. So, the names and emails of the online respondents as well as the organization names weren’t collected. All digital information is placed into a secure database that is only accessible to those with permission. Participants’ identities were never disclosed to or discussed with outside parties. To avoid violating participant anonymity or making them uncomfortable, suggestions were taken from the supervisor and ethics committee.

**Chapter Summary**

In this chapter, the researcher discussed the research design and the systematic design flow to conduct the quantitative study. Pilot testing was conducted before proceeding to the final survey. It discussed how the study selected Lalitpur as its study area and considered 207 accessible companies as the population of the area. Sampling was done using Krejcie and Morgan formula and the sample was generated by random sampling. The study employed a quantitative survey approach to collect which contained skills ratings based on expectations and observations of employers. The quantitative survey used a 5-point Likert scale as the data collection tool for this study. Descriptive statistics were used for summarizing data, and paired samples t-tests were employed for inferential analysis. The value of Cronbach's Alpha was used to explain the reliability of the study. Finally, the ethical consideration of the study was detailed which followed the research process.
CHAPTER IV

DEMOGRAPHIC VARIABLES AND IMPORTANCE OF EDUCATIONAL QUALIFICATIONS

This chapter provides a quantitative snapshot of the demographic variables of the respondents and the respondents’ organizations. For the respondent details, the variables include their current role in the organization, the seniority level of their role, the total years of experience in managerial/leadership positions, and the total years of experience in IT-related companies. For the organization details, the operating area, the operating nature, and employee details are provided. Employee details include total employees and total employees in programming-related roles. Similarly, the descriptive data related to the requirement of educational qualifications and IT-related background have also been presented.

Demographic Details of the Respondents and Organizations

The demographic variables collected via the questionnaire are of two categories: personal and organizational. The personal details of the respondents include their current role in the organization, the level of their leadership/managerial role (entry, mid, senior), total years of experience in that particular position, and total years of experience in the IT-related sector. Similarly, the organizational details include the operation area (national, international), the operating nature, total employees, and total employees in a programming-related role. Other four variables related to the organization are the percentage of programming-related employees with a bachelor's level or higher, the minimum qualification required for an entry-level programmer position, the most hired educational qualification for an entry-level programmer
position, and the extent of the requirement of an IT related educational background for an entry-level programmer position. These variables are presented using descriptive and illustrative statistics.

**Table 5 Details of Respondents and their Current Organization**

<table>
<thead>
<tr>
<th>Category of Variables</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Roles of respondents</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CEO</td>
<td>14</td>
<td>10.9</td>
</tr>
<tr>
<td>Managing Director</td>
<td>10</td>
<td>7.8</td>
</tr>
<tr>
<td>CTO</td>
<td>9</td>
<td>7.0</td>
</tr>
<tr>
<td>Project Manager</td>
<td>8</td>
<td>6.3</td>
</tr>
<tr>
<td>Others</td>
<td>82</td>
<td>64.06</td>
</tr>
<tr>
<td><strong>Seniority level</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entry level Leadership / Management</td>
<td>2</td>
<td>1.6</td>
</tr>
<tr>
<td>Mid-level Leadership / Management</td>
<td>41</td>
<td>32.0</td>
</tr>
<tr>
<td>Senior level Leadership / Management</td>
<td>85</td>
<td>66.4</td>
</tr>
<tr>
<td><strong>Organizations’ Operating Area</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Internationally</td>
<td>73</td>
<td>57.0</td>
</tr>
<tr>
<td>Only within Nepal</td>
<td>55</td>
<td>43.0</td>
</tr>
<tr>
<td><strong>Organizations’ Operating Nature</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product development</td>
<td>91</td>
<td>71.1</td>
</tr>
<tr>
<td>SaaS provider</td>
<td>22</td>
<td>17.2</td>
</tr>
<tr>
<td>Others</td>
<td>15</td>
<td>11.71</td>
</tr>
<tr>
<td><strong>Total employees</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-50</td>
<td>8</td>
<td>.656</td>
</tr>
<tr>
<td>50-100</td>
<td>0</td>
<td>.81</td>
</tr>
<tr>
<td>100-200</td>
<td>0</td>
<td>.81</td>
</tr>
<tr>
<td>200-500</td>
<td>3</td>
<td>.34</td>
</tr>
<tr>
<td>Above 500</td>
<td>0</td>
<td>.78</td>
</tr>
<tr>
<td><strong>Total employees in programming role</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-50</td>
<td>14</td>
<td>9.06</td>
</tr>
<tr>
<td>50-100</td>
<td>0</td>
<td>.81</td>
</tr>
<tr>
<td>100-200</td>
<td>1</td>
<td>.34</td>
</tr>
<tr>
<td>200-500</td>
<td>0</td>
<td>.78</td>
</tr>
<tr>
<td>Above 500</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>28</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Table 5 provides a comprehensive overview of the background of respondents and their current organization. It provides information on the diverse job positions held by the survey respondents and their seniority level. Additionally, the
operating area, operating nature, and number of employees are presented.

Among the respondents, the most common roles are CEO (10.9%), Managing Director (7.8%), CTO (7%), and Project Manager (6.3%). The other common roles include COO, Manager, Team Leads, and Technical Leads (see Table D1 for more details). It encompasses a spectrum of roles, ranging from executive positions like Managing Director to technical roles such as Software Engineer and Technical Lead. Additionally, it highlights the presence of project management positions like Project Manager and Director of Project Management, as well as managerial roles like HR Manager and Engineering Manager. Specialized roles such as Data Science Lead, DevOps Engineer, and Product Manager further enrich the array of expertise within the survey sample. This diversity underscores the significance of their collective insights in evaluating the expectations and prerequisites for entry-level programming positions, enhancing the robustness of the study’s findings. In this table, the group ‘others’ that accounts for 64.06% includes other 82 items that were inputted by the respondents. Some of these roles are Director, Head of Developer Team, Head of Operations, Team Lead, and Team Manager, among others (See Table D1 for details). Table 5 also depicts the distribution of survey respondents across three leadership or management levels within organizations. The largest group consists of Senior level professionals, representing 66.4% of the total respondents followed by Mid-level professionals (32.0%), while Entry level professionals constitute the smallest segment, with just 1.6%. This distribution underscores the predominance of senior-level expertise in the survey, enriching the study with extensive insights and experiences.

Similarly, the respondents were asked about the total years of experience in their current position, and total years of experience in the IT-related sector. Table D2 (see Appendix) provides a comprehensive overview of the survey respondents' years of experience, focusing on both managerial/leadership roles and their overall tenure in IT-related companies. In terms of managerial/leadership experience, the mean is 5.6 years. However,
the data also reveals a standard deviation of 3.4, suggesting that some respondents have significantly more or less experience in managerial positions. The 75th percentile suggests that 25% have 7 or more years of experience in a leadership/managerial role. The range spans from a minimum of 1 year to a maximum of 18 years, reflecting the diversity in experience levels. Similarly, for the total years in IT-related companies, the mean was 9.6 years. It exhibits a slightly higher standard deviation of 4.38, indicating a somewhat wider spread of experience levels.

Respondents were asked a few questions about the details of the organization. Two of these questions were related to the operations of the organization; area (internationally or just in Nepal) and nature (what kind of software development activities they are mostly involved in). The remaining questions dealt with employee details such as the total number of employees and total programming employees. Table 5 illustrates that most of the respondent companies (57%) work internationally while 43% of the companies operate only within Nepal. Regarding the nature of the operation and the services they provide, most of the respondent companies (71.1%) work in product development (e.g., developing apps, websites, etc.), the second highest (17.2%) being SaaS providers (e.g., accounting systems, billing system, etc.) Others comprise 11.7% (See Table D3 for details).

Table 5 also provides insights into the distribution of total employees within the surveyed organizations, differentiating between the total number of employees and those specifically in programming roles. Most organizations (76.56%) have 0-50 total employees. While considering the total number of employees in programming roles, most organizations (89.06%) have 0-50 programming employees. On average, these organizations have approximately 64.90 employees, while the median value, at 19.50, suggests that half of the organizations have fewer than 20 employees (see Table D4 for details). The relatively high standard deviation of 115.12 signifies a wide spread of employee counts. The average of programming employees is notably lower at 25.16, with a median of 12.00, indicating a concentration of organizations with
a smaller programming workforce. The standard deviation is 38.88, suggesting less dispersion compared to the total employee count.

**Educational Qualifications and Background**

Regarding the educational qualifications, they were asked how many of the programming employees in their organization had a Bachelor’s degree or higher. Similarly, respondents were asked to provide answers to questions related to the requirements of educational qualifications and background of the applicants for entry-level programming positions. First, they were asked what was the minimum educational requirement for an entry-level programming role in their organization. They were then asked which is the most hired educational qualification in their organization. Finally, they were asked to rate the requirement of an IT related background.

**Table 6 Percentage of Programming Employees with Bachelor's Level of Education or Higher**

<table>
<thead>
<tr>
<th>Percentage of programming employees</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-30</td>
<td>1</td>
<td>.8</td>
</tr>
<tr>
<td>31-40</td>
<td>3</td>
<td>2.3</td>
</tr>
<tr>
<td>41-50</td>
<td>2</td>
<td>1.6</td>
</tr>
<tr>
<td>51-60</td>
<td>4</td>
<td>3.1</td>
</tr>
<tr>
<td>61-70</td>
<td>1</td>
<td>.8</td>
</tr>
<tr>
<td>71-80</td>
<td>10</td>
<td>7.8</td>
</tr>
<tr>
<td>81-90</td>
<td>29</td>
<td>22.7</td>
</tr>
<tr>
<td>91-100</td>
<td>78</td>
<td>60.9</td>
</tr>
<tr>
<td>Total</td>
<td>128</td>
<td>100.0</td>
</tr>
</tbody>
</table>

The Table 6 illustrates percentage of the programming employees with a Bachelor’s or higher education. More than a third of the respondents indicated that most of their programming employees hold at least a Bachelor’s degree or higher. Furthermore, 22.7% of the respondents specified that a substantial portion, ranging from 81% to 90%, of their programming workforce possesses a Bachelor’s level education or higher. An even more substantial 60.9% of respondents reported that an overwhelming
majority, between 91% and 100%, of their programming employees have attained at least a Bachelor’s degree or a higher level of education. These findings underscore the prevalence of highly educated individuals within the programming workforce, highlighting the significance of educational qualifications in the field.

**Table 7 Educational Qualifications and Background for Entry-level Programmer Positions**

<table>
<thead>
<tr>
<th>Category of Variables</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Minimum Required Educational Level</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Bachelor’s level</td>
<td>71</td>
<td>55.5</td>
</tr>
<tr>
<td>2. Diploma or secondary or equivalent</td>
<td>15</td>
<td>11.7</td>
</tr>
<tr>
<td>3. Training Certification or self-acquired skills</td>
<td>42</td>
<td>32.8</td>
</tr>
<tr>
<td>4. Master’s level or higher</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>5. SEE or equivalent</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td><strong>Most Hired Educational Level</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Bachelor’s level</td>
<td>112</td>
<td>87.5</td>
</tr>
<tr>
<td>2. Diploma or secondary or equivalent</td>
<td>4</td>
<td>3.1</td>
</tr>
<tr>
<td>3. Training Certification or self-acquired skills</td>
<td>2</td>
<td>1.6</td>
</tr>
<tr>
<td>4. Master’s level or higher</td>
<td>1</td>
<td>0.8</td>
</tr>
<tr>
<td>5. SEE or equivalent</td>
<td>8</td>
<td>6.3</td>
</tr>
<tr>
<td><strong>Requirement of an IT-related Educational Background</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not required</td>
<td>8</td>
<td>6.3</td>
</tr>
<tr>
<td>Slightly required</td>
<td>17</td>
<td>13.3</td>
</tr>
<tr>
<td>Moderately required</td>
<td>38</td>
<td>29.7</td>
</tr>
<tr>
<td>Highly required</td>
<td>37</td>
<td>28.9</td>
</tr>
<tr>
<td>Significantly required</td>
<td>28</td>
<td>21.9</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>128</td>
<td>100.0</td>
</tr>
</tbody>
</table>

According to Table 7, among the surveyed organizations, the majority, accounting for 55.5%, demand a Bachelor’s level of education as the minimum qualification for entry-level programmers. In contrast, a smaller percentage of organizations, 11.7%, are open to candidates with a Diploma or secondary education or equivalent qualifications. A significant portion, 32.8%, value Training Certification or self-acquired skills, indicating a willingness to consider individuals who may have acquired relevant skills through non-traditional education or training paths. This diversity in hiring qualifications emphasizes the flexibility and
varying criteria that organizations employ when recruiting entry-level programmers.

