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Computational Intelligence for Equity-Aware STEM Student Recruitment

Noor Abid and Svetlana Yanushkevich
Biometric Technologies Laboratory, Schulich School of Engineering, University of Calgary, Canada
noor.abid@ucalgary.ca, syanshk@ucalgary.ca

***Abstract*—This paper makes a contribution to the CI platform aimed at enhancing the efficiency of student recruitment procedures. Our study entails a comprehensive follow-up audit of this domain, and identifies the key challenges to the integration of equity-conscious practices into the recruitment process. We propose an innovative solution designed to bridge the relevant socio-technological gaps, that is a self-aware recruitment engine. This engine functions within two interconnected conceptual paradigms: machine learning and probabilistic reasoning. To illustrate our approach, we offer a demonstrative example that showcases its practical application.**

***Index Terms*—Student recruitment, self-aware engine, STEM, machine learning, causal models, equity, diversity, inclusion**

I. Introduction

Student recruitment is the process of identifying qualified students and persuading them to apply [3]. This process becomes more complicated in the Equity, Diversity, Inclusion (EDI) dimensions [11]. It is influenced by multiple factors such as recruitment strategies, resource availability, demographics, and mindsets. These factors must be harmonized to achieve equity-aware STEM student recruitment, in particular. The fundamental goal of this emerging topic is to re-examine and re-frame the equity-aware STEM student recruitment engine through the lens of computational intelligence (CI). This paper serves as a meaningful contribution to this endeavor.

Student recruitment is considered in various coordinates, such as student-centered quality education, campus, financial considerations, opportunities and resources, and the people at the university [13]. A ”student satisfaction” index is a relevant measure that includes university rating, student expectations, perceived quality, perceived value, and student loyalty [12]. Students' interest in STEM careers is influenced by family, out-of-school learning experiences, inside-of-school learning experiences, and media influences [7]. Exploratory and confirmatory factorial analysis used in [15] showed that the predictors of career aspirations include students' opinions on technical topics, the content of school subjects, and related classroom experiences.

From a conceptual standpoint, we distinguish the CI approaches within student recruitment as twofold: a) machine learning, entailing the identification of pertinent data patterns [2], [14], and b) machine reasoning, entailing the provision of expert-guided recommendations for informed decision-making [4], [5].

Limited data on recruitment at STEM universities are available globally. One example is the Norwegian project Lily, aimed at “understanding the priorities, experiences, and motivational factors underlying young people's educational choice” [10]. About 5007 students who chose STEM-related education at a public university or a university college answered a specifically designed survey. In this paper, we use data from [10] for a case study of the causal models combined with EDI-awareness.

II. Self-aware recruitment engine

In this work, we re-examine and re-frame the EDI-aware student recruitment engine based on our previous work [1], using machine reasoning models such as Bayesian Network (BN). Our re-framing calls for the concept of the self-aware learning and reasoning loop illustrated in Fig. 1. The concept of self-awareness has been established in education, psychology, philosophy, and cognitive science [8]. Self-aware computing is a new paradigm for systems to proactively gather information, maintain knowledge about their own internal states and environments, and then utilize this knowledge to reason about behaviors. In Fig. 1, the empirical (perceived) data from an object of observation (a student), is used as a basis for the ongoing learning process. The learned model forms the system's knowledge base, providing the basis for the system's reasoning process. The latter may trigger actions affecting both the behavior of the system (self-adaptation) and possibly impacting the environment.

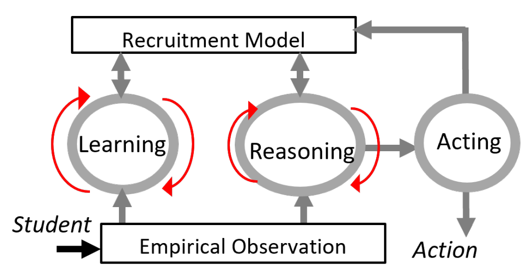


Fig. 1. Concept of self-aware learning-reasoning loop.

