Looking for a Major in Computing? Technical Knowledge versus Broader Social Values *

Irene Zanardi[1][0000−0002−7339−6259], Serena Versino[2][0000−0002−9860−9142], Karolina Bolesta[3][0000−0002−9668−5782], Anna Szlávi[4][0000−0002−4041−6217], and Monica Landoni[1][0000−0003−1414−6329]

[1] Università della Svizzera italiana, Via Giuseppe Buffi 13, 6900 Lugano, Switzerland
[2] University of Pisa, Largo Bruno Pontecorvo, 3, 56127 Pisa (PI), Italy
[3] Warsaw School of Economics, Niepodległości 162, 02-554 Warsaw, Poland
[4] Norwegian University of Science and Technology, Høgskoleringen 1, 7034 Trondheim, Norway.

Abstract. Since universities have a crucial role in training the next generation of experts in the field, this exploratory study aims to investigate how universities present computing majors to prospective students to better understand potential barriers to diversity and inclusion. The study analyzes textual descriptions of computing majors, and titles and learning outcomes of compulsory courses of four European universities. The findings suggest that while universities acknowledge the social embeddedness of computing in majors' descriptions, their curricula prioritize technical knowledge over helping students understand the broader social impact of their future work. The misalignment between the values of prospective students, who care for the social perspective, and how universities present the field could limit diversity and inclusion. This research aims to contribute to the understanding of how universities can promote themselves and their courses to attract a more diverse and inclusive student population in computing majors, by proposing a method for objectively unveiling existing communication mismatch.

Keywords: gender diversity · inclusiveness · university · computing · lexical analysis · text analysis · curricula · diversity · society · social sciences · social computing.

1 Introduction

The importance of computing education is growing as technology becomes more prevalent in society. Universities must train students to meet the demand for experts in the field. However, the number of students pursuing a degree in computing remains low [14], and diversity in both education and industry is still far from being achieved [11, 31, 3]. One possible reason is the perceived misalignment between the values of young people [28] and those associated with computing.

* This project was partially supported by COST Action CA19122 - EUGAIN (European Network for Gender Balance in Informatics).

Therefore, how universities promote themselves, as well as the messages they deliver when engaging with prospective students, are all crucial factors to consider.

We examined the descriptions of computing majors provided to potential students on the official websites of four European universities. We focused on the descriptions of bachelor's and master's degrees, as well as the titles and learning outcomes of compulsory courses. We tokenized and lemmatized the documents. Next, we analyzed the word frequency count and the relative document frequency of each lemma. Lemmas were finally divided into educational, social, and technical lemmas. Findings show that while descriptions of computing majors acknowledge the link between computing and society, the presentation of compulsory curricula does not. This suggests that universities may prioritize preparing students for specific technical tasks over helping them in understanding the broader social context in which their work will be used. Additionally, it implies that how universities present computing may not align with the values of prospective students, potentially limiting diversity and inclusion in the field.

Our exploratory paper contributes to computing education in several ways. First, it examines of how universities present computing majors to prospective students, providing valuable insight into how universities communicate about the field. This information can be used to refocus and tune in to society's and individuals' needs. Second, the paper highlights how much emphasis universities place on social aspects of computing in their curricula. As Generation Z students have a stronger sense of purpose and a desire to make a positive difference in society [28, 35], they may be more drawn to computing majors that are clearly connected to social issues. By paying attention to how they present themselves and their courses, universities can work to increase diversity and inclusion in computing. Finally, following the described methodology, we produced an initial lexicon of highly representative lemmas that can be used in future studies to broaden the scope of analysis and include a larger sample of universities.

2 Related work

Generation Z students, or digital natives [41], were born between 1997 and 2012 [12] and have different values than previous generations [15, 4]. They are the most racially and ethnically diverse generation to date [6] and social media has further given them the opportunity to connect with people from various cultures and backgrounds [26]. As a result, Gen Z is fully aware of its social responsibilities, responds to calls for equity and inclusion [35], and expects and values diversity and social sustainability in the workplace [36] and in universities [45]. In terms of career motivations, Gen Z seeks self-actualization [43], through the pursuit of a path that allows them to contribute to humanity while remaining true to their values [5]. As a result, aligning professional and personal values is critical for them [5].

