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What Can We Learn from Recommendations of Early-Career Engineers? Assessing Computing and Software Engineering Education Using a Career Monitoring Survey

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ABSTRACT

This paper presents an analysis of the skills and professional competencies that recent graduates from computing and software engineering programmes recommend for current students. Previous studies have not investigated the viewpoints of early-career engineers, and the current study addresses this research gap. The data used in this study comes from nationwide career monitoring surveys for former university students who graduated five years earlier. We analyzed the responses to questions about the skills and competencies needed in the software or computing jobs and compared them with the satisfaction and career paths of the respondents. According to the results, three types of skills and competencies are paramount: Soft skills in general, programming skills, and the practical experience gained during university studies. A logistic regression analysis revealed that soft skills are recommended by those who are most satisfied with their careers. Practical skills are more likely to be recommended if the respondent is less satisfied with their studies. Based on the findings, we concluded that the responses from the career monitoring survey could be used as an indicator of how well studies prepare graduates for the industry.

CCS CONCEPTS

• **Social and professional topics → Computing education**.

KEYWORDS

career monitoring survey, student evaluation of teaching, curriculum development

1 INTRODUCTION

Assessing the quality of teaching and the content of studies is arguably difficult. It is particularly challenging in rapidly developing computing and software engineering fields. Traditionally teaching quality has been evaluated using student evaluations of teaching (SETs). However, SETs are not an ideal measure for quality: First, SETs and student learning are not related [22], and the validity of student evaluations remains disputed [14, 18, 20, 21, 24]. Second, while SETs can provide some insights for assessing teaching quality, they can only be used for current students, making it hard to assess the impact and industry relevance of the study programme.

One way to assess study programmes in a holistic way is to tap into the experiences of our graduates and their subsequent career and job success. After all, competent graduates are likely to follow more prosperous career paths. Understanding the competency and skill needs in software engineering work is important, not only for educating more industry-ready graduates but also for other reasons such as tackling diversity issues in hiring processes [12, 13].

There exists widely accepted curriculum recommendations for computer science and software engineering, created in cooperation by ACM and IEEE ([2]), and accepted definitions of what knowledge and skills are included in software engineering ([4]). In addition to the comprehensive set of core knowledge, such as requirements engineering, software design, and verification & validation, these skills include communication with stakeholders, effective teamwork, and lifelong learning. Recent research has distinguished the knowledge and skills needed by good software engineers. However, the research on knowledge and skills has investigated two opposites of practitioners: Students [23] and experienced practitioners (for example [10, 11]). This focus has overlooked the population of early-career practitioners: Former students, who have recently entered the software industry and started their career paths. Therefore, the the current study aims to fill the research gap on the knowledge and skills for early-stage software professionals.

We accomplish these goals by analysing the results of a nationwide career monitoring survey. The survey targeted former students who have graduated 5 years earlier. The respondents were asked, among other things, to evaluate the quality of their studies, and satisfaction with their career so far.

More specifically, the objective of this paper is to investigate **to what extent can recommendations of early-career engineers be utilized for curriculum development?**

In particular, the research questions of this study are as follows:

- RQ1: What recommendations for skills and competencies emerge from the career monitoring survey?
- RQ2: How does the satisfaction towards working career and completed degree affect the skill and competency recommendations?
- RQ3: How does the career path of the respondents affect the recommendations?

2 RELATED RESEARCH

Garousi et al. [5, 6] have published several studies about closing the gap between software engineering education and industrial needs, including a meta-analysis. According to the meta-analysis [5], studies published between 2013 and 2018 list configuration management, software engineering process, design, testing, quality, requirements, project management, and professional practice as key knowledge gaps between engineering education and industry needs.

In addition to general skills, the soft skills a software professional needs have been a target of recent studies, with information gathered both from academic literature [16], recent PhD graduates [23], and from the industry [15, 17]. The study of Papoutsoglou et al. investigated job advertisements for software developers and found that communications, interpersonal, analytical, and problem-solving skills were sought after in them [17]. Similar results were found in an interview of software developer team leads [15], with leadership skills and teamwork as additional valued skills. In the studies of Li et al. interviews were conducted to further explain the personal characteristics of great software engineers [10, 11]. Despite the industry needs and curriculum support, Voitenko et al. [23] found that a significant number of software engineering PhD students had not developed soft skills and had no intention to study them in the future.