Similarly, Table 7 also illustrates that the most hired educational qualification in the companies is Bachelor’s level (87.5%) and the least is SEE (or equivalent) at 0.8%. Applicants with a Master’s (or higher) and applicants with a Diploma (or secondary equivalent) aren’t most hired either. In addition to the qualification, respondents were asked to rate the requirement of an IT-related background for entry-level programming positions. It was done on a 5-point Likert scale, 1 being not required and 5 being significantly required.

According to Table 7, most of the employers agree that an IT related educational background is important. A minority (6.3%) considers it "Not required," indicating openness to diverse backgrounds. A larger group (13.3%) views it as "Slightly required," suggesting some value in such education. The majority (29.7%) falls under "Moderately required," balancing education with practical skills. Another substantial portion (28.9%) deems it "Highly required," and 21.9% find it "Significantly required," making formal education a critical criterion.

**Chapter Summary**

This chapter summarized the related demographic variables of the respondents and the companies they are currently involved in. It presented demographic information on the respondents, such as their roles, seniority levels, and years of experience in managerial and IT positions. Among the respondents, most of them were in senior-level management/leadership positions like CEO, CTO, etc. The organizations were mostly worked internationally. Product development and SaaS were the highest involved sectors of these organizations. The organizations had approximately 65 employees on average and 25 employees in programming-related roles on average. Similarly, it summarizes the data related to the requirements of educational qualifications and background for an entry-level programming position in their company. It presented the minimum required qualification and the most-hired qualification for these positions is Bachelor’s. Furthermore, it
explored the importance of an IT-related educational background for entry-level programming positions and found that most employers agree on the importance of an IT-related background.
CHAPTER V
SKILL MISMATCH

This chapter presents the data about employers’ perception of the KSA (Knowledge, Skills, Attitude) match and what kind of actions are usually taken by them to mitigate the gap. Subsequently, the analysis of skills rating of expectations and observations is presented, both in clustered categories and individually. It also presents the priority rating of skills using importance score. Similarly, mean differences of expectations and observations including an average gap analysis have been tabulated to analyze the skills with high importance and high gaps using the Ranked Discrepancy Score model and a gap analysis framework. Finally, the statistical significance of the mean differences has been calculated using various inferential tools. Additionally, it also presents the significance test of association of the differences among different applicant types based on their educational qualification.

Perception of KSA (Knowledge, Skills, and Attitude) Match

The respondents were asked “To what extent you do agree that in general, the applicants meet the core competencies as demanded by the entry-level programming job?”, 1 being strongly disagree and 5 being strongly agree. Though the subsequent ratings would provide us with a nuanced picture of the skill mismatch issue, this question provided a pre-analysis of employers’ perceptions.
Table 8 Employers’ Perception of KSA Match

<table>
<thead>
<tr>
<th>Rating</th>
<th>Knowledge</th>
<th>Skills</th>
<th>Attitude</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>%</td>
<td>n</td>
</tr>
<tr>
<td>No Match</td>
<td>5</td>
<td>3.9</td>
<td>12</td>
</tr>
<tr>
<td>Slightly Matched</td>
<td>10</td>
<td>7.8</td>
<td>30</td>
</tr>
<tr>
<td>Moderately Matched</td>
<td>52</td>
<td>40.6</td>
<td>45</td>
</tr>
<tr>
<td>Highly Matched</td>
<td>52</td>
<td>40.6</td>
<td>32</td>
</tr>
<tr>
<td>Significantly Matched</td>
<td>9</td>
<td>7.0</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>128</td>
<td>100.0</td>
<td>128</td>
</tr>
</tbody>
</table>

The analysis of Table 8 sheds light on employers' perceptions of how well applicants match the Knowledge, Skills, and Attitude (KSA) expectations for entry-level programming positions. Very few respondents, only 7%, believe that the applicants significantly matched the KSA expectations. In terms of attitude, a low percentage (7.8%) of respondents said that applicants highly matched the attitude expectation, while a significant 40.6% believed that applicants highly matched the knowledge requirement and 25% felt that they highly matched the skills requirement.

The distribution of responses for knowledge is quite balanced. An equal number of respondents, 40.6%, indicated that applicants moderately and highly meet the knowledge expected for entry-level programming jobs. However, the perception of skills was more varied. As per the table, the majority (35.2%) saw applicants as moderately meeting skill requirements, while roughly a quarter perceived either slight or high skill match. In terms of attitude, the distribution is more varied. A significant proportion, 37.5%, of respondents believed that applicants moderately meet the attitude required for entry-level programming jobs. About 26.6% felt that applicants slightly met the attitude requirement. However, a notable 21.1% of respondents believed that applicants do not meet the attitude expectations for these jobs.

This analysis reflects the perceptions of employers regarding the match of applicants' KSA with the expectations for entry-level programming positions. It suggests that while knowledge and skills are perceived more positively, there are concerns regarding
attitude, with a notable proportion of respondents feeling that applicants fall short in this aspect. To further understand this dynamic, the respondents were asked to rate the actions that could potentially address the mismatch issue of entry-level programming jobs. Respondents indicated their agreement level on a five-point Likert scale with an option for ‘Not applicable’. The results are given in Table 9.

### Table 9 Actions Needed to Address the Mismatch Issue of Entry-level Programming Jobs

<table>
<thead>
<tr>
<th>Actions</th>
<th>Mean</th>
<th>Not applicable (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Provide training and development</td>
<td>4.67</td>
<td>1</td>
</tr>
<tr>
<td>Provide exposure visits</td>
<td>3.99</td>
<td>22</td>
</tr>
<tr>
<td>Hire foreign employees</td>
<td>2.6</td>
<td>22</td>
</tr>
<tr>
<td>Outsource work</td>
<td>3.13</td>
<td>13</td>
</tr>
<tr>
<td>Undertake only capacity work</td>
<td>3.32</td>
<td>4</td>
</tr>
<tr>
<td>Offer higher remuneration</td>
<td>3.25</td>
<td>7</td>
</tr>
</tbody>
</table>

*Note: N = 128*

Based on Table 9, notably, there is a strong consensus among respondents who agree that “providing training and development” is a crucial solution with the highest mean value of 4.67 with only one respondent indicating that it isn’t applicable while hiring foreign employees with the lowest mean of 2.4 is the least favorable action to reduce the skill gap. Similarly, “providing exposure visits” is the second highest favorable action. However, many of the other respondents didn’t find it applicable at all indicating a mixed response. Outsourcing work, undertaking only capacity work, and offering higher remuneration received an approximately neutral response. This highlights the complexity of addressing the skills mismatch issue, with training and development being the most favored strategy among respondents.

### Skills Rating

The questionnaire administered to assess skills for entry-level programming positions included a comprehensive range of 45 skills categorized into four distinct sets: technical skills, personal skills, interpersonal skills, and portfolio requirements containing 22, 14, 5, and 4 variables in each respectively. The ratings were done in pairs of expectation ratings and observation ratings for all the
skills. For each set, the average was calculated to compare them on a uniform scale.

**Expectations and Observations**

The expectations and observations rating provided by the respondents were grouped into four categories and an average for each group was calculated. Table 10 below presents the mean distribution of the expectations and observations.

**Table 10 Average Ratings of Skills Expected and Observed for Entry-level Programming Positions**

<table>
<thead>
<tr>
<th>Categories</th>
<th>Mean of average of expectations</th>
<th>Std. deviation</th>
<th>Mean of average of observations</th>
<th>Std. deviation</th>
<th>Mean difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical</td>
<td>3.27</td>
<td>.66</td>
<td>2.72</td>
<td>.68</td>
<td>0.55</td>
</tr>
<tr>
<td>Personal</td>
<td>3.99</td>
<td>.57</td>
<td>3.02</td>
<td>.84</td>
<td>0.96</td>
</tr>
<tr>
<td>Interpersonal</td>
<td>3.28</td>
<td>.80</td>
<td>2.6</td>
<td>.94</td>
<td>0.67</td>
</tr>
<tr>
<td>Portfolio</td>
<td>3.38</td>
<td>.89</td>
<td>2.66</td>
<td>.99</td>
<td>0.72</td>
</tr>
</tbody>
</table>

The data in Table 10 reveals that employers hold moderately high expectations for technical skills, with an average expectation score of approximately 3.27, while observations show that candidates fall slightly short of these expectations, with an average score of approximately 2.72. For personal skills, employers have notably higher expectations, averaging around 3.99, whereas observations indicate a wider variability among candidates, with an average score of approximately 3.02. Similarly, employers moderately expect strong interpersonal skills, averaging around 3.28, while observations reveal more diverse interpersonal skill levels, averaging around 2.6. Expectations for portfolio are relatively high, with an average expectation score of approximately 3.38, but observations demonstrate considerable variability, with an average score of around 2.66.

From Table 10, we can also observe that the standard deviations for "Average of personal related skills observations" and "Average of interpersonal related skills observations" are relatively
high, with values of approximately 0.84 and 0.94, respectively. This implies that there is significant variability in how respondents perceive the personal and interpersonal skills of entry-level programmer candidates based on their observations. In other words, there is less consensus among employers when it comes to assessing these skills. On the other hand, the standard deviations for "Average of technical related skills observations" and "Average of portfolio related observations" are somewhat lower, indicating a relatively narrower range of opinions or ratings among respondents for technical and portfolio.

Skill Discrepancy

The main purpose of this study was to explore the possible mismatch of skill i.e., if the applicants for entry-level programming positions do have the skills as required/expected by the employers. To get a general idea of the possible discrepancy, a difference in the means of expectations and observations was calculated.

In this process of exploring the skill mismatch, first, the mean difference of averages of expectation and observations rating was calculated for each skill category. Table 10 presents the mean difference of average skill ratings between expectations and observations for various skill categories in entry-level programmer candidates. The table indicates the extent to which employers' expectations align with the observed skills of candidates. The largest mean difference is observed in personal-related skills, with a substantial gap of 0.96, indicating that employers have significantly higher expectations for these skills compared to what is observed in candidates. This suggests that there may be a notable disparity between what employers' desire in terms of personal skills, such as communication and problem-solving, and the actual abilities of candidates in this category. Similarly, interpersonal-related skills exhibit a mean difference of 0.67, indicating that employers' expectations in this area are moderately higher than what they observe in candidates. Technical skills have a relatively smaller mean difference of 0.55, suggesting that employers' expectations are somewhat closer to what they observe in candidates. Finally, portfolio related items show a mean difference of 0.72, indicating that employers have moderately higher
expectations for these skills compared to observations. These findings underscore the importance of aligning expectations with observed skills and may inform strategies for candidate evaluation and skill development programs.

The mean differences between expected and observed skill ratings for various individual technical, personal, and interpersonal skills, and portfolio provide a more nuanced analysis (see Table D5). A range of mean differences has been observed. For most of the skills, positive mean differences were observed i.e., observations lower than expected. However, for “Windows OS” and “Hardware troubleshooting and maintenance”, it is negative meaning the expectation is low for these skills. The skills which demonstrated a considerable positive mean difference (>1) i.e., lower observations include: Version management tools, Testing and Test-driven development, learning attitude, Working independently, Motivation, Problem-solving, Professionalism, Ownership, Time management, and Collaboration. It is also noteworthy that most of these skills with substantial positive differences fall under the “Personal skills” category.