The computing community recognizes the importance of addressing the social aspects of the field. The topic has received increasing attention over the years:

researchers stress the necessity of including ethics in any computing curriculum to promote individual accountability and awareness [17, 39, 8]. Furthermore, the connection with real-life problems must be emphasized to make the usefulness of any STEM discipline clear [23, 18], increase motivation and engagement [44], and maintain a positive attitude toward the field [7]. Aside from ethics and practical teaching methods, the impact of computing on society calls for a significant shift in mentality [9] in order to understand the potential and the roles that technology can have for social change [2]. The field is inextricably linked to – and may even be considered part of – social sciences, and, as such, should embrace their complexities [9]. This mentality shift presupposes a transformation of the curricula of computing disciplines, where social science courses should be included [9], promoting a focus on *people* rather than *things* that could attract more diversity [20] and fit better with the role of computer scientists in society [18, 9]. Indeed, occupations that focus on *people* are feminine-typed, and they attract more women compared to disciplines rooted in *things* [30, 32, 10], such as traditional computing, which is considered a masculine field [38]. The mismatch between perceived required skills in computing and self-concept of one's abilities can impact self-efficacy, which in turn can influence aspirations [13, 27, 19]. As stereotypes can influence how we perceive ourselves and our place in the world [40], it is critical to pay attention to how we present the profession of the computer scientist, as well as computing curricula, in order to ensure equal opportunities and diversity in the field.

Universities play a crucial role in shaping people's perceptions of computing. They provide valuable information to students, including the *what*, *how*, and *why* of computing professionals' work, that is critical in forming aspirations and career choices [22, 24]. Their websites, in particular, serve as an essential point of contact for prospective students [42]. Unlike traditional media, internet enables teenagers to actively seek information about potential careers [29, 50], and how universities present the field can have a significant impact on students' choices [24, 20].

3 Methodology and results

3.1 Objective and research questions

When it comes to forming aspirations, institutions' messages are critical in providing prospective students with career information [24, 22]. Focusing on the social embeddedness of computing can create a bridge between computing and students' values, while respecting and reflecting technology's role in society. We examine the descriptions and programs of computing majors at four European universities. Our goal is to understand which topics universities focus on to describe their majors and present their curricula on their websites, and consequently picture how computing could be perceived by prospective students. We will specifically address the following research questions: **(RQ1)** To what degree computing majors present computing as a field that has an impact on society? **(RQ2)** What could students expect to learn from the courses by reading their learning outcomes and their titles? **(RQ3)** Is there alignment between students' values and the values proposed by the universities?

3.2 Data collection and exploration

This exploratory study focused on a small sample of four European universities. In order to provide significant diversity, universities were chosen based on their size, gender balance, social impact, and non-computing majors. The latter, in particular, defines the student population they serve as well as the possibility of interdisciplinary offers. Concerning their social impact, we focused on two scores of the Sustainability Rankings [48]: *Equality*, which aggregates data on the research done regarding Sustainable Development Goals (SDGs) *Gender Equality* and *Reduced Inequalities* [37], operational activities, students and staff ratios, and national-level statistics on equality; and *Life Quality*, which aggregates data on the impact of the university on health and wellbeing, the research done regarding SDGs *No Poverty*, *Zero Hunger*, *Good Health*, *Clean Water* [37], and national-level statistics. Once the four universities were selected [Tab. 1], we identified their computing majors. For each one of the 32 majors, we gathered three types of texts from their websites.

Table 1. Characteristics of the four universities

Features	**Univ 1**	**Univ 2**	**Univ 3**	**Univ 4**
Size	+	+	-	-
Diversity	+	-	-	+
Impact	+	+	-	-
Offer	-	+	+	-

First, we collected the text of majors' descriptions to analyze how they are presented to prospective students. Then, we moved on to each major's compulsory courses in order to understand what universities consider essential. For each course, we collected its title and text about its learning outcomes. While titles were chosen because they convey the essential topics of the course, we gathered learning outcomes as they list the expected knowledge and skills that students should achieve [16], thus aligning better with our search for the teaching of social aspects of technology. The resulting dataset contains 282 titles of compulsory courses, 232 learning outcomes and 32 majors' descriptions. The difference between the total number of titles and learning outcomes is due to 19% of missing learning outcomes that were not disclosed on the websites.