3 METHODS

3.1 Data

The data used in this study comes from Finnish career monitoring surveys. The yearly survey is sent to all students who graduated from Finnish universities with a master's degree five years earlier. The Ministry of Education and Culture coordinates it and is jointly carried out by the Finnish universities.

The sample includes respondents of career monitoring surveys who graduated from computer science, software engineering, and information technology programmes between 2012 and 2014. In Finnish higher education, it is common to apply directly to five years long master's programs and get awarded a bachelor's degree halfway through the studies. Additionally, we further restricted the sample to those responses that contained an answer to the open-ended question *What kinds of skills or competencies would you encourage current students to obtain to prepare them for future working life?*. The size of the resulting sample is 450 responses, consisting of both numeric and open-ended data.

To estimate the sufficiency of the sample size, we can use publicly available statistics from the Ministry of Education and Culture[1]. In total there were 2763 master's degrees awarded between 2012 and 2014. The overall response rate to the survey was 34% (951 respondents in total) from which we narrowed the sample down to all responses with open-ended text answers. This included 450 responses, which gives us a sample size of 16% of all eligible respondents.

The demographic characteristics of the sample are summarized in Table 1.

3.2 Measures

The survey questions relevant to this study are presented in Table 2. The first two variables, *career satisfaction* and *degree satisfaction*, are measured with items *How satisfied are you with your career so far?* and *How satisfied are you overall with the degree you completed in 20xx in terms of your career?* The response scales range from very dissatisfied (1) to very satisfied (6).

Career path is a categorical variable. As shown in Table 2, initially, the variable consisted of six categories. However, categories 4 and 5 were pooled into "Other" due to small *n*. Frequencies of the reduced career path categories and mean values of career and degree satisfaction by category are presented in Table 3.

As shown in Table 3, the most satisfied graduates are those who have worked continuously since graduation either for the same employer or as an entrepreneur (career satisfaction M=4.87, degree satisfaction M=4.90) or for several employers or temporary jobs without breaks (career satisfaction M=4.87, degree satisfaction M=4.92). Periods of unemployment between employers reduce satisfaction (career satisfaction M=4.38, degree satisfaction M=4.38), and graduates belonging to the career path category "Other" are the least satisfied (career satisfaction M=3.96, degree satisfaction M=4.10) with their career and the master's degree.

Recommendation of the skills and competencies is an open-ended question. The following subsection describes the coding of the responses in detail.

3.3 Coding process

To answer the first research question, we employed an inductive coding approach [19] on the open-ended survey responses. These responses were answers to the survey question *What kinds of skills or competencies would you encourage current students to obtain to prepare them for future working life?* All 450 suggestions were coded in the iterative process, where the authors read all the responses and generated suitable codes for each. Inductive coding was used together with creativity and knowledge of the field (authors x and y are software engineering researchers with extensive experience in both the industry and academia). Overall, the coding of the responses consisted of the following steps:

(1) *Familiarization with the data.* All authors were involved in the preliminary inspection of the data. Over time the inspections turned more formal, and eventually, the authors were able to start generating the codes and classification of the responses.
(2) *Generating initial codes.* After the initial inspection, the authors read all 450 responses while coming up with descriptive names for the categories or themes that the response could be classified in. This resulted in a set of initial codes used in the classification of responses. The codes were then converted into a data collection form. This instrument was used

[1] https://vipunen.fi/en-gb/university/Pages/Opiskelijat-ja-tutkinnot.aspx

Table 1: Demographic characteristics of the sample (N=450)

	n	%	Mean	Median	SD	Min	Max
Gender							
Male	349	77.56					
Female	99	22.00					
n/a	2	0.44					
Nationality							
Finnish	392	87.11					
Foreigner	58	12.89					
Graduation year							
2012	115	25.56					
2013	144	32.00					
2014	191	42.44					
Age at graduation	450		29.52	28.00	5.27	22.00	56.00

Table 2: The most important survey questions used in this study

Career satisfaction How satisfied are you with your career so far? (1=Very dissatisfied, 6=very satisfied).
Degree satisfaction How satisfied are you overall with the degree you completed in 20xx in terms of your career? (1=Very dissatisfied, 6=very satisfied).
Career path Which of the following options best describes your career so far? (Select one) (1) Continuously working for the same employer or as an entrepreneur since graduation. (2) Working for several different employers or temporary jobs or assignments or working with a grant. Not many breaks. (3) Changing employers or duties, with breaks, studies or periods of unemployment in between. (4) Unemployment alternating with occasional temporary jobs, practical training and contract or freelance work. (5) Mainly outside the labour force: for example, studies and/or parental leave for most of the time. (6) Other, please specify.
Recommendation of the skills and competencies What kinds of skills or competencies would you encourage current students to obtain to prepare them for future working life? (Open-ended)

by the authors to record the number of occurrences for each code.