**Association of Expectations and Observations among Different Skill Categories**

As observed in Table 10, it can be noted that the mean of the average of expectations is considerably higher than the mean of the average of expectations for all the skill categories. The next matter of interest would be to check if there is an association of expectations among different skill categories within the expectations. For example, when employers have high expectations of technical skills, do they also have high expectations for personal skills?
Table 11 Correlation among Average Expectation Ratings of Different Skill Categories

<table>
<thead>
<tr>
<th>Skill categories</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expectations</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Technical</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>2. Personal</td>
<td>.596*</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>3. Interpersonal</td>
<td>.415*</td>
<td>.494*</td>
<td>1</td>
</tr>
<tr>
<td>Observations</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Technical</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>2. Personal</td>
<td>.683*</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>3. Interpersonal</td>
<td>.570*</td>
<td>.772*</td>
<td>1</td>
</tr>
</tbody>
</table>

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

The correlation analysis between different skill categories' expectations, as shown in Table 11, revealed that there was a positive correlation among all pairs of skills. It means employers who had higher expectations for technical skills tended to have correspondingly higher expectations for personal skills and interpersonal skills. Similarly, employers with higher expectations for personal skills also had higher expectations for technical and interpersonal skills. The Pearson coefficient lies between 0.3 to 0.7 which indicates a moderate strength of correlation. This correlation is significant at a 0.001 significance level.

Similarly, according to Table 11, the correlation analysis among different skill categories' observations highlighted positive relationships between the ratings of these categories. Specifically, employers who observed higher possession of technical skills also observed higher personal and interpersonal skills correspondingly higher. Similarly, employers who observed higher for personal skills observed higher for technical skills and interpersonal. The Pearson coefficient is between 0.3 to 0.7 for the correlation between personal and technical as well as technical and interpersonal skills, which suggests a moderate relationship. Additionally, for personal and interpersonal skills, the coefficient is > 0.7 which indicates a strong relationship. It suggests that when employers observe personal skills in applicants, their interpersonal skills observations tend to be higher as well. These findings underscore a consistent pattern where employers who observe higher competency levels in one skill category are likely to observe higher competency levels in
other skill categories, indicating a consistent and coherent approach to evaluating candidates' observed skills in entry-level programming positions.

**Statistical Significance of the Mean Differences**

It has been established that there is a mean difference in expectation versus observations of different skill categories. To test the statistical significance of this mean difference, a parametric test needs to be conducted. To adopt the t-test as the parametric test for the purpose of this study, certain assumptions need to be fulfilled. The prerequisites for conducting a t-test encompass having measurements on either ratio or interval scales, obtaining a sample through simple random sampling, ensuring the data follows a normal distribution, maintaining an adequate sample size, and ensuring homogeneity of variance (Kim & Park, 2019). The t-test is to be conducted on the average skill ratings of expectations and observations of different skill categories, which are scale data. Similarly, for the individual skill variables, a Likert scale has been used which can be treated as an interval measure. Thus, it meets the first assumption. Secondly, the study used random sampling to select a list of respondent companies from a given list, which is acceptable for a t-test. Thirdly, the sample size of 128 (> 30) is acceptable for this study. The two others are assumptions of homogeneity of variance and test of normality.

According to Kwak and Kim (2017), the central limit theorem states that “if the sample size is sufficiently large, the means of samples obtained using a random sampling with replacement are distributed normally with the mean and the variance regardless of the population distribution” (p. 145-146). Therefore, some sources recommend that when each group's sample size is substantial, the t-test can be used without the need for a normality test (Kim & Park, 2019). Mishra et al. (2019) agree and state that for medium-sized samples between 50 and 300, the distribution of the sample can be concluded to be normal. However, Kim & Park (2019) recommend that even if the sample size is sufficient, the normality test needs to be conducted first. The normality was tested using Skewness and Kurtosis (Table D6 and Table D7).
The normality assumption is fulfilled when the skewness coefficient is within the range of ±2 and the kurtosis coefficient is within the range of ±7 (Byrne, 2010, as cited in Demir, 2022). As per Table D6, the test of normality using skewness and kurtosis suggests that the average ratings of skill expectations and observations in the technical, personal, and interpersonal skill categories and portfolio do not significantly deviate from a normal distribution. The skewness and kurtosis values for these skill categories fall within a range that is indicative of normality i.e., the skewness coefficient is within the range of ±2 and the kurtosis coefficient is within the range of ±7 (Demir, 2022). Similarly, to test the normality of individual items within each skill category, the skewness and the kurtosis values were calculated (see Table D7). The skewness and kurtosis values for each skill item fall within an acceptable range as discussed earlier and suggest no significant deviation from a normal distribution. Thus, a paired sample \(t\)-test can be used to test the statistical significance of the difference observed in different skill ratings of expectations versus observations for each skill item.

For the last assumption on the homogeneity of variance, Levene's test for variance homogeneity is more commonly used when you are conducting independent samples \(t\)-tests or analysis of variance (ANOVA) to compare the means of two or more independent groups. However, for the purpose of this study we are comparing paired samples (skills expected versus skills observed), the variance within each group is implicitly controlled because the skills ratings are paired. Therefore, violations of the assumption of equal variances in the paired samples \(t\)-test are less of a concern (Lehman et al., 2013; Newcastle University, 2023). Thus, a paired sample \(t\)-test can be used to test the statistical significance of the mean difference observed in different average skill ratings of expectations versus observations.
Table 12 presents the results of paired sample t-tests for different skill categories' average ratings, specifically the difference between average expectation ratings and observation ratings. In each pair, the mean difference between the average expectation ratings and observation ratings is positive, indicating that, on average, the expectation ratings are higher than the observation ratings across all skill categories. The t-statistics are quite large for all pairs, which suggests a significant difference between the two sets of ratings. The p-values (Sig. 2-tailed) for all pairs are very close to zero (p < 0.05), indicating strong evidence to reject the null hypothesis. Hence all the hypotheses H01, H02, and H03 are rejected. This means that the observed differences between expectation and observation ratings are statistically significant. In summary, the results of these paired sample t-tests suggest that there are statistically significant differences between the average expectation ratings and observation ratings in each skill category. This indicates a consistent pattern where employers tend to rate applicants' skills higher in their expectations compared to what they observe in practice.

Similarly, paired sample t-tests were conducted for the expectations and observations ratings of each skill under each skill category (see Table D8). The results are described below.

**Technical Skills**

In the analysis of paired sample t-tests comparing employers' expectations with their observations of technical skills in applicants for entry-level programming positions, several technical skills stand out as significant (see Table D8). Skills such as Unix/Linux OS, command line interface, basic concepts of
programming, skill, and knowledge in at least one programming language, object-oriented programming, data structures, database modeling, database query language, system analysis and design, design patterns, version management tools, testing, and test-driven development, how the web works, and recent trends in software development all exhibit highly significant differences. Employers have significantly higher expectations for these skills compared to what they observe in applicants. On the other hand, basic computer literacy, Windows OS, hardware troubleshooting and maintenance, as well as computer networking, show no significant differences, meaning that employers' expectations align closely with their observations in these areas. These findings indicate where there may be gaps between employers' expectations and the actual skills demonstrated by applicants, highlighting areas for potential improvement in the hiring process or the skills development of candidates.

**Personal Skills**

In the evaluation of paired sample t-tests comparing employers' expectations with their observations of personal skills in applicants for entry-level programming positions, a consistent pattern of significance emerges (see Table D8). Across all personal skills, including oral communication (in any language), written communication (in any language), oral communication (in the English language), written communication (in the English language), active listening, critical thinking, creative thinking, problem-solving, learning attitude, working independently, motivation, professionalism, ownership, and time management, there are highly significant differences. Employers consistently have significantly higher expectations for these personal skills compared to what they observe in applicants. This indicates a notable gap between what employers anticipate in terms of personal skills and the actual skills demonstrated by candidates, suggesting that there may be opportunities for enhancing skill development and aligning expectations in the hiring process.
Interpersonal Skills

In the assessment of paired sample $t$-tests for interpersonal skills in applicants for entry-level programming positions, it is evident from Table D8 that employers consistently have significantly higher expectations than what they observe in candidates. This significant gap is observed across various interpersonal skills, including project management, collaboration, conflict management, relationship management, and organizational culture fit. The $t$-test results reveal that employers' expectations significantly outweigh their observations for all these skills. This implies that applicants generally fall short of employers' expectations in the realm of interpersonal skills, suggesting that there is room for improvement and alignment between employer expectations and applicant performance in these areas.

Portfolio Requirements

The paired sample $t$-tests for various portfolio requirements in candidates for entry-level programming positions reveal a consistent pattern of employers holding significantly higher expectations than what they observe in applicants (see Table D8). This trend is observed across different aspects, including professional CVs and cover letters, personal or college projects, project demonstrations, and previous work or internship experience. In each case, employers anticipate a more substantial alignment with their expectations, but the $t$-tests consistently indicate a significant difference, indicating that most applicants do not meet these expectations. This finding underscores the need for candidates to enhance these aspects of their profiles to better align with employer expectations during the hiring process.

Priority Rating of Skill Expectations

Importance score was used for the purpose of finding the most important skills among the 45 skill items. The importance score was calculated by multiplying the frequency of each rating by the rating value (1 to 5) and summing the values. For example, learning attitude had 0 ratings for No expectation, 0 ratings for slight expectation, 4 ratings for moderate expectations, 29 ratings
for high expectation, and 95 ratings for significant expectation. The importance score was calculated as $0\times1 + 0\times2 + 4\times3 + 29\times4 + 95\times5 = 603$. The importance score percentage was calculated by dividing the importance score by the total possible score i.e. $603/640 = 94.22\%$. The mean is just the importance score divided by the number of respondents i.e., $603/128 = 4.71$. Based on the expectation rating provided by the respondents, the importance score was calculated for each skill. Table 13 presents the importance score, importance score percentage, and mean of different 20 skills sorted from highest to lowest (see Table D9 for details).

**Table 13 Priority Rating Calculation for Individual Skills’ Expectations**

<table>
<thead>
<tr>
<th>Expectations</th>
<th>Importance rating</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>IS</th>
<th>IS %</th>
<th>$\bar{x}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning attitude</td>
<td></td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>29</td>
<td>95</td>
<td>603</td>
<td>94.22%</td>
<td>4.71</td>
</tr>
<tr>
<td>Basic concepts of programming</td>
<td></td>
<td>1</td>
<td>2</td>
<td>16</td>
<td>32</td>
<td>77</td>
<td>566</td>
<td>88.44%</td>
<td>4.42</td>
</tr>
<tr>
<td>Time management</td>
<td></td>
<td>0</td>
<td>3</td>
<td>16</td>
<td>44</td>
<td>65</td>
<td>555</td>
<td>86.72%</td>
<td>4.34</td>
</tr>
<tr>
<td>Basic computer literacy</td>
<td></td>
<td>4</td>
<td>4</td>
<td>15</td>
<td>31</td>
<td>74</td>
<td>551</td>
<td>86.09%</td>
<td>4.30</td>
</tr>
<tr>
<td>Motivation</td>
<td></td>
<td>0</td>
<td>2</td>
<td>15</td>
<td>55</td>
<td>56</td>
<td>549</td>
<td>85.78%</td>
<td>4.29</td>
</tr>
<tr>
<td>Skill and knowledge in at least one programming language</td>
<td></td>
<td>1</td>
<td>6</td>
<td>17</td>
<td>36</td>
<td>68</td>
<td>548</td>
<td>85.63%</td>
<td>4.28</td>
</tr>
<tr>
<td>Professionalism</td>
<td></td>
<td>1</td>
<td>3</td>
<td>22</td>
<td>49</td>
<td>53</td>
<td>534</td>
<td>83.44%</td>
<td>4.17</td>
</tr>
<tr>
<td>Ownership</td>
<td></td>
<td>2</td>
<td>8</td>
<td>22</td>
<td>40</td>
<td>56</td>
<td>524</td>
<td>81.88%</td>
<td>4.09</td>
</tr>
<tr>
<td>Organizational culture fit</td>
<td></td>
<td>2</td>
<td>3</td>
<td>23</td>
<td>54</td>
<td>46</td>
<td>523</td>
<td>81.72%</td>
<td>4.09</td>
</tr>
<tr>
<td>Working independently</td>
<td></td>
<td>1</td>
<td>9</td>
<td>28</td>
<td>39</td>
<td>51</td>
<td>514</td>
<td>80.31%</td>
<td>4.02</td>
</tr>
<tr>
<td>Active listening</td>
<td></td>
<td>0</td>
<td>3</td>
<td>34</td>
<td>50</td>
<td>41</td>
<td>513</td>
<td>80.16%</td>
<td>4.01</td>
</tr>
<tr>
<td>Problem solving</td>
<td></td>
<td>1</td>
<td>4</td>
<td>35</td>
<td>41</td>
<td>47</td>
<td>513</td>
<td>80.16%</td>
<td>4.01</td>
</tr>
<tr>
<td>Collaboration</td>
<td></td>
<td>2</td>
<td>9</td>
<td>27</td>
<td>38</td>
<td>52</td>
<td>513</td>
<td>80.16%</td>
<td>4.01</td>
</tr>
<tr>
<td>Oral communication (in any language)</td>
<td></td>
<td>3</td>
<td>6</td>
<td>30</td>
<td>45</td>
<td>44</td>
<td>505</td>
<td>78.91%</td>
<td>3.95</td>
</tr>
<tr>
<td>Object oriented programming</td>
<td></td>
<td>2</td>
<td>13</td>
<td>29</td>
<td>46</td>
<td>38</td>
<td>489</td>
<td>76.41%</td>
<td>3.82</td>
</tr>
<tr>
<td>Critical Thinking</td>
<td></td>
<td>1</td>
<td>8</td>
<td>38</td>
<td>48</td>
<td>33</td>
<td>488</td>
<td>76.25%</td>
<td>3.81</td>
</tr>
<tr>
<td>Windows OS</td>
<td></td>
<td>8</td>
<td>7</td>
<td>34</td>
<td>34</td>
<td>45</td>
<td>485</td>
<td>75.78%</td>
<td>3.79</td>
</tr>
<tr>
<td>How the web works</td>
<td></td>
<td>5</td>
<td>12</td>
<td>31</td>
<td>38</td>
<td>42</td>
<td>484</td>
<td>75.63%</td>
<td>3.78</td>
</tr>
<tr>
<td>Written communication (in any language)</td>
<td></td>
<td>2</td>
<td>8</td>
<td>38</td>
<td>51</td>
<td>29</td>
<td>481</td>
<td>75.16%</td>
<td>3.76</td>
</tr>
<tr>
<td>Creative Thinking</td>
<td></td>
<td>1</td>
<td>8</td>
<td>44</td>
<td>44</td>
<td>31</td>
<td>480</td>
<td>75.00%</td>
<td>3.75</td>
</tr>
</tbody>
</table>