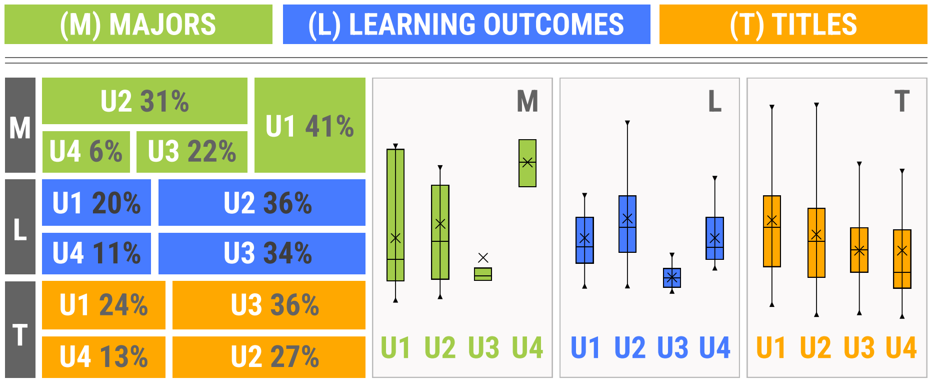

Fig. 1. a) Treemap of universities by corpus. b) c) d) Length distribution of majors, learning outcomes, titles.

Fig. 1 depicts four charts that describe the corpus. Overall, university 4 is the least represented in the corpus. We calculated the length of each corpus as the count of characters in the strings. After the distribution normalization of the lengths of each corpus, the majors showed a bimodal distribution, with two peaks around 1000 and 3000-4000 characters length, whilst titles and learning outcomes showed an unimodal distribution, respectively around 25 and 1000 characters. University 4 provided the highest contribution in the majors (Mdn, M = 3,534)[Fig. 1-b]. Next, the length distributions of learning outcomes are shown, with university 2 providing the highest contribution (Mdn = 1,229; M = 1,494)[Fig. 1-c]. Finally, the last chart shows the length distributions of titles, with university 1 contributing the most (Mdn = 33; M = 35) [Fig. 1-d].

3.3 Data pre-processing and analysis

We standardized corpora appearance, reduced data sparseness and applied data cleaning approaches. We converted the text into lower case characters, removing punctuation, unnecessary symbols and stop words[5]. In the Tokenization process, the lexical analyzer chopped the streams of characters into tokens[6][25] and retrieved the terms used in the corpus. Then, we tagged the tokens using the Part-of-speech tagging (POS)[7]. In order to reduce the dimensionality of the description of documents within the vocabulary, we applied the Lemmatization approach. As a result, we removed the inflectional morphology of tokens and built the vocabulary of our domain using canonical forms, the lemmas [8] [34].

[5] Stop words are frequent terms that don't offer meaningful information for the analysis's purposes [49].
[6] Tokens are collections of characters that have a collective meaning.
[7] POS determines the part of speech tag, e.g. noun, verb, adjective, etc. for each term[21].
[8] A lemma is a single dictionary entry with a single meaning[33]

Term frequency and relative document frequency were calculated for each entire corpus as well as for each university separately. In the vocabulary of learning outcomes and majors we analyzed the frequencies of nouns, which denote the topics present in a text [1]. For titles we considered all lemmas, since, due to the shortness of titles, verbs and adjectives can carry meaningful information. The corpora were analyzed using LIWC [47], a software that performs word count as well as other types of more sophisticated text analysis. We counted the occurrences of lemmas in each collection. Moreover, for each collection we calculated relative document frequency. For majors and titles we considered lemmas that appeared more than one time, since the first corpus contains only 32 documents, and the second corpus contains short texts. For learning outcomes, the biggest corpus of the three, we established the threshold equal to half of the total average of the frequencies, considering only lemmas that appeared more than three times.

Finally, we divided the lemmas into three categories: educational, social, and technical. To compare the coding and control mismatches, one of the authors and a computing professional performed separate categorization. Before coding, the context in which lemmas appeared was specified to the computing professional to aid in interpreting their meaning. Because of the small sample size, the coders were able to easily check lemmas in the texts where it appeared to resolve any particular ambiguity. **Educational lemmas** represent the university's organization and people, such as *exam* and *student*, learning methods and tools, such as *project* and *laboratory*, and cognitive abilities, such as *comprehension* and *problem-solving*; **social lemmas** refer to society and the impact of technology on society, such as *society*, *culture*, and *ethics*, as well as lemmas referring to people and their interaction with technology, such as *user*, *experience*, and *usability*; **technical lemmas** refer to technology in general, such as *computer*, lemmas referring to STEM disciplines, such as *mathematics* and *electronics*, lemmas referring to software and programming, such as *system*, *software*, and *algorithm*, lemmas referring to data management, such as *data*, *information*, and *modeling*, and lemmas referring to application design, such as *design*, *tool*, and *component*.

Furthermore, because the cybersecurity field deals with human and social issues [17], we decided to classify *security* as a social lemma. We calculated Cohen's kappa to see if the definitions were clear and effective, and it confirmed a high inter-rater reliability value (k = 0.97). After combining the coding sheets, we calculated the absolute frequency in the corpus, frequency in comparison to other lemmas, and percentage in the vocabulary for each of the three categories.