(3) *Processing of all the data.* After the initial inspection, we proceeded to codify all answers. The work was divided between all three authors. The responses were codified using the survey form created in the previous step. The data collection form was also updated during the coding process to include codes that might have been previously overlooked.
(4) *Reviewing the results.* After all responses were codified, the resulting classification was reviewed.

3.4 Statistical analysis

Logistic regression analysis [8] was used to examine factors affecting the recommendation of the skills and, thus, to answer the research questions RQ2 and RQ3. First, skills and competencies identified during the coding process were further grouped into larger categories: soft skills, hard skills[2] and practical experience. Second, the categories were converted into corresponding dichotomous variables. The variables take on two values, 0 and 1. The value 1 denotes the recommendation of the skill or skills belonging to the skill category in question, and 0 denotes the non-recommendation.

Third, the following model was fitted using maximum likelihood estimation:

$$\begin{aligned} Pr(skill = 1) = F(&\beta_0 + \beta_1 CS + \beta_2 DS + \beta_3 CP2 + \beta_4 CP3 \\ &+ \beta_5 CP4 + \beta_6 AGE + \beta_7 FEMALE + \beta_8 FOREIGNER), \end{aligned} \quad (1)$$

where $F(z) = e^z/(1 + e^z)$ is the cumulative logistic distribution, CS is career satisfaction, DS is degree satisfaction, and CP_2-CP_4 are career path categories. In addition, gender, age and nationality were included as control variables. The outcome variable *skill* is one of the three dichotomous variables, *soft skills*, *hard skills*, or *practical experience*, presented above.

4 FINDINGS

4.1 Emerged skills

We started our analysis by coding the open-ended recommendations for skills that graduates would encourage current students to obtain to prepare them for future working life. The prevalence of the emerged skills and competencies (i.e. the proportion of respondents that recommended each skill category) is depicted in Figure 1. In the open-ended recommendations, the most valued soft skills were

[2]Hard skills refer to more technical skills such as programming while soft skills refer to wide-ranging personal and interpersonal skills.

Table 3: Descriptive statistics for career path

Career path category	n	%	Mean career satisfaction	Mean degree satisfaction
1. Continuously working for the same employer or as an entrepreneur	183	40.67	4.87	4.90
2. Working for several employers or temporary jobs	173	38.44	4.87	4.92
3. Breaks or periods of unemployment between employers	42	9.33	4.38	4.38
4. Other	52	11.56	3.96	4.10

teamwork, communication, life-long learning, and critical thinking. In technical skills, programming and certain specific focuses such as the cloud or version control were valued. Practical professional experience was also highly valued.

4.2 Factors affecting the recommendation of skills

Three logistic regression models were fitted to the data to test whether degree satisfaction, career satisfaction, and career path affect the probability of early-career practitioners recommending different types of skills. Results of the analysis are presented in Table 4.

According to the results, the recommendation of soft skills is positively related to career satisfaction ($p<0.05$) and gender ($p<0.01$). In other words, the higher the career satisfaction, the more likely it is that an early-career practitioner would recommend current students to obtain soft skills. Given that other variables remain constant, female practitioners are more likely to recommend soft skills. In addition, there is some evidence that the practitioners who have suffered from periods of unemployment are more likely to recommend soft skills compared to those who have worked for the same employer or as an entrepreneur since graduation ($p<0.1$).

As to the recommendation of hard skills, the logistic regression model was not statistically significant ($\chi^2(8) = 13.05$; $p=0.110$).

In turn, recommendation of practical experience is negatively related to degree satisfaction ($p<0.05$), gender ($p<0.05$), and nationality ($p<0.05$). Thus, the higher the degree satisfaction, the less likely an early-career practitioner would recommend current students to gain practical experience during their studies. In addition, female practitioners and practitioners of foreign origin are less likely to recommend practical experience compared to males and Finnish citizens.

5 DISCUSSION

According to our analyses, many early-career computer science and information technology practitioners recommend that current students obtain soft skills, especially teamwork and communication skills. More specifically, the logistic regression analysis revealed that the more satisfied the person is with their career, the more likely they are to recommend soft skills. This finding is in line with previous research that has distinguished soft skills as a distinguishing trait for outstanding software engineers [10, 11, 23].