*Note: 1 = Not required, 2 = Slightly required, 3 = Moderately required, 4 = Highly required, 5 = Significantly required, IS = Importance score, IS % = Importance score percentage, $\bar{x}$ = Mean*
In overall, the top ten skills with the highest importance score were Learning attitude, Basic concepts of programming, Time management, Basic computer literacy, Motivation, Skill and knowledge in at least one programming language, Professionalism, Ownership and Organizational culture fit. It is noteworthy that, out of the top ten, five belong to personal skills, four belong to technical skills and one belongs to the interpersonal category. Based on the detailed importance ranking in Table D9, In the technical skills category, the top five important skills were Basic concepts of programming, Basic computer literacy, Skill and knowledge in at least one programming language, Object-oriented programming, and Windows OS. In the personal skill category, the top five were Learning attitude, Time management, Motivation, Professionalism, and Ownership. In the interpersonal skills category, the top important was Organizational culture fit while Personal or college projects were the most important in portfolio expectations. If we look at the top 20 skills, we find that 70% of them (12) are from the personal skills category, 6 from technical, and 2 from the interpersonal skills category. It has been found that soft skills (personal plus interpersonal) are the most important according to the employers’ expectations rating. The top ten least important skills according to the employers were Relationship Management, Previous work or internship experience, Conflict Management, Project Management, Design patterns, System analysis and design, Documentation tools, Project management tools, Hardware troubleshooting and maintenance, and Computer networking.

**Discrepancy Categorization**

For the purpose of this study, it is of interest to find which skills among the 45 rates skills have the highest discrepancies. This could be easily done by sorting the mean differences from highest to lowest, thereby giving us a list of the top ten skills with the highest mean difference, for example. However, Narine and Harder (2021) suggested the use of a Ranked Discrepancy Score (RDS) model to categorize the discrepancy and prioritize the skill with the highest discrepancies as such. RDS model uses the ranks (positive, negative, and ties) to assign weights to the items, unlike the mean.
difference calculation where each item has equal weight. The formula given by Narine and Harder (2021) has been used to calculate the RDS value. The negative RDS values indicate a significant gap, while positive RDS values suggest the absence of a gap or need. The value is then categorized based on adapted categories of Robinson and Garton (2008). a) High gap with aa RDS greater than -80 b) Mid gap with an RDS ranging from -50 to -79 c) Low gap with an RDS ranging from -30 to -49 d) Negligible gap with an RDS less than. In this way, the RDS model has been used to find which skills have significant gaps and sort them from highest to lowest.

**Table 14 Ranked Discrepancy Score Calculation of Average Skill Rating**

<table>
<thead>
<tr>
<th>Expectations and observations</th>
<th>Wilcoxon signed rank</th>
<th>Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Negative ranks (NR)</td>
<td>Positive ranks (PR)</td>
</tr>
<tr>
<td>Technical Skills</td>
<td>104</td>
<td>21</td>
</tr>
<tr>
<td>Personal Skills</td>
<td>105</td>
<td>18</td>
</tr>
<tr>
<td>Interpersonal Skills</td>
<td>95</td>
<td>19</td>
</tr>
<tr>
<td>Portfolio</td>
<td>88</td>
<td>23</td>
</tr>
</tbody>
</table>

Note: N = 128; RDS = NR% x (-1) + PR% x (1) + TR% x (0) (Narine & Harder, 2021)

Based on Table 14, for all the skill categories, the RDS falls within Category II (Mid), indicating a substantial gap where employers have significantly higher expectations than what is observed. This suggests a consistent pattern of skill mismatch across various skill categories in the data, highlighting the need for alignment between employer expectations and candidate performance. The largest discrepancy identified by the RDS was for personal skills followed by technical skills and interpersonal skills. Portfolio expectations had the lowest gap as per the RDS.

Similarly, the RDS calculation was done for each skill (see Table D10). From Table D10 for RDS calculation and discrepancy categorization, it can be observed that most of the skills (18 out of 45) fall in the mid discrepancy category while 16 skills fall under the low discrepancy and 11 under the negligible category. No skills fall under the high discrepancy category. In the technical skills
category, the distribution is almost equal among mid, low, and negligible categories. The discrepancy is most notable in the case of personal skills where 10 out of 14 skills are in the mid discrepancy category. Interpersonal skills primarily fall within the low to mid categories, indicating moderate to low gaps. For portfolio expectations, a substantial number falls within the low category, with some skills categorized as negligible. It suggests that for a substantial number of skills in the personal and technical skills category, there exists a gap between what is expected and observed skills.

In the category of technical skills, the top five with gaps (highest to lowest) according to the RDS value are Basic concepts of programming, Testing and Test-driven development, Data Structures, Database modeling, and Object-oriented programming. Similarly, for the personal skills category, the top five are Learning attitude, Time management, Ownership, Problem solving, and Professionalism. Organizational culture fit has the greatest gap in the interpersonal category and Project demo has the greatest gap in the portfolio expectations category. From an overall perspective, the top ten skills with the highest gaps were Learning attitude, Time management, Ownership, Problem-solving, Professionalism, Motivation, Critical Thinking, Working independently, Basic concepts of programming and Testing and, Test-driven development. It is also noteworthy that eight out of the top ten are related to the personal skills category.

**Average Gap Analysis**

To get a more nuanced analysis of the average gaps, scatter plots were created to present a visual illustration of average gap (expectations versus observations) values versus their importance score. The average importance has been calculated using the importance score converted to a 0 to 1 scale. The importance score calculated in Table D9 has been divided by 5 (the highest Likert point of this study) to get the average importance thus converting it into a 0 to 1 scale to be used in the scatter plot. On the other hand, the average discrepancy or gap is based on the RDS model by Narine and Harder (2021), as discussed earlier. The average
importance is plotted on the X-axis, and the average gap is plotted on the Y-axis. Four quadrants with low/high importance and low/high gap have been created from the scatter plots (Figure 10).

**Figure 10 Average Gap Analysis Framework**

![Diagram showing four quadrants with labels: Q1 - Low importance, low gap; Q2 - Low importance, high gap; Q3 - High importance, low gap; Q4 - High importance, high gap.](image)

Source: Garousi et al. (2019)

As shown in the framework above (Figure 10) adapted from Garousi et al. (2019), Q1 represents low importance and low gap, Q2 represents low importance and high gap, Q3 represents high importance and low gap, Q4 represents high importance and high gap. Similarly, the average importance and average gap were plotted on the four-quadrant scatter plot for each skill of the four categories to understand which of the skills fall in which category.

Figure E1 shows that out of the 22 technical skills assessed, 8 skills fall in the quadrant Q4 i.e., high importance and high gap. It suggests that these are the ones that should be considered the most in decreasing the skill discrepancy for the technical category (see Table D11 for details). These skills are Basic concepts of programming, Skill and knowledge in at least one programming language, Object-oriented programming, Data Structures, Database...
modeling, Database query language, Version management tools, and Testing and test-driven development. It is also noteworthy that two of the skills (Computer Networking and Hardware maintenance) fall in the low importance and low gap, suggesting these skills need not be prioritized for programming positions.

Figure E2 shows the average gap analysis of personal skills. Out of 14 personal skills, 10 i.e., more than 70% of the skills fall in the Q4 quadrant. Thus, it is evident that most of the personal skills are of high priority but have higher gaps, suggesting a careful consideration of how these skills need to be imparted to the students (see Table D12 for details). These skills include Learning attitude, Time management, Ownership, Problem-solving, Professionalism, Motivation, Working independently, Active listening, Critical thinking, and Creative thinking. Among these, learning attitude, time management, and ownership are the top three personal skills with high importance but high gaps. It was also found that communication skill (oral and written) in both English or any language wasn’t found to have a major gap though it was considered important. This contrasts with other research that found large gaps in communication.

Figure E3 shows that out of 5 interpersonal skills, two skills viz. collaboration and organizational culture fit are of high importance but with high gaps (see Table D13 for details). This is in concurrence with what experts and previous researchers have mentioned. Particularly, experts mentioned organizational culture fit was crucial for the company. Similarly, project management, conflict management, and relationships were found to be of high importance but there were no gaps in observations. It must be noted that the importance rating in these skills was very low compared to other skills. This necessitates further research into how gaps weren’t observed in such complex skills.

In terms of Portfolio expectations, Figure E4 shows that none fall in Q4 suggesting these expectations are of high priority but comparatively with fewer gaps. It is noteworthy that the Project demo and projects are close to the original line. Thus, it can be inferred that these two have considerably higher gaps and need to be prioritized (see Table D14 for details).
High Importance, High Gaps

Based on the average gap analysis above, the items with high importance and high gaps are particularly important because they signify critical areas where there is a substantial misalignment between the skills expected by employers and the skills possessed by IT graduates. These are the skills that need to be prioritized for decreasing the skill discrepancy. These items with high importance but high gaps are tabulated in Table 15.

**Table 15 Items with High Importance and High Gaps**

<table>
<thead>
<tr>
<th>Technical</th>
<th>Personal</th>
<th>Interpersonal</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Basic concepts of programming</td>
<td>1. Learning attitude</td>
<td>1. Organizational culture fit</td>
</tr>
<tr>
<td>2. Skill and knowledge in at least one programming language</td>
<td>2. Time management</td>
<td>2. Collaboration</td>
</tr>
<tr>
<td>3. Object-oriented programming</td>
<td>4. Problem-solving</td>
<td></td>
</tr>
<tr>
<td>5. Database modeling</td>
<td>7. Working</td>
<td></td>
</tr>
<tr>
<td>6. Database query language</td>
<td>8. Active listening</td>
<td></td>
</tr>
<tr>
<td>8. Testing and test-driven development</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Based on Table 15, it can be noted that eight technical skills among 22 have been considered of high importance by employers but have been found to have higher gaps. Similarly, more than 70% of the personal skills and 2 interpersonal skills fall into this category of discrepancy. However, there were no items from portfolio expectations that fall into this category. Similarly, details of other discrepancy categorizations of each item (high importance-low gap, low importance-high gap, low importance-low gap) are presented in Table D11, Table D12, Table D13, and Table D14.

Curriculum Mapping

To further understand the 20 skills with high importance and high gaps, they were cross-checked with the curriculum of eight different courses (discussed earlier as well) which is presented in Table 16. It was important to check if the curriculum was missing
anything in providing and equipping students with the requisite skills and knowledge.