3.4 Results

Content of majors' descriptions. The Tab. 2 shows that the major descriptions emphasize the social aspects of computing, with 80% mentioning society (P = 0.81). Other topics that are frequently discussed include *ethics* (P = 0.25), *innovation* (P = 0.25), and *users* (P = 0.25). With the exception of university 3, which mentions only *communication* and *society* and only in less than a third of the majors (P = 0.29), *security* is a consistent topic (P = 0.22). University 2 emphasizes *culture* (P = 0.3) and the *impact* of computing (P = 0.3), whereas university 4 emphasizes *responsibility* (P = 1.0). University 1 has a higher rate of descriptions containing *ethics* (P = 0.38) and *users* (P = 0.54), and all of its descriptions mention *society*. Likewise, *society* is mentioned in all of the descriptions for University 4, but it should be noted that it has fewer majors overall.

Despite the emphasis on social aspects in the majors, the vocabulary composition and frequency of social lemmas indicate that descriptions are primarily concerned with technical aspects of the discipline. As shown in Tab. 3, only 10% of the vocabulary is social-related (P = 0.1), with slightly higher percentages for university 1 (P = 0.12) and lower percentages for the other universities. In terms of frequency, social-related lemmas account for only 7% of the vocabulary's total frequency. University 3 in particular has the lowest frequency of social-related lemmas (P = 0.02). On the contrary, technical terms are more widespread, accounting for nearly half of the nouns in the descriptions (P = 0.49), while educational lemmas are slightly less common (P = 0.44).

Table 2. Majors' descriptions corpus. Most common social and technical lemmas with relative document frequency (rDOCF). Corpus is compared to each university.

	Corpus		**Univ 1**		**Univ 2**		**Univ 3**		**Univ 4**	
	Lemma	rDOCF	Lemma	rDOCF	Lemma	rDOCF	Lemma	rDOCF	Lemma	rDOCF
Social	society	P = 81.3	society	P = 100	society	P = 70.0	communication	P = 28.6	ethics	P = 100
	ethics	P = 25.0	user	P = 53.8	culture	P = 30.0	society	P = 28.6	responsibility	P = 100
	innovation	P = 25.0	ethics	P = 38.5	impact	P = 30.0	N/A	N/A	society	P = 100
	user	P = 25.0	innovation	P = 38.5	innovation	P = 30.0	N/A	N/A	N/A	N/A
	security	P = 21.9	security	P = 38.5	experience	P = 20.0	N/A	N/A	N/A	N/A
Technical	system	P = 75.0	program	P = 84.6	computer	P = 100	informatics	P = 71.4	analysis	P = 100
	design	P = 62.5	development	P = 76.9	science	P = 90.0	science	P = 71.4	business	P = 100
	computer	P = 59.4	information	P = 76.9	system	P = 80.0	design	P = 57.1	computer	P = 100
	science	P = 59.4	technology	P = 76.9	application	P = 70.0	software	P = 57.1	design	P = 100
	technology	P = 59.4	system	P = 69.2	design	P = 70.0	technology	P = 57.1	econometrics	P = 100

Table 3. Vocabulary composition of majors' descriptions according to categories.

Percentages of unique lemmas					
	Corpus	**Univ 1**	**Univ 2**	**Univ 3**	**Univ 4**
E	P = 0.43	P = 0.44	P = 0.47	P = 0.49	P = 0.37
S	P = 0.10	P = 0.12	P = 0.09	P = 0.03	P = 0.06
T	P = 0.47	P = 0.45	P = 0.44	P = 0.48	P = 0.58
Percentages of categories on total frequencies					
	Corpus	**Univ 1**	**Univ 2**	**Univ 3**	**Univ 4**
E	P = 0.44	P = 0.49	P = 0.41	P = 0.39	P = 0.35
S	P = 0.07	P = 0.08	P = 0.06	P = 0.02	P = 0.06
T	P = 0.49	P = 0.43	P = 0.53	P = 0.58	P = 0.59

Content of courses' titles and learning outcomes. Unsurprisingly, the analysis of the courses' titles reveals a distinct lack of social sciences courses. Only a small percentage (P = 0.05) of the titles mention social aspects of computing [Table 4]. The frequent lemma *system* (F = 24) appears in titles such as *Distributed Systems*, *System Security*, and *Intelligent Systems*, followed by *Data* (F = 20), as in *Database* and *Data Mining*, and *design* (F = 20), as in *Software Design*, *Algorithm Design*, and *User Experience Design*. With the exception of University 1, which has a higher number of unique social lemmas (P = 0.15), this trend is consistent across all universities. *Security* is the most frequently encountered lemma, followed by *communication* and *usability*. The absence of references to social science and social aspects can also be found in the learning outcomes corpus. As shown in Tab. 5, educational terms account for more than half of the total frequencies (P = 0.52), with technical terms coming in second (P = 0.43). However, with the exception of university 1, which has a slightly higher number of educational lemmas, technical terms make up the majority of the vocabulary (P = 0.59). Social lemmas account for a small portion of the vocabulary (P = 0.05) and a small portion of the frequencies (P = 0.05).