One explanation for this result could be that studies have provided the respondents with good technical skills so far, and they would now require more interpersonal, management, or communication skills to advance in their careers. This conclusion is further backed up by the analyses on the technical or hard skills; Technical competencies or programming skills were as likely to be recommended by any respondent – with no statistical differences in career or degree satisfaction.

On the other hand, the more dissatisfied the person is with their university studies, the more likely they are to recommend more practical experience. It also seems that the people who are dissatisfied with their master's degree and recommend practical experience have had adverse career development due to the lack of experience.

In addition, the progress of the career seems to affect the recommendations. Those practitioners who have had breaks or periods of unemployment between employers are slightly more likely to recommend obtaining soft skills. This could be due to how companies stress interpersonal or teamworking skills in their hiring processes.

As to the use of career monitoring survey results in the curriculum development, results of the data analysis suggest that although industry-relevant technical skills need continued emphasis, soft skills and professional experience are needed to support graduates to do well during their early careers. These results are well in line with previous studies, for example the investigations into computing professionals' technical skills (e.g. [3, 7]), soft skills (e.g. [1, 23]), and personal traits ([9–11]). Overall, soft skills seem to be paramount for engineering jobs in the computing field.

6 CONCLUSIONS

This study investigated the recommendations for skills and competencies by recent graduates from computer science and information technology programmes to current students. To answer RQ1 *what recommendations for skills and competencies do recently graduated students have for current students?* The recommendations consisted of, for example, soft skills related to working or leading as an effective member of a software engineering team, core programming skills, and practical experience. Critical thinking and life-long learning were also mentioned frequently.

For RQ2, *how does the satisfaction towards working career and completed degree affect the skill and competency recommendations?* The more satisfied recent graduate is with their career, the more likely they are to recommend soft skills. Conversely, the less satisfied they are with the master's degree, the more likely they recommend obtaining practical experience.

For RQ3 *how does the career path of the respondents affect the recommendations?* Graduates who have had unemployment periods recommend more likely soft skills, possibly due to them being required during the recruitment process.