Table 16 Mapping of Skills into the Curriculum of IT Courses

<table>
<thead>
<tr>
<th>Skills</th>
<th>Possible related topics in IT courses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic concepts of programming and Skill and knowledge in at least one programming language</td>
<td>Fundamentals of Programming, C Programming, C++ Programming Language, Programming Logic and Techniques, Java Programming, Web Technologies I &amp; II, Labs</td>
</tr>
<tr>
<td>Object-oriented programming</td>
<td></td>
</tr>
<tr>
<td>Database modeling and database query language</td>
<td>Database Management System, Relational Database Design, System Analysis and Design, Software Engineering,</td>
</tr>
<tr>
<td>Testing and test-driven development</td>
<td></td>
</tr>
<tr>
<td>Professionalism, Motivation, Working independently, Active listening,</td>
<td></td>
</tr>
<tr>
<td>Critical thinking, Creative thinking, Collaboration</td>
<td></td>
</tr>
<tr>
<td>Organizational culture fit</td>
<td>Internship, Organization Management, Organizational Structure Systems, Project Communication Management, Professional Issues, Ethics and Computer Law,</td>
</tr>
</tbody>
</table>

Table 16 presents a mapping of different high-importance and high-gap skills with the curriculum of IT courses taught in Nepal. The curricula of such eight courses were used for this
purpose. It is considerably difficult to map the topics with soft skills because soft skills can’t necessarily be ‘taught’. Technical skills are easier nonetheless. Though this table is not exhaustive, it can be observed that most of the technical skills have related units in all of the eight courses. Basic concepts of programming and Skill and knowledge in at least one programming language, Data Structures, Object-oriented programming, Database modeling, and database query language were taught in all of the courses. Thus, it is evident that the knowledge related to these technical skills isn’t missed out, at least in the curriculum design. On the other hand, Software Testing and Development related topics were present only in two engineering-related courses offered by Kathmandu University and Tribhuvan University. Version or source control, which is a crucial skill in development and was found to be of high priority for employers was found in only one of the courses.

In the realm of soft skills, though there aren’t specific courses or topics that match the required soft skills, there are topics within the courses where there is an opportunity for the teacher or facilitator to develop these skills by employing different teaching methods. Similarly, group projects are mandatory and credit-based elements for course fulfillment. Most of them have an end-semester final project while few of them employ minor and major projects.

Skill Mismatch across Different Applicant Types Based on Educational Qualifications

Before rating the expectations and observations, the respondents were asked to answer the question “When rating these entry-level skills, which type of applicant are you rating? Applicant with at least:”. The options were: a) Training certification or self-acquired skills b) SEE or equivalent c) Diploma or secondary level or equivalent in any field d) Diploma or secondary level or equivalent in IT-related fields e) Bachelor or higher in any field and f) Bachelors or higher in IT-related fields. This was done for the purpose of unit analysis and further exploring if the skill mismatch varied across different kinds of applicants based on their educational qualifications.
Table 17 Distribution of Different Applicant Types Based on Educational Qualification

<table>
<thead>
<tr>
<th>Educational level</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training certification or self-acquired skills</td>
<td>31</td>
<td>24.2</td>
</tr>
<tr>
<td>Diploma or secondary level or equivalent in any field</td>
<td>3</td>
<td>2.3</td>
</tr>
<tr>
<td>Diploma or secondary level or equivalent in IT related fields</td>
<td>13</td>
<td>10.2</td>
</tr>
<tr>
<td>Bachelors or higher in any field</td>
<td>45</td>
<td>35.2</td>
</tr>
<tr>
<td>Bachelors or higher in IT related fields</td>
<td>36</td>
<td>28.1</td>
</tr>
<tr>
<td>Total</td>
<td>128</td>
<td>100.0</td>
</tr>
</tbody>
</table>

The findings illustrated in Table 17 reveal a diverse pool of applicants under consideration. A significant portion of respondents, 35.2%, were rating applicants with bachelor's degrees or higher in any field. Additionally, 28.1% of respondents evaluated applicants with bachelor's degrees or higher in IT-related fields, highlighting the relevance of specialized education in the IT sector. A noteworthy 24.2% of respondents assessed applicants with training certifications or self-acquired skills, emphasizing the importance of practical skills and certifications in the job market. Finally, smaller percentages of respondents rated applicants with secondary-level diplomas or equivalent qualifications, both in IT-related and non-IT fields. And none of the respondents were evaluating an applicant with SEE or equivalent qualification suggesting that no employer would expect someone with that qualification. This analysis demonstrates the diversity in applicants' educational backgrounds and provides valuable insights into how these qualifications may influence the ratings of entry-level skills and competencies for programming positions.

It would be of interest for further studies to explore if the mean difference between expectations and observations differed according to the type of applicant. For example, it was noted earlier that most of the employers expected the applicant to have at least a Bachelor’s degree. So, does an applicant with a Bachelor’s degree have a lesser skill mismatch compared to other applicant types? It was also found that most employers agree that having an IT-related educational background is of utmost importance. So, does an applicant with an IT-related background have lesser skill
discrepancy? The mean difference across different applicant types was calculated to explore this question of interest as presented in Table D15. From the table, it is observed that across most types of applicants, there is a positive mean difference of expectations versus observations for different skill categories, meaning employers tend to have higher expectations in terms of skills than what they actually observe. However, for “Diploma or secondary level equivalent”, the mean difference is negative for the interpersonal skills category which suggests that employers have observed higher than expected from such applicants. However, the limitation of small frequency for each type of applicant has to be acknowledged.

**Statistical Significance of Association between the Skill Mismatch and the Type of Applicant**

It has been established that there is a mean difference in expectation versus observations of different skill categories across different applicant types based on their educational qualification. To check if there is an association between the mean differences observed in expectations and observations with the type of applicant, an analysis of variance (ANOVA) can be used as a statistical test. To adopt ANOVA as the parametric test for the purpose of this study, certain assumptions need to be fulfilled. ANOVA is based on the same assumptions as t-tests, that is measurements on either ratio or interval scales, random sampling, a normal distribution of data, and three or more groups with homogeneity of variance (Cohen et al., 2002; Kim & Park, 2019). It has been established earlier that the difference between average ratings of expectations and observations meets the three assumptions. The homogeneity of variances is calculated using Levene’s test (see Table D16). Based on the table, we observe that the p-value is > 0.05 for every group which suggests that there is no significant difference in variances between the groups based on the mean and median. Thus, it passed the final assumption of homogeneity of variances and one-way ANOVA can be used to test the statistical significance of association between the mean differences observed in expectations and observations with the type of applicant.
The analysis of variance (ANOVA) results in Table 18 shows that there are no statistically significant differences in skill expectations and observations observed across different groups of applicant types in technical-related skills, interpersonal-related skills, and portfolio expectations. For the difference in personal-related skills, there is a marginal p-value of 0.074, suggesting a potential difference, although it is not statistically significant. However, since the sample sizes of the five groups of applicants are not equal (see Table 17), the Welch test can be used to further test the significance.

**Table 18 One-way ANOVA for Association Between the Skill Mismatch and the Type of Applicant**

<table>
<thead>
<tr>
<th>Difference of average of expectations and observations between groups of applicant types df</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical</td>
<td>4</td>
<td>1.11</td>
</tr>
<tr>
<td>Personal</td>
<td>4</td>
<td>2.18</td>
</tr>
<tr>
<td>Interpersonal</td>
<td>4</td>
<td>1.59</td>
</tr>
<tr>
<td>Portfolio</td>
<td>4</td>
<td>2.03</td>
</tr>
</tbody>
</table>

From Table 19, it can be observed that for all skill categories, the test statistics are relatively small, indicating that the means of expectations and observations are not significantly different. Further, all the p-values are relatively high (greater than 0.05), which implies that there is not enough evidence to conclude that there are significant differences in means between expectations and observations for these skill categories across different applicant types.

**Table 19 Robust Tests of Equality of Means using Welch Test**

<table>
<thead>
<tr>
<th>Difference of average of expectations and observations between groups of applicant types df</th>
<th>Statistic</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical</td>
<td>1.12</td>
<td>1.11</td>
<td>.386</td>
</tr>
<tr>
<td>Personal</td>
<td>2.42</td>
<td>2.18</td>
<td>.093</td>
</tr>
<tr>
<td>Interpersonal</td>
<td>1.02</td>
<td>1.59</td>
<td>.428</td>
</tr>
<tr>
<td>Portfolio</td>
<td>2.39</td>
<td>2.03</td>
<td>.099</td>
</tr>
</tbody>
</table>
Chapter Summary

This chapter presented the data about employers’ perception of the KSA (Knowledge, Skills, Attitude) match. It was found that the employers are slightly positive about the knowledge and skills match but consider the applicants falling short of expectations on the attitude part. Most employers agree on providing training and development on the job to mitigate the gap. The analysis of skills rating of expectations and observations was presented, both in clustered categories and individually. Statistical significance of the mean differences of expectations versus observations was calculated using a $t$-test which showed there is a significant mean difference across all the skill categories. Priority rating of the expectations showed that most of the skills in the personal category like learning attitude, time management, and motivation were considered the most important along with a few technical skills like basic programming concepts and programming skills. Average gap analysis of the skills using the Ranked Discrepancy Score showed that most of the personal and few technical skills fell in the ‘high importance and high gaps’ category. Finally, a one-way ANOVA showed that there was no significant association between differences in skill expectations and observations observed across different groups of applicant types based on their educational qualifications.
CHAPTER VI
FINDINGS AND DISCUSSIONS

This chapter presents the key findings and summary of the statistical tests. Firstly, it lists the summary of the statistical tests concerning the hypotheses presented in Chapter 1. Then, it summarizes the findings related to the importance of educational qualifications and background, the major skill demands of employers, and the discrepancies observed in expectations versus observations. Finally, it presents the findings related to the association between the mean differences in skill expectations and observations among the type of applicant based on their educational qualifications. Based on these findings, discussions on skill mismatch issues have been presented through the lens of human capital theory.

Major Findings

This study embarked on an exploration of a pressing concern in the software development industry: the challenge of skill mismatch in entry-level programming positions. To dissect this issue comprehensively, skills were categorized into four distinct areas: technical, personal, interpersonal, and portfolio. The aim was to gain a deeper understanding of the skill demands of employers, the disparities between applicant skills and employer expectations, and whether these variations were influenced by the educational qualifications of applicants.

This study had three null hypotheses that there is no significant difference in employers’ expectations versus observations for each skill category; technical, personal, and interpersonal. The tools of statistical significance rejected all three null hypotheses, which are presented in Table 20.
Table 20 Summary of Statistical Tests

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_01$ There is no significant difference in technical skills expected by employers of the software industry and skills possessed by IT graduates for entry-level programming positions.</td>
<td>Rejected</td>
</tr>
<tr>
<td>$H_02$ There is no significant difference in personal skills expected by employers of the software industry and skills possessed by IT graduates for entry-level programming positions.</td>
<td>Rejected</td>
</tr>
<tr>
<td>$H_03$ There is no significant difference in interpersonal skills expected by employers of the software industry and skills possessed by IT graduates for entry-level programming positions.</td>
<td>Rejected</td>
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</table>

Table 20 reveals that a significant difference was found between expectations and observations for technical skills overall. Further analysis of individual technical skills showed that out of 22 technical skills, only 4 viz. basic computer literacy, Windows OS, hardware troubleshooting and maintenance, and computer networking, showed no significant differences. For personal and interpersonal skills, overall, it was found that there is a significant difference between employers’ expectations and observations. Further analysis of individual personal and interpersonal skills showed significant differences for each skill item i.e. 14 personal and 5 interpersonal skills. Similarly, a significant difference was found for portfolio requirements i.e. CV, personal or college projects, project demonstrations, and previous work or internship experience.