Table 4. Percentages unique lemmas of titles' vocabulary categorized as social.

Percentages of unique lemmas					
	Corpus	**Univ 1**	**Univ 2**	**Univ 3**	**Univ 4**
S	P = 0.05	P = 0.15	P = 0.05	P = 0.02	P = 0

Table 5. Vocabulary composition of learning outcomes according to categories.

Percentages of unique lemmas					
	Corpus	**Univ 1**	**Univ 2**	**Univ 3**	**Univ 4**
E	P = 0.36	P = 0.50	P = 0.43	P = 0.37	P = 0.37
S	P = 0.05	P = 0.08	P = 0.02	P = 0.01	P = 0.08
T	P = 0.59	P = 0.42	P = 0.55	P = 0.62	P = 0.56
Percentages of categories on total frequencies					
	Corpus	**Univ 1**	**Univ 2**	**Univ 3**	**Univ 4**
E	P = 0.52	P = 0.56	P = 0.57	P = 0.40	P = 0.49
S	P = 0.05	P = 0.09	P = 0.02	P = >0.01	P = 0.03
T	P = 0.43	P = 0.35	P = 0.41	P = 0.60	P = 0.49

According to Tab. 6, the most frequently used term is *ethics*, which appears in roughly one-tenth of the documents (P = 0.12), closely followed by *security* (P = 0.11). The four universities studied yielded disparate results. University 1 has a higher overall presence of social terms, particularly *ethics* (P = 0.39), *user* (P = 0.27), and *security* (P = 0.24). University 2 uses the word *awareness* more frequently (P = 0.16). University 4 has a distinct vocabulary, referring to *culture* (P = 0.13), *ethics* (P = 0.13), and *philosophy* (P = 0.10). University 3 makes the fewest references to society, with only the lemma *experience* present (P = 0.5).

Table 6. Courses' learning outcomes corpus. Most common social and technical lemmas relative document frequency (rDOCF). Corpus is compared to each university.

	Corpus		**Univ 1**		**Univ 2**		**Univ 3**		**Univ 4**	
	Lemma	rDOCF	Lemma	rDOCF	Lemma	rDOCF	Lemma	rDOCF	Lemma	rDOCF
Social	ethics	P = 0.12	ethics	P = 0.39	awareness	P = 0.16	experience	P = 0.05	culture	P = 0.13
	security	P = 0.11	user	P = 0.27	security	P = 0.12	N/A	N/A	ethics	P = 0.13
	user	P = 0.09	security	P = 0.24	environment	P = 0.07	N/A	N/A	life	P = 0.10
	awareness	P = 0.07	innovation	P = 0.19	impact	P = 0.05	N/A	N/A	philosophy	P = 0.10
	innovation	P = 0.06	audience	P = 0.15	N/A	P = N/A	N/A	N/A	society	P = 0.10
Technical	system	P = 0.43	system	P = 0.46	system	P = 0.67	system	P = 0.31	model	P = 0.63
	design	P = 0.36	design	P = 0.41	design	P = 0.59	design	P = 0.26	data	P = 0.53
	application	P = 0.33	information	P = 0.27	application	P = 0.53	computer	P = 0.22	application	P = 0.33
	model	P = 0.26	application	P = 0.25	tool	P = 0.34	application	P = 0.19	business	P = 0.33
	tool	P = 0.23	model	P = 0.24	computer	P = 0.30	algorithm	P = 0.14	information	P = 0.23

4 Discussion

Majors present computing as a field that has an impact on society. This is consistent with the acknowledged social component of computing and its disciplines [9, 2]. However, while social references can be found in the texts, they primarily focus on the technical aspects of the field. Social lemmas have a low presence in the whole vocabulary and a low frequency, suggesting a general reference to society rather than a specific and in-depth one. Differences among the four universities were also observed. University 1, which is bigger and has higher gender balance and impact rankings, scores highly in all the results. Interestingly, university 3, which has the opposite characteristics, has the lowest values overall. University 2, which offers more non-computing majors and has lower gender diversity than university 1, shows slightly lower values. University 4, which is high in gender diversity but low in all the other characteristics, shows the highest values in the relative document frequency, but low values in variety of social terms in the vocabulary and in their frequency. However, this discrepancy could be due to its small contribution to the corpus. One possible explanation for these differences may be found in the characteristics of the universities. However, given the small sample size and exploratory nature of the exploratory study, further investigation is needed to fully understand the potential correlations.