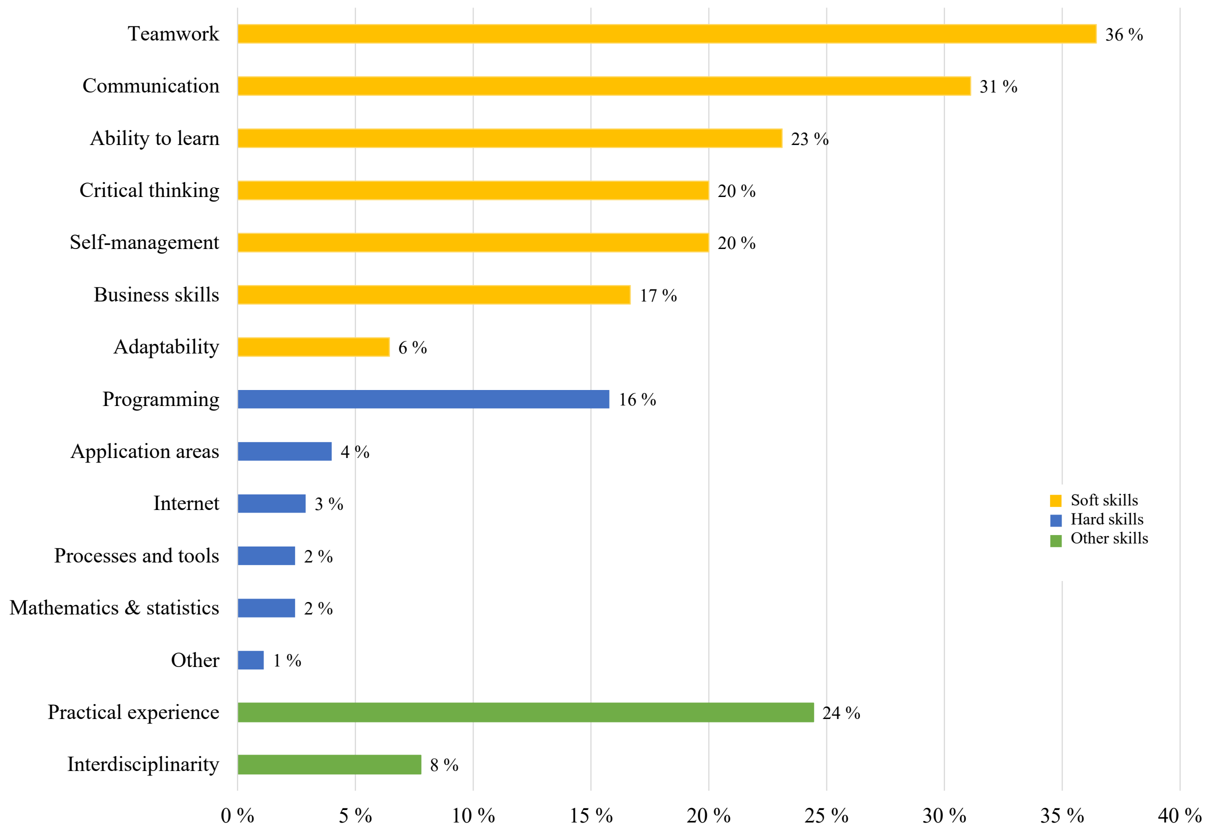

Figure 1: The skills and competences recommended by the recently graduated practitioners (N = 450)

Finally, to answer the main question guiding the current study *to what extent can recommendations of early-career engineers be utilized for curriculum development* we conclude that the career monitoring survey can provide useful insights into how well students have been prepared for the working life. We were able to elicit actionable feedback for including competencies needed in the industry. These insights could be used as indications of how well the study programmes are in touch with industry requirements, which is an important quality consideration for higher education. The good response rates to the career monitoring survey (16% for the open-ended feedback and 34% for the numeric feedback) suggest that a good portion of alumni are willing to contribute to the assessment and development of their old degree programmes.

We can also see that the survey responses provide similar results to the ones distinguished in the literature. According to our results, soft skills like teamwork, communication, and the ability to learn are common suggestions from the early-career professionals, which is in line with the job requirements distinguished by the work of Papoutsoglou et al. [17] and Garousi et al. [5, 6]. Therefore, the career monitoring survey is a viable source of data for the continuous development of university studies.

The main contribution of this study is the exploration of the usefulness of career monitoring surveys in measuring the quality of computing education. Higher education research has formed a consensus that student evaluations of teaching (SETs) are not very reliable measures of teaching quality [20, 21]. To complement the shortcomings of the SET metrics, this study investigated what recommendations emerge from early-career engineers, and what factors affect those recommendations.

We acknowledge that many factors were uncontrollable in this process - for example, we had to analyze the career monitoring survey results post-hoc. In addition, our sample is not random because graduates who have failed in their careers presumably are not as likely to answer career surveys as those who have succeeded. Therefore, there is a risk of selection bias. However, we feel that the sample size is adequate for the analyses, and the results support findings in related literature. Our data set is geographically limited to one country, and thus more experiments in different contexts are necessary. In future work, we should evaluate to what extent the cultural context affects the skill recommendations. We also encourage other educators to explore how to elicit improvement suggestions from engineers in different career phases.

Table 4: Results of logistic regressions

	Soft skills[a]	Hard skills[a]	Practical experience[a]
Constant	-1.581	0.244	2.121*
	(-1.54)	(0.23)	(2.03)
Career satisfaction	0.297*	-0.096	-0.138
	(2.48)	(-0.76)	(-1.18)
Degree satisfaction	0.155	-0.183	-0.270*
	(1.25)	(-1.42)	(-2.24)
Career = Several employers or temporary jobs[b]	-0.132	0.211	0.273
	(-0.51)	(0.78)	(1.03)
Career = Breaks or periods of unemployment between employers[b]	1.018[o]	-0.615	0.558
	(1.93)	(-1.17)	(1.40)
Career = Other[b]	0.098	-0.032	0.571
	(0.25)	(-0.08)	(1.49)
Age at graduation	0.017	-0.013	-0.047
	(0.69)	(-0.50)	(-1.82)
Gender = Female[c]	0.887**	-0.457	-0.624*
	(2.70)	(-1.42)	(-2.07)
Nationality = Foreigner[d]	-0.064	0.642	-0.905*
	(-0.19)	(1.94)	(-2.18)
Observations	446	446	446
$\chi^2(8)$	24.43**	13.05	29.26***
Pseudo R^2	0.051	0.029	0.059

[a] Dependent variable: skills or competencies are recommended = 1, not recommended = 0

[b] Reference group is Continuously working for the same employer or as an entrepreneur since graduation

[c] Reference group is Male

[d] Reference group is Finnish

z-statistics in parentheses

[o] $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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