The study revealed that employers within the software development industry consistently hold high skill expectations for prospective candidates across technical, personal, and interpersonal skills. Among technical skills, programming-related skills like Basic concepts of programming, Skill and knowledge in at least one programming language, Object-oriented programming, and Data Structures were highly demanded. Proficiency in Version management tools, Testing and Test-driven development, and Software development frameworks also ranked high in employer expectations. Personal skills like Critical Thinking, Problem-solving, learning attitude, and Ownership were highly valued. Interpersonal skills like Collaboration, and Organizational culture
fit were also considered equally important. Lastly, under the portfolio category, employers substantially expect a Professional CV and/or cover letter and Personal or college projects. These findings shed light on the holistic skill set demanded by employers for entry-level programming positions, encompassing a blend of technical, personal, and interpersonal skills, essential for success in the software development industry.

The study found that most organizations require a Bachelor’s degree as the minimum qualification, reflecting the industry’s historical reliance on academic credentials. Interestingly, a third of the respondents valued Training Certification or self-acquired skills as a hiring criterion, suggesting recognition of practical skills acquired outside of traditional educational institutions. Despite this, only 6.3% of companies have “Training Certification or self-acquired skills” as the most hired, indicating a contradiction in hiring practices. It was also found that more than half of the organizations consider an IT-related educational background important when hiring for an entry-level programmer position. The ANOVA test was used to explore the association between the mean differences in skill expectations and observations and the type of applicant based on their educational qualification. The ANOVA result indicates that the skill mismatch observed does not exhibit a statistically significant association with the type of applicants.

Discussions

The study emphasized finding if there was a skill mismatch in entry-level programming positions within the software development industry. Dividing the requirements and expectations into four different categories and forming a framework for the study, differences in expectations and observations were analyzed. Further analysis of individual skills was conducted. This section discusses the findings of the skill mismatch issue concerning existing literature, the conceptual framework of skill mismatch, the framework for skills required in programming, and the human capital theory (HCT).
Employers’ Major Expectations

This study explored the conundrum of ‘technical skills’ versus ‘soft skills’ based on the expectations of employers in the IT industry. It was revealed that soft skills (personal plus interpersonal) are the most important according to the employers’ expectations rating. Notably, within the top ten, five fall into personal skills, four fall into technical skills, and one in interpersonal skills. Among personal skills, the top five were Learning attitude, Time management, Motivation, Professionalism, and Ownership. Organizational culture fit stood out as the most important in the interpersonal skills category, while Personal or college projects held the highest significance in portfolio expectations. A closer examination of the top 20 skills reveals that 70% of them (12) belong to the personal skills category, where six are technical skills, and two are interpersonal skills. This study found that soft skills (personal and interpersonal) received a considerably higher mean rating than the technical skills category which is consistent with the previous studies (Draus et al., 2022; Lee & Han, 2008; Noll & Wilkins, 2002; Stamm, 2023; Tesch et al., 2008; Younis, 2022).

For a programming position, the first ability or skill required of a graduate should be related to programming languages and writing codes. “Basic concepts of programming” and “Skill and knowledge in at least one programming language” were rated among the top ten by the employers. So, there is no doubt a graduate must be able to write codes. However, on discussion with the experts, they don’t deny that they considered soft skills over technical ones. The reason they provided was that technical skills (like writing codes) could be easily trained or taught at the workplace in a very short time, provided that the applicant has a sound understanding of at least the ‘basic concepts of programming’ like loops, variables, conditional statements, data structure, or OOP. However, soft skills (like collaboration) are hard to develop in a short period of time. The learning attitude, for instance, doesn’t come overnight. Thus, the recruiters and managers sought out applicants who already had soft skills. But it is also important to note that for entry-level programming
positions, the recruiters and managers highly expect the applicants
to have at least a good understanding of the basics of programming
(Lee & Han, 2008; Tomic´ et al., 2017). Garousi et al. (2019) claim
that soft skills have become more important in recent years because
the software industry practices agile practices that are “strongly
based on communication and interaction” than traditional waterfall
models. Patacsil and Tablatin (2017) found that teamwork and
communication were the highest-ranked skill requirements
followed by leadership and management skills. In addition, the
other top important skill requirements were problem-solving,
lifelong learning, curiosity, self-learning, English language
proficiency, attitude, adaptability, and creativity (Bringula et al.,
2016; Istiyowati et al., 2020; Jebreen & Nabot, 2021; Lundberg et al.,
2020). This study also found these soft skills among the top-rated
by employers. Thus, it is imperative that while focusing on the skill
and knowledge related to programming, educators, educational
institutions and students should equally prioritize the development
of these mentioned soft skills.

Technical Skills

Specifically, in the technical skills category, the top five
crucial skills were Basic concepts of programming, Basic computer
literacy, Skill and knowledge in at least one programming
language, Object-oriented programming, and Windows OS.
Among the top five technical skills, the two skills related to basic
computer literacy and Windows OS aren’t specifically related to
programming or software development. However, they are key
skills nonetheless because someone who isn’t computer literate and
doesn’t know how to operate a Windows OS (or any other OS) will
not be able to complete any tasks related to programming at all.
After all, programming is ultimately done on a computer. In
conversations with industry experts, they had mentioned that these
two skills were rather ‘assumed’ than expected. It was assumed that
an IT graduate would be able to operate a computer with ease in
any OS. The remaining three skills, basic concepts of programming,
skill and knowledge in at least one programming language, and
OOP can be, however, considered the most important skills needed
to be acquired by a graduate (Woratschek & Lenox, 2014). Basic
concepts of programming lay the foundation for a soon-to-be programmer. IIDS (2023) found coding and programming as the topmost expertise of the respondent programmers. It includes fundamental concepts such as variables, data types, conditional statements, loops, and functions. These are like the building blocks of writing a program. The advanced concepts are built upon the ideas of these blocks which can be used to write codes for desktop applications, web applications, and mobile games, among others. After developing these basic concepts, one would have to have a mastery of any one programming language. A programmer would use any one programming language to develop ideas into products while employing basic and advanced concepts. Object-Oriented Programming (OOP) is a programming paradigm that promotes code modularity and reusability. OOP principles, such as encapsulation, inheritance, and polymorphism, allow developers to build maintainable, scalable, and extensible software. It was found from the analysis of a few curricula of IT related degrees that these skills and knowledge are explicitly included. However, the study revealed that graduates don’t possess these basic required skills. Thus, educational institutions and educators should focus on improving the implementation and teaching methods by focusing on lab exercises and projects to emphasize the mastery of fundamental programming concepts, knowledge, and skills.

This study also found that among the 22 technical skills, hardware troubleshooting and maintenance, and computer networking were the least important and had no significant discrepancy. Draus et al. (2022) found something similar about hardware support and networking. On the other hand, Sharma (2023) found that employers in the ICT sector expected basic hardware skills which is in contrast to the findings of this study. This cites a possibility that hardware and networking related competencies aren’t much required for programming jobs and are included in the curriculum for developing a general ICT related skill. It becomes imperative that for the institutions that specifically focus on producing a workforce for the software industry, these two topics can be of less focus. So, it becomes a matter of choice based on the objective of the course.
Non-Technical Skills

Among the top expected soft skills (personal and interpersonal), learning attitude, ownership, and organizational culture fit were the most sought after according to this study. This is also consistent with previous studies. Learning attitude has been termed self-learning habit, learnability, ability to work independently, and curiosity, in different research that contribute to the applicant’s overall employability (IIDS, 2023; Premuzic & Frankiewicz, 2019; Lee & Han, 2008; Tang et al., 2001; Woratschek & Lenox, 2014). The nature of the software industry is itself in constant flux; continuous innovation and fast technological changes happen regularly. New programming languages, tools, and frameworks are developed and innovated regularly. To stay relevant and competitive, software professionals need to be committed to learning and adapting to these changes. Someone with a learning attitude is open to new ideas, innovation, creativity, and constructive feedback which provide the graduates with continuous learning and thus provide a competitive edge in the job market. Similarly, ownership is a vital attribute in the software industry as it reflects an individual's sense of responsibility, accountability, and commitment to their work. In the context of software development, taking ownership means not only completing tasks but also ensuring the quality, reliability, and timely delivery of the software product. It implies a proactive approach to problem-solving, a willingness to do extra, and a dedication to continuous improvement. In the software industry, where teamwork and collaboration are common, ownership fosters trust and reliability among team members. On the other hand, organizational culture fit (not to be confused with job fit) has been growing as an important requirement for most of the software companies in Nepal based on job ads analysis and discussions with industry experts. This person-organization (P-O) fit has been termed as ‘adaptability’ in various research and found to be of utmost importance to employers (Istiyowati et al., 2020; Tang et al., 2001). Employers are seeking hires who fit the values, norms, and practices of the company they work for. Sekiguchi (2004) claims that positive organizational outcomes are observed when there is a P-O
fit and notes numerous studies that have shown a positive correlation between P-O fit and work attitude, job satisfaction, commitment, teamwork, and increased productivity among others. Someone who is ‘fit’ for the company automatically has better work performance, team collaboration, and job satisfaction. Thus, it increases the retention of the employee. Additionally, it is beneficial for the company as a ‘happy’ employee is willing to be innovative and perform better for the overall development of the company. Contrarily, it has also been found that there may be negative outcomes of high P-O fit (Sekiguchi, 2004). Based on this study, it can be concluded that for employers in the Nepali software industry, hiring an applicant who fits and matches the organizational culture and values is of utmost priority. So, it becomes important for further research to explore what the ‘fit’ actually refers to and how this ‘fit’ can be developed.

The Case of Skill Mismatch

The findings of this study reveal a significant disparity between the skills expected by employers and those possessed by graduates seeking entry-level programming positions. Across various skill categories, including technical, personal, interpersonal, and portfolio expectations, employers’ expectations consistently outweighed their observations of graduates' skills. This discrepancy underscores the existence of a skill mismatch within Nepal's software industry.

Adopting the framework of ILO, this study approached skill mismatch as an encompassing term to mean a qualitative discrepancy of skills required vs possessed. It was particularly interested in the ‘skill gap’, among the seven categories of skill mismatch as per the ILO framework, which is the lack of skill or skills required to perform a job. Similarly, within the structure given by Bui and Porter (2014) which was used for this study, it was found that a significant expectation-performance gap exists among the graduates of IT-related courses. Based on the findings of this study, it can be concluded that there is a significant ‘skill gap’ in terms of technical, personal, and interpersonal skills. From a job-fit perspective, it can be concluded that all four components of job-fit that were considered for this study viz. P-J, P-P, P-G, and P-O fit
showed a negative congruence. That means, there was no fit of the applicants to the job, person, group, and organization. Applicants aren’t ‘fit’ for the jobs and significantly lack the skills required to perform tasks and jobs required for that position.

**High Importance and High Gaps**

As discussed earlier on the average gap analysis topic, the skill discrepancies were categorized into four groups: high importance-high gap, high importance-low gap, low importance-high gap, and low importance-low gap. 8 technical skills among 22 have been considered of high importance by employers but have been found to have higher gaps. Among the eight, the three items are: i) basic concepts of programming, ii) skill and knowledge in programming language, and iii) data structures are considered among the ‘basics’ that an applicant graduate ‘must have’ before any other skills. The remaining five like OOP, database skills, version control, and testing are more advanced concepts that are certainly sought after by employers in recent years as discussed previously. The more concerning finding is here that even the ‘basics’ have higher gaps, that is the applicants aren’t able to demonstrate their skills in even the fundamentals of programming.

This is a critical issue because after a significant investment of money, time, and effort by the students and the institutions, the return is almost nil. This raises questions about the effectiveness of teaching methods, the training of educators, the adequacy of the curriculum, and the availability of proper infrastructure and lab-based classes. It is possible that traditional teaching methods employed in IT-related courses may not adequately prepare students to apply theoretical knowledge to practical scenarios. Educators may need additional training or professional development opportunities to enhance their pedagogical approaches and ensure alignment with industry standards and best practices. Additionally, the availability and accessibility of resources such as computer labs, software tools, and equipment for conducting practical exercises may be limited in some educational institutions. Insufficient infrastructure can hinder students' ability to engage in meaningful hands-on learning experiences and practice programming skills in a supportive environment. Further
research is required to delve deeper into the root causes of why graduates are unable to develop even the fundamental programming skills expected by employers.