Students can expect to learn mainly technical aspects of computing. Despite the fact that majors mention social aspects, an interesting result of the analysis highlights a disparity between how universities present their majors and how they present their curricula. While all four universities emphasized the social aspects of computing in their overall majors' descriptions, the courses' titles and learning outcomes did not reflect this emphasis. Only a small proportion of courses' titles ($P = 0.05$) mentioned social aspects of computing, and the learning outcomes corpus revealed a distinct lack of references to social science and social aspects. This disparity raises questions about the extent to which universities integrate social and ethical considerations into computing education. It implies that, while majors' descriptions emphasize the significance of social aspects, universities may not consider them as important when describing the learning outcomes of their courses.

There is misalignment between computing curricula and students' values. Current computing curricula falls short in aligning with the majors and courses offered. In relation to the literature, it also does not align with the values and interests of students [45]. A glance at the courses' titles and learning outcomes reveals that the majority of the content is heavily technical in nature. This lack of diversity in mandatory offerings not only limits students' knowledge but also overlooks the crucial role that computing plays in shaping society. Furthermore, learning outcomes focus primarily on the theoretical side of computing, such as algorithms, data, and information management, as well as the practical side of designing and coding applications and systems. What is missing, however, is the connection between the practical side of computing and its impact on people, including the importance of social sciences as a theoretical basis [9]. This lack of emphasis on the practical social implications of computing may deter students who are interested in using their skills to drive positive change in society [35, 28].

4.1 Implications, limitations and future work

The next generation of computing professionals need to be able to see beyond the technical aspects and to understand how their work will impact individuals, groups and the society as a whole. To do this, the curriculum and its presentation must be re-evaluated to include a more diverse range of course offerings that encompasses the social and ethical implications of computing. This will help students to understand the *why* behind what they are learning, and not just the *what* and *how*. Moreover, as the Gen Z is deeply involved in social causes [35, 28] and an alignment of values between their career motivations and what their career has to offer [5], it is crucial to incorporate the social value of computing into the presentation of curricula. This will assist students in seeing the potential of their skills to make a positive impact in the world, and align their career goals with their personal values. Because of its presentation as a mainly technical field, computing is commonly masculine-typed and consequently women are discouraged at taking part in it [40]. This is why it is important that institutions pay attention to how they present themselves through their websites, which are reliable sources of information that are essential to depict computing to prospective students [24].

The small sample size of this exploratory study calls for caution in interpreting the results. First off, since the values were examined in the literature, this paper does not directly investigate the mismatch between students' values and university curricula. This means that we do not assert that students at the four universities believe they are misaligned. Additional research could concentrate on using qualitative methods to clearly highlight perceptions. Second, although the data cannot be generalized, it does highlight the disconnect between computing's societal applications and its teaching methods. Further research with a larger and more diverse sample of institutions, selected according to but not limited by the factors mentioned here, is needed to determine if this is a widespread trend and if there are variations among universities that can be linked to specific institutional characteristics. This exploratory study analyzed only three types of texts found on university websites, which were chosen to represent universities' presentation of their majors and curricula. However, it would be beneficial to examine other texts present on university websites in more depth. Furthermore, by expanding the sample size to include more universities and texts, it would be possible to compare computing disciplines as defined by the CC2020 [17] and see if some are more socially oriented than others. Finally, it may be worthwhile to directly involve the people behind the descriptions to assess their understanding of the issues raised by this exploratory study. This could better define the opportunities for change and highlight any potential underlying issues that need to be addressed.

5 Conclusion

This study looked at how four universities present their computing majors and courses on their websites, as these are the first point of contact with prospective students, in order to identify references to social-related topics. The findings reveal that, while computing majors are recognized as socially embedded, the emphasis is primarily on the technical aspects of the field. Moreover, the descriptions of the considered majors are not aligned with those of the courses offered, as well as with students' values and interests. Furthermore, the exploratory study raises concern that a lack of emphasis on the social implications of computing may discourage students who want to work for the greater good.