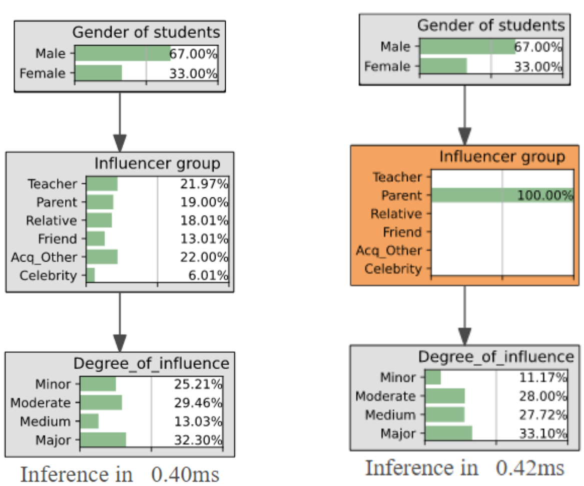
Similar to the learning mode of a self-aware recruitment engine, the reasoning mode (Fig. 1) can be implemented using causal networks such as BN, credal networks, Dempster-Shafer networks, and fuzzy causal networks [9]. A BN was chosen in our paper. A causal graph becomes a BN upon assigning its nodes the Conditional Probability Tables (CPTs). Conditional probabilities reflect the probabilistic cause-effect relation.

III. Case Study

In this paper, a subset of the numerical data from [10] was the count of answers to a questionnaire about the person influencing the student's decision to choose STEM. These counts were converted into the frequencies of occurrence, in order to create CPTs as shown in Fig. 2. A fragment of a BN created using pyAgrum library, which is a Python wrapper for the C++ aGrUM library, is shown in Fig. 3. The three nodes in the BN example are Gender, Influencer group, and STEM Choice/Recruitment. There are two values for the variable 'Gender'. The variable 'Influencer group' assumes one of six values: T (Teachers), P (Parents), R (Relatives), F (Friends), A (Acquaintances and Others, and C (Celebrities). The first six columns of the CPT contain '1' to indicate one of the six groups at a time, with other groups encoded as '0'. The last four columns represent the degree (probability) of influence: Minor, Moderate, Medium, or Major.

T	P	R	F	A	C	Minor	Moderate	Medium	Major
1	0	0	0	0	0	0.47	0.24	0.20	0.09
0	1	0	0	0	0	0.20	0.23	0.35	0.22
0	0	1	0	0	0	0.50	0.23	0.18	0.10
0	0	0	1	0	0	0.29	0.28	0.30	0.13
0	0	0	0	1	0	0.34	0.29	0.28	0.10
0	0	0	0	0	1	0.83	0.11	0.04	0.01

Fig. 2. A CPT constructed using the statistics of the degree of influence (from Minor to Major) of the six groups of influencers.



(a) (b)

Fig. 3. A causal network and the initial CPTs representing the recruit gender, their indication of the influencers on their decision to choose STEM, and the extent of such influence (a); Inference scenarios that investigate to what degree parents influence the choice of STEM (b).

The simple BN created for this subset of variables has three nodes: the Gender of the first-year undergraduate students participating in the study of their STEM university choice, the Influencer group, and the extent of the Influencer's contribution on the choice of STEM education (Fig. 3).

Consider the following scenario: assuming the influencing group is parents, what is the reported degree of parental influence that students attribute to their decision to pursue STEM? As shown in Fig. 3(b), the Parent group has a Major influence on 33.1% of respondents, followed by Moderate at 28.00%, Medium at 27.72%, while only 11.17% of students described their parents' influence as Minor.

IV. Conclusion and Future Work

The key conclusions from our work on re-examining and re-framing a recruitment engine for STEM are as follows: (1) There is an imbalance in applying the CI to the task of student recruitment: application of machine learning is dominating while other insightful approaches such as machine reasoning are not given the proper attention. (2) Self-aware computing is useful for exploring achieved results, identifying gaps, systematizing them, and envisioning the horizon. "Dehumanization" of recruitment process identified in [6] addresses the problem of explainability and transparency of CI; we plan to investigate this problem in the EDI context.

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References

[1] N. Abid, V. Shmerko, and S. Yanushkevich, Audit of Computational Intelligence Techniques for EDI-aware Systems, *Proc. IEEE Int. Joint Conf. Neural Networks*, Padua, Italy, 2022, pp. 1–8.

[2] A. Bai and S. Hira, An intelligent hybrid deep belief network model for predicting students employability, *Soft Comput.*, 2021, vol. 25, pp. 9241–9254.

[3] G. S. Bapat and S. S. Gankar, Students recruitment strategies at higher educational institutes: A new world perspective – A review of the literature on higher education marketing, *Int. J. Advance Res., Ideas and Innovations in Technology*, 2020, vol. 5, issue 3.

[4] J. A. Chen, M. S. Tutwiler, and J. F Jackson. Mixed-Reality Simulations to Build Capacity for Advocating for Diversity, Equity, and Inclusion in the Geosciences. *J. Diversity in Higher Education*, 2020.

[5] G. Crisp, E. Doran, and N. A. S. Reyes, Predicting Graduation Rates at 4-year Broad Access Institutions