Among the 14 personal skills, 10 skills, which is more than 70%, have been found to have high importance and high gaps. Sharma (2023) found that the level of employability of students in the ICT sector in Nepal was mostly low for core skills, organizational skills, and personality attributes. As found in the literature and discussed tremendously by many researchers, soft skills are of crucial importance for increasing employability not only in the IT industry but also in general. Nevertheless, it has also been found that these “soft skills” are equally hard to ‘teach’. So, researchers suggest different approaches to ‘developing’ or ‘building’ the soft skills of students like cooperative learning, group projects, project-based learning and assessments, onboarding and pre-hiring training programs by institutions and employers, and others (Garousi et al., 2019; Janse van Rensburg & Goede, 2019; Lundberg et al., 2020; Radermacher, 2012; Roberts, 2014; Tuzun et al., 2018; Zhang, 2012). When students work on group projects and assume different roles, they are exposed to different skills like collaboration, creativity, critical thinking, listening, ownership, etc. Onboarding programs by employers specifically help garner skills related to professionalism and organizational culture. However, it can also be argued that organizational culture differs according to companies and thus might be different from different perspectives. The ‘organizational culture fit’ is mostly developed at the workplace more than it could be done at educational institutions (Metilda & Neena, 2016). Future research can focus on how educational institutions and employers can collaborate to design workplace-infused programs to enhance students’ technical and non-technical skills.

**Importance of Work-Based Learning Experiences**

It was found from the study that in most IT-related courses, group projects are mandatory and credit-based elements for course fulfillment. Some courses require an internship as part of the degree fulfillment. As noted by Sharma (2023), internship increases the employability of graduates by developing their core skills.
According to Zhang and Ma (2023), project-based learning has a more pronounced impact on student learning outcomes in engineering and technology disciplines and is more effectively implemented in labs. Mohabuth (2018) found that work-based learning (WBL) in Computer Science enhanced students’ practical skills, and knowledge and positively influenced academic performance. Industrial internships promote the learning and growth of students through practical experience and develop their skills like teamwork and motivation (Ali & Muhammad, 2018). The group projects can also be implemented in a WBL model by collaborating with software companies. These group projects and internships can serve as one of the areas for developing the required technical and non-technical skills. As discussed earlier, involvement in these work-based experiences indirectly ‘exposes’ students to be involved in processes that demand them to think creatively and critically, to work in teams, to own their project, and to dig deeper into programming concepts and learn more about what isn't taught in classes. Students can also be involved in independent projects or ‘pet’ projects either in groups or individually. These pet projects aren’t part of the course fulfillment and don’t get them marks. However, students can have an ample pool of opportunities to learn, demonstrate, and develop their skills. From an employability perspective, such work-based learning (either personal or college projects or internships) gives the applicants a ‘competitive advantage’ over other applicants. Employers agree that those applicants who have honestly been involved in making projects and who can demonstrate them with confidence have a higher chance of getting hired. Projects and internships make it easier for recruiters to assess the applicants’ competencies without doing a ‘technical test’. However, despite the provision of projects and internships as mandated by the course, students don’t seem to have gathered the skills as expected. This suggests that an ineffective implementation of internship and work-based learning experiences could have led to the skill mismatch issue. This implies that colleges and other educational institutions ought to concentrate on how best to carry out college projects and other work-based learning opportunities.
To improve the implementation of work-based learning, further research should consider delving deeper into specific challenges hindering the effectiveness of these experiences. For example, it could explore issues such as the quality of supervision and mentorship during internships, the relevance of project topics to industry needs, the level of engagement and autonomy afforded to students during group projects, and the integration of feedback mechanisms to facilitate learning and skill development. Additionally, the potential strategies for enhancing work-based learning should be studied, such as strengthening collaboration between educational institutions and industry partners, providing professional development opportunities for educators on effective supervision and mentorship practices, and incorporating reflective activities into work-based learning experiences to promote deeper learning and skill acquisition. Furthermore, future research should underscore the need for ongoing evaluation and improvement of work-based learning initiatives to ensure their alignment with industry requirements and their effectiveness in preparing students for the demands of the software industry. Further research is required to highlight the potential of work-based learning in reducing the skill mismatch in Nepal's software industry.

**From the Perspective of Human Capital Theory**

This study approached the skill mismatch issue from the lens of Human Capital Theory (HCT), according to which, education offers individuals a pathway to develop their skills, knowledge, and attitudes, thereby accumulating human capital. This human capital provides them with economic and social mobility. Inherently, it aids in the nation’s economic growth. Based on the proposed employability framework in Figure 7, it is believed that investing in education and training will improve students' employability and job fit. In the context of computer science, this could involve gaining job-specific technical skills like learning programming languages, understanding algorithms and data structures, gaining experience with software development practices, and more. It could include gaining soft skills like problem-solving, collaboration, learning attitude, and others. However, the findings of a significant expectation-performance
skill gap across all the skill categories challenge this assumption of human capital theory. Graduates haven’t accumulated the necessary human capital during their education in IT related degrees, which suggests that their degrees may not yield the expected returns in employment and salary. Due to this skill mismatch issue, Nepal hasn’t been able to build the necessary human capital to harness the full economic potential of its rapidly growing software industry.

One of the crucial roles of education lies in boosting the employability of students. However, courses offered by different educational institutions are failing to meet this objective of developing human capital. So, employers are forced to take the matter into their own hands and employ coping strategies. This study found that most of the employers agreed on “providing training and development” and “providing exposure visits” as two important actions to be undertaken to reduce the disparity between the skills possessed by the graduates and those sought by the software industry standards. The findings of this study are consistent with the previous studies. Bartaula (2023), IIDS (2023), and SEEP Nepal (2018) found that employers employ various skill development training for employees as a coping strategy to address the mismatch issue. As educational institutions are failing to equip the students with the necessary skills, it requires the employers’ further investment of time and money. So, it is important to ask, “What are the possible actions to reduce this mismatch?”. Sharma (2023) noted that inadequate curriculum and weak university-industry relations as the reasons for the reasons of low employability of graduates in the ICT sector. Bartaula (2023) found that the stakeholders of the IT industry anticipate alignment of curriculum with industry requirements through strong university-industry collaboration. However, in this study, when a curriculum mapping was done with the highest rated skills according to the employers, it was found that almost all of the technical skills required for entry-level programming roles were present in the courses. However, no explicit scope of soft skills development was found in the curriculum mapping. Thus, it is evident that the knowledge related to these technical skills isn’t missed out, at least
in the curriculum design. How they have been taught and what approaches are being used by the institutions to develop student skills in these prospects is a different question of study. DCE graduates viewed that the curriculum needs to be updated as per the needs of the market, unrelated parts of the curriculum should be removed, new topics according to market needs must be included and practical labs and exposure trips should be prioritized during training (Basnet & Kim, 2010). IT professionals shared a similar view on the curriculum-employment link. Sharma (2023) also adds that adequate practicum, work-based learning, internships, and engagement in extra-curricular activities could increase the employability of the graduates. Bartaula (2023) concurs with the actions regarding internship and exposure to real-life problems. These work-based and industry-based activities can harness and develop the skills required. As discussed earlier, educational institutions and software industries need to collaborate on creating and enriching experiences like workplace exposure visits, bootcamps, hackathons, career prep camps, etc.

This study also found that most of the employers considered a Bachelor’s degree and an IT-related background of importance. However, graduates of these formal IT related degree programs don’t possess the required skills, as found from the study. Similarly, it was found that there are no statistically significant differences in skill expectations and observations observed across different groups of applicant types based on their educational qualifications. This begs the question “Are the IT-related degrees worth it?” And, it also becomes necessary to ask: “Are there any alternatives?” Xu and Fletcher (2017) found that the accumulation of human capital is significant, even when a formal credential is not obtained. Alternative pathways like coding bootcamps, online courses, and short-term training programs, which are non-degree programs but emphasize practical skills, contribute to mitigating the skill mismatch issue in the programming field (Columbia Engineering, 2021; Premuzic & Frankiewicz, 2019; Kasriel, 2018; Xu and Fletcher, 2017; Jaggars & Bailey, 2010; Schroeder, 2022). As employers prioritize practical skills and experience, these alternative pathways offer a quicker and more effective route to building a skilled
workforce, challenging the traditional emphasis on formal academic degrees (Lee & Han, 2008; Tomic´ et al., 2017; Fuller et al., 2022). These programs offer focused, efficient, and targeted training in programming skills, aligning with the evolving trend in the workforce that prioritizes skills over traditional degrees (Lee & Ko, 2015; Sharp & Sharp, 2017). This shift towards recognizing the value of skills acquired through alternative pathways becomes crucial in the context of Nepal as well. However, further research is required to understand this complex dynamic of ‘alternative pathways’ to produce a skilled workforce for the software industry.

The Role of TVET in Bridging the Skill Gap

The significance of Technical and Vocational Education and Training (TVET) becomes apparent in light of the skill gap issue identified in this study to address unemployment problems and support economic development (UNESCO, 2021). TVET has the potential to bridge the skills gap by equipping students with practical and pertinent skills required for success in particular professions including software development enabling graduates to acquire hands-on skills essential for job creation, performance enhancement, and job security (Rukundo & Sikubwabo, 2021; TVET Journal, 2023). Since TVET initiatives are developed in partnership with local employers, allowing them to be customized to meet the exact requirements of the labor market, students acquire skills that are highly sought-after and are adequately prepared to embark on their careers after completing their studies. As found from the study, general education in computer science related degrees may be able to provide students with a theoretical foundation and broad understanding of the field but not fully meet the industry’s skill requirements. This gap can be filled by TVET programs, which focus on practical skills and are often more aligned with the immediate needs of the workforce. Therefore, integrating TVET programs into the computer science education system could be a viable solution to address the skill gap in the industry. As discussed earlier, work-based learning can potentially improve the practical skills of students in programming related degrees. TVET models like apprenticeships, and on-the-job training possess the potential as well as an opportunity to address the skill gap issue. It can be
achieved through the provision of a real-life work environment by involving the use of industry experts as trainers, exposure to industry operations and tools, and providing the opportunity for immediate application of acquired skills in the workplace (Oviawe et al., 2017).

CTEVT has been offering Diploma and Pre-Diploma courses in Computer Engineering and Information Technology in Nepal. These courses contain topics related to programming that could provide students with the knowledge and skills necessary to be prepared for entry-level programming roles in software companies. However, these courses aren’t producing as satisfactory results as expected. From this study, it was found that only a smaller percentage of organizations (11.7%) are open to hiring candidates with a Diploma or equivalent qualification. In the discussions with experts, it was noted that almost all of them had no idea about the existence of graduates of CTEVT’s IT related programs. Similarly, Basnet & Kim (2010) found that only 5.3% of graduates of Diploma in Computer Engineering were working as programmers. The authors found outdated curriculum, absence of practical labs, and weak link with industry as some of the concerns.

Despite the potential of formal TVET degrees in producing a skilled workforce for the software industry, challenges persist in their effectiveness. The employers aren’t very aware of the graduates with such degrees either. Further research is needed to explore strategies for enhancing TVET programs, including strengthening industry partnerships, upskilling trainers, and improving infrastructure. On the other hand, numerous non-academic institutions provide short courses on specific areas of software development like web development, mobile app development, databases, data science, machine learning, and specific languages like Python, JavaScript, Java, SQL, etc. Accrediting short courses on specific software development areas through TVET institutions can serve as a pathway for graduates to acquire specialized skills and transition smoothly from education to employment. These short courses can work as a ‘bridge’ and help graduates in transition from school to work through specialized work-based learning approaches. Graduates of IT related courses
who have learned general theoretical background from educational institutions and are interested in pursuing a career in software development can be prepared for the industry through short on-the-job training programs. Future research should investigate the impact of such initiatives, the possibility of accreditation, and assess their effectiveness in meeting the needs of Nepal's evolving software industry.

**Chapter Summary**

This chapter first summarized the key findings of the research. Then it discussed the issue of skill mismatch found from the study alongside previous literature. Major employers’ expectations were identified which can be a focus of information for concerned stakeholders. Similarly, the skills with high importance and high gaps were identified which became the crux of the skill mismatch issue. This chapter also discussed the skill mismatch from the perspective of human capital theory and thus emphasized the importance of further research on the importance of projects, internships, the role of TVET programs, and ‘alternative pathways’ to produce a work-ready human capital justifying the investment of time, money and effort.
CHAPTER VII
RECAPITULATION, CONCLUSION AND IMPLICATIONS

This chapter serves as a culmination of the entire research endeavor, providing a summary of the key elements and findings. It revisits the research problem, objectives, methods, and results, offering a clear overview of what has been accomplished throughout the study. Then, it discusses possible implications for students, educational institutions, employers, policymakers, and future research.