References

1. Abbott, R. J. Program design by informal English descriptions. Commun. ACM 26, 11 (1983), 882–894. (1983)
2. Abebe, R., Barocas, S., Kleinberg, J., Levy, K., Raghavan, M., Robinson, D. G. Roles for computing in social change. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency. 252–260. (2020)
3. Barr, V. Gender diversity in computing: are we making any progress?, 5–5 pages. (2017).
4. Baysal Berkup, S. Working with generations X and Y in generation Z period: Management of different generations in business life. Mediterranean journal of social Sciences 5, 19 (2014), 218–218. (2014).
5. Bohdziewicz, P. Career anchors of representatives of generation Z: some conclusions for managing the younger generation of employees. Zarządzanie Zasobami Ludzkimi 6 (113)-" Managing Diversity in the Context of International HRM" (2016), 57–74. (2016).
6. Turner, A. Generation Z: Technology and social interest. The journal of individual Psychology 71, 2 (2015), 103–113. (2015).
7. Christensen, R., Knezek, G. Tyler-Wood, T. Alignment of hands-on STEM engagement activities with positive STEM dispositions in secondary school students. Journal of Science Education and Technology 24, 6 (2015), 898–909. (2015).
8. Cohen, L. Precel, H. Triedman, H. Fisler, K. A New Model for Weaving Responsible Computing Into Courses Across the CS Curriculum. In Proceedings of the 52nd ACM Technical Symposium on Computer Science Education. 858–864. (2021).
9. Connolly, R. Why computing belongs within the social sciences. Commun. ACM 63, 8 (2020), 54–59. (2020).
10. JC Cuddy, A., Fiske, S. T. Glick, P. Warmth and competence as universal dimensions of social perception: The stereotype content model and the BIAS map. Advances in experimental social psychology 40 (2008), 61–149. (2008).
11. Canedo, E. D. Tives, H. A., Marioti, M. B., Fagundes, F. Siqueira de Cerqueira, J.A. Barriers faced by women in software development projects. Information 10, 10 (2019), 309. (2019).
12. Dimock, M. Defining generations: Where Millennials end and Generation Z begins. Pew Research Center 17, 1 (2019), 1–7. (2019).
13. Eccles, J. S., Wigfield, A. From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. Contemporary educational psychology 61 (2020), 101859. (2020).

14. Eurostat. 2022. ICT specialists workforce continued to grow in 2021. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20220505-1
15. Fodor, M., Jaeckel, K. What does it take to have a successful career through the eyes of generation Z-based on the results of a primary qualitative research. International Journal on Lifelong Education and Leadership 4, 1 (2018), 1–7. (2O18).
16. European Centre for the Develooment of Vocational Training. Accessed: January 2022. Learning outcomes. https://www.cedefop.europa.eu/en/projects/learning-outcomes
17. Task Force. Computing Curricula 2020: Paradigms for global computing education. Association for Computing Machinery, New York, NY, USA. (2020).
18. Friedman, B., Kahn, P. H. Educating computer scientists: Linking the social and the technical. Commun. ACM 37, 1 (1994), 64–70. (1994).
19. Gottfredson, L. S. Gottfredson's theory of circumscription, compromise, and self-creation. Career choice and development 4 (2002), 85–148. (2002).
20. Grabarczyk, P. Freiesleben, A. Bastrup, A. Brabrand, C. Computing Educational Programmes with more Women are more about People & less about Things. In Proceedings of the 27th ACM Conference on on Innovation and Technology in Computer Science Education Vol. 1. 172–178. (2022).
21. Hotho, A. Nürnberger, A., Paaß, G. A brief survey of text mining. Journal for Language Technology and Computational Linguistics 20, 1 (2005), 19–62. (2015).
22. LS Jahn, J., Myers, K. K. Vocational anticipatory socialization of adolescents: Messages, sources, and frameworks that influence interest in STEM careers. Journal of Applied Communication Research 42, 1 (2014), 85–106. (2014).
23. LS Jahn, J., Myers, K. K. "When will I use this?" How math and science classes communicate impressions of STEM careers: Implications for vocational anticipatory socialization. Communication Studies 66, 2 (2015), 218–237. (2015).
24. Jan, M. T., Ammari, D. Advertising online by educational institutions and students' reaction: a study of Malaysian Universities. Journal of Marketing for Higher Education 26, 2 (2016), 168–180. (2016).
25. Johnson, M., Zelenski, J. Lexical Analysis. Web.stanford.edu (2012). https://web.stanford.edu/class/archive/cs/cs143/cs143.1128/handouts/040
26. Lanier, K. 5 Things HR professionals need to know about generation Z: thought leaders share their views on the HR profession and its direction for the future. Strategic HR review (2017).
27. Lent, R. W., Brown, S. D., Hackett, G. Toward a unifying social cognitive theory of career and academic interest, choice, and performance. Journal of vocational behavior 45, 1 (1994), 79–122. (1994).
28. Leslie, B., Anderson, C., Bickham, C., Horman, J., Overly, A., Gentry, C., Callahan, C., King, J. Generation Z perceptions of a positive workplace environment. Employee Responsibilities and Rights Journal 33, 3 (2021), 171–187. (2021).
29. Levine, K. J., Aley, M. Introducing the sixth source of vocational anticipatory socialization: Using the internet to search for career information. Journal of Career Development 49, 2 (2022), 443–456. (2022).
30. Lippa, R. Gender-related individual differences and the structure of vocational interests: The importance of the people–things dimension. Journal of personality and social psychology 74, 4 (1998), 996. (1998).
31. Statista. 2022. Software developer gender distribution worldwide as of 2022. https://www.statista.com/statistics/1126823/worldwide-developer-gender/
32. Lippa, R. A., Preston, K., Penner, J. Women's representation in 60 occupations from 1972 to 2010: More women in high-status jobs, few women in things-oriented jobs. PloS one 9, 5 (2014), e95960. (2014).