Recapitulation of the Research

There is a critical issue of skill mismatch and unemployment in the software industry in Nepal. Though thousands of students graduate yearly from educational institutions that offer a degree in IT-related fields, they complain of not being able to find a job. On the other hand, employers of the software industry argue that the applicants don’t have the necessary skills for even an entry-level position in the programming field. The research began by identifying and delineating the research problem, which revolved around the issue of skill mismatch of IT graduates. The objectives set for this study aimed to assess the mismatch between skills required by employers for entry-level programming jobs and the skills acquired by students of IT-related courses. The study explored to answer the research question: Is there a difference in skills possessed by the applicants for an entry-level programming job in accordance with the expectations of employers?

This study was conducted under the guidance of the post-positivist research paradigm and adopted a quantitative survey methodology to gather data, utilizing a questionnaire developed with reference to prior research by Tesch et al. (2008). The study area encompassed the Lalitpur district in Nepal, and the survey was
conducted with respondents in managerial positions within IT companies, including CEOs, CTOs, senior developers, tech leads, team leads, and managers. 128 responses were collected through the survey. Additionally, experts from the software industry in Lalitpur and Kathmandu were consulted to validate the skills required for entry-level programming positions and refine the questionnaire. Data collection was conducted using a Likert-scale-based questionnaire that assessed both employers’ expectations and observations of entry-level programming skills. The skills were rated in pairs, allowing for the identification of discrepancies between expected and observed skill levels. Data analysis encompassed data cleaning, descriptive statistics, and inferential statistics. SPSS version 25 was utilized for statistical analysis. The paired samples t-test was employed to assess mean differences between skills expected and observed ratings. The results showed a significant skill gap across all the skill categories (technical, personal, interpersonal, and portfolio). Similarly, the paired samples t-test of individual items showed a significant gap for 41 out of 45 items. Only the four technical skills showed no significant gap.

In addition, the Narine and Harder (2021) Ranked Discrepancy Score (RDS) model allowed for the classification of skill gaps into four categories, ranging from substantial gaps to negligible gaps, providing a nuanced understanding of skill expectation discrepancies. The RDS showed that most of the skills (18 out of 41) fall in the mid-discrepancy category while 16 skills fall under the low discrepancy and 11 under the negligible category. A closer examination of the top 20 skills reveals that 70% of them (12) belong to the personal skills category, six are technical skills, and two are interpersonal skills. Furthermore, a scatter plot of average importance versus average discrepancy was plotted in four quadrants to conduct a gap analysis and list out the skills with high importance and high gaps. 20 of 41 skills fall in this category; 8 technical, 10 personal, and 2 interpersonal skills.
Conclusion

This study highlights the essential roles of soft skills from the perspectives of the employers in which effective communication, collaboration, problem-solving, critical thinking, and learning attitude were indispensable for both job performance and fostering a productive workplace. It also sheds light on the importance of technical skills since entry-level IT positions demand a solid understanding of fundamental programming concepts and proficiency in at least one programming language. Additionally, active involvement in hands-on projects and other work-based learning increases employability by developing their holistic skills. On the other hand, it mainly sheds light on the prevalence of significant differences between the expectations and observations of employers for entry-level programming jobs across all skill categories (technical, personal, and interpersonal). The findings of the expectation-performance gap from this study indicate that educational institutions in Nepal are falling short in preparing graduates to meet the demands of the rapidly growing software industry. While graduates may possess theoretical knowledge, they often lack the practical skills and soft skills essential for success in the workplace. Furthermore, many graduates demonstrate deficiencies in basic programming concepts and languages, highlighting a critical gap in their education. This highlights a critical need for the improvement in alignment of educational programs and industry needs as well as for practice-based education in educational institutions such as group projects and workshops to foster soft skills. Educational institutions and industry stakeholders must collaborate to implement practical and work-based learning approaches that bridge the gap between theoretical knowledge and real-world application. By investing in innovative teaching methods and curriculum upgrades, institutions can better prepare graduates to excel in the dynamic IT industry. With the increasing demand of programming employees in software development companies, it is a matter of urgency for stakeholders to collaboratively address the skill mismatch issue in harnessing the full economic potential of Nepal’s rapidly growing software industry.
Implications of the Study

This chapter highlights the implications of the research findings for students, educational institutions, employers, policymakers, and future research endeavors. By recognizing and addressing these implications, stakeholders can collectively work to enhance the employability of IT graduates in an ever-changing software industry.

Implications for Students

This study has implications for students and fresh graduates of IT related courses on various grounds ranging from skills development to change in learning attitude.

Focus on Skill Development

This study emphasizes the value of having a wide variety of skills for undergraduates looking to enter the software development industry. It was found that while managers and recruiters prioritize soft skills like learning attitude, communication, teamwork, and critical thinking, it is equally important for students to concentrate on developing a solid foundation in technical skills. Future graduates will benefit from these findings by knowing what technical skills employers' value and how to develop them. Similarly, students will be more aware of the importance of participating in soft skills development through training and extracurricular activities.

Hands-On Experience

Hands-on experience increases the employability of graduates. Students should actively engage in hands-on projects, internships, hackathons, and other practical experiences. These opportunities enable them to apply what they’ve learned in a real-world practical scenario, develop soft skills like problem-solving, collaboration, and ownership, and build a portfolio of projects that can be showcased to potential employers. Additionally, the ability to demonstrate personal or college projects with confidence is a significant advantage during job interviews. The projects could be hosted either on GitHub or websites or a simple demo video uploaded to YouTube. This gives the employers an opportunity to
take a peek into student’s skills before even conducting the interview. Well-executed projects can set them apart from other candidates in a competitive job market. Thus, the findings of the study about the importance of projects in skills development and increasing employability will encourage students to work on group projects inside and outside their colleges.

**Learning Attitude**

This is one of the most important soft skills desired by employers of the software industry, according to the findings of this study. Though other soft skills might be harder to assess during a short hiring interview, ‘learning attitude’ is quite visible based on what the applicant knows about the recent trends of the rapidly evolving software industry, the problems they have faced while doing projects, and how they might have solved them, etc. Thus, students will focus on cultivating a learning attitude, continuously learning from internal and external sources, online and offline media, their teachers, peers, and mentors. This proactive approach to learning ensures they remain competitive and adaptable in a dynamic job market.

**Implications for Educational Institutions**

Based on the study, it has been implied that educational institutions need to focus on curriculum enhancement, effective implementation of college projects, and strengthening relations with the industry.

**Curriculum Enhancement**

Though the analysis of the curricula didn’t show much misalignment with the skills requirement by the employers, a few topics were missing from the majority of the curricula that have been considered important in recent years. This includes incorporating technical topics, such as software testing and version control. Similarly, from a workplace perspective, newer software development methodologies like Agile and the necessary project management tools like Trello and Jira should also be introduced to students. As a result, educational institutions can adapt and
improve their courses regularly to meet the changing demands of the software industry.

**Emphasis on Hands-on Projects to Cultivate Technical and Non-technical Skills**

From this study, it was found that both technical and non-technical skills were important for the employability of IT graduates, while non-technical skills were more prioritized. From different research, it has been found that hands-on projects, lab work, and industry internships are key to developing these skills. Practical experience complements theoretical knowledge, making graduates more job-ready. In addition to theory, colleges and universities should place a strong emphasis on practical skills development. Thus, educational institutions can emphasize making such programs integral components of IT courses. Similarly, educational institutions can employ teaching methodologies that encourage cooperative learning, and team collaboration, and enhance skills like critical thinking, problem-solving, teamwork, and communication.

**Industry Collaboration**

The findings of this study imply that educational institutions should collaborate with the software industry to ensure that academic programs stay relevant. Establishing partnerships with local businesses, conducting industry-specific workshops, and offering certification programs are some ways to close the knowledge and skills gap between academic institutions and what employers actually need. Regular student visits to software companies can give students a bigger picture of what it is like to work as a programmer in these areas. Similarly, guests (senior programmers) can visit the institutions to demonstrate what they work on and how they work in workplaces. This can give students a perspective into what sort of tools and technologies they need to learn that may not be necessarily included in the curriculum.

**Implications for Employers of the Software Industry**

Based on the findings of this study, employers can be more aware of the skill mismatch issue of IT graduates and be more
prepared for hiring processes. Employers can invest in recruitment strategies that identify candidates with growth potential, even if they lack certain technical skills. They could invest in collaborating with educational institutions to run on-the-job training programs and apprenticeship programs that can bridge specific skill mismatches and gaps, ensuring that new hires quickly become productive team members. On the other hand, since soft skills are found to be of utmost importance for employers in the long run, employers should prioritize the assessment of soft skills. They should devise more holistic assessments like interviews, group discussions, and scenario-based assessments that can reveal a candidate’s communication, collaboration, and problem-solving abilities. Assessing learning attitude is particularly important for entry-level positions. So, the recruiters and managers involved in hiring processes can design hands-on tasks and problems that could show their potential learning attitude.

**Implications for Policymakers**

This study found that despite much financial and time investment in the IT education sector to produce a workforce, a significant skill mismatch has been found. It was revealed that soft skills are considered rather important for applicants of entry-level programming positions. This will inform the policymakers to encourage the alignment of educational programs with the requirements of the software industry. Policymakers can focus on facilitating partnerships between educational institutions and local businesses and offer incentives for industry-specific training programs. Similarly, policymakers can create incentives for educational institutions to adapt their curricula to meet evolving industry requirements and can support initiatives that promote internships, apprenticeships, and on-the-job training opportunities.

**Implications for Future Research**

This study focused only on the Lalitpur district of Nepal. Hence, future studies can be conducted in Kathmandu, or other major cities/districts with a significant number of IT companies to capture the broader picture of the skills gap as well as to make a comparative analysis of various dimensions of existing gaps.
Similarly, future research can also be conducted focusing on skill mismatch and gap distributions based on gender, geographical regions, or other socio-demographic variables which may offer insights into potential disparities that may exist within the workforce. This study also sets an avenue to conduct studies based on actual skills assessment with hands-on tests drawing upon the limitation of perception-based surveys. Studies based on rigorous skill assessment surveys can provide more accurate findings and thereby nuanced understanding of the graduates’ skill levels. Further research can also be carried out on these variables from a qualitative perspective to generate a deeper understanding of the phenomenon. Qualitative approaches allow researchers to explore the subjective experiences and perceptions of graduates, educators, and employers, shedding light on the underlying reasons for the observed discrepancies. Hence, experiences on the reasons behind the gaps in soft and hard skills, their impact, and such can be explored in-depth.


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About the Author

Mr. Amrit Puri is an Educator and Project Lead for Code Chautari. He teaches Computer Literacy, Programming, and Computational Thinking. He is interested in refining programming pedagogy, addressing the digital divide, and empowering self-directed learning through problem-based classes and alternative learning platforms. He explores innovative ways of learning, including AI-based tutors, to provide personalized educational experiences. His previous experience includes working as a Content Generation Team Lead at Karkhana, a Science Teaching Fellow at Teach for Nepal, and a Software Engineer at Cloudfactory.

This publication provides an in-depth analysis of the skills mismatch that exists in entry-level programmer positions for IT graduates. It examines the expectations and observations of employers in this regard and aims to shed light on the factors that contribute to this mismatch. It explores the various skills that are required for entry-level programming jobs and compares them with the skills possessed by IT graduates.

Linking Education with Labor Markets (LELAM) Project 2024

Linking Education and Labor Markets: Under what conditions can Technical Vocational Education and Training (TVET) improve the income of the youth? (LELAM-TVET4INCOME) a six-year project (2017-2022) implemented in Nepal, Benin, Chile and Costa Rica. The Swiss Federal Institute of Technology (ETH Zurich) is the leading partner of the project. The LELAM project is financed by the Swiss Agency for Development and Cooperation (SDC) and the Swiss National Science Foundation (SNSF) under their joint “Swiss Programme for Research on Global Issues for Development” (r4d program). The project aims to understand how policymakers in low-and middle-income countries can improve the youth labor-market situation by strengthening social institutions and their interdependence with formal, non-formal, and informal TVET. It also aims to analyze the conditions under which TVET improves gainful employment and job quality, thereby improves the income of youth.