33. Manning, C., Schütze, H. Foundations of Statistical Natural Language Processing. MIT Press. Cambridge. (1999).
34. Manning, C. D., Raghavan, P., Schütze, H. Introduction to Information Retrieval. Cambridge University Press (2008). https://nlp.stanford.edu/IR-book/html/htmledition/stemming-and-lemmatization-1.html
35. Meehan, M. 2016. The next generation: What matters to Gen We. (2018). Retrieved from Forbes website: https://www.forbes.com/sites/marymeehan/2016/08/11/thenextgenerationwhatmatters-to-gen-we.
36. Nguyen Ngoc, T., Dung, M. V., Rowley, C., Pejić Bach, M. Generation Z job seekers' expectations and their job pursuit intention: Evidence from transition and emerging economy. International Journal of Engineering Business Management 14 (2022), 18479790221112548. (2022).
37. UN Department of Economic and Social Affairs. 2022. The 17 goals. https://sdgs.un.org/goals
38. Papastergiou, M. Are computer science and information technology still masculine fields? High school students' perceptions and career choices. Computers & education 51, 2 (2008), 594–608. (2008).
39. Parameswaran, M., Whinston, A. B. Social computing: An overview. Communications of the association for Information Systems 19, 1 (2007), 37. (2007).
40. Payton, F. C., Berki, E. Countering the negative image of women in computing. Commun. ACM 62, 5 (2019), 56–63. (2019).
41. Prensky, M. Digital natives, digital immigrants part 2: Do they really think differently? On the horizon. (2001).
42. Schimmel, K. Motley, D., Racic, S., Marco, G., Eschenfelder, M. The importance of university web pages in selecting a higher education institution. Research in Higher Education Journal 9 (2010), 1. (2010).
43. Silinevica, I., Meirule, L. Generation Z Enters into the Latvian Business Environment. Latgale National Economy Research 1, 11 (2019), 97–107. (2019).
44. Strayhorn, T. L., Long III, L. L., Kitchen, J. A., Williams, M. S., Stenz, M. E. Academic and social barriers to Black and Latino male collegians' success in engineering and related STEM fields. (2013).
45. Symonds, Q. Do students care if their universities value social sustainability? (2022). https://www.qs.com/do-students-care-if-their-universities-value-social-sustainability/
46. Symonds, Q. QS World University Rankings: Sustainability 2023. (2022). https://www.topuniversities.com/university-rankings/sustainability-rankings/2023
47. Tausczik, Y. R., Pennebake, J. W. The psychological meaning of words: LIWC and computerized text analysis methods. Journal of language and social psychology 29, 1 (2010), 24–54. (2010).
48. Symonds, Q. Do students care if their universities value social sustainability? (2022). https://www.qs.com/do-students-care-if-their-universities-value-socialsustainability/
49. Vijayarani, S. Ilamathi, J. Nithya, M. Preprocessing techniques for text mining-an overview. International Journal of Computer Science & Communication Networks 5, 1 (2015), 7–16. (2015).
50. Vranken, I., Vandenbosch, L. Exploring Late Adolescents' Ex- periences with Career-Related Messages on Entertainment TV and in Social Media in Belgium: A Focus Group Study. Journal of Adolescent Research, 07435584221140611. (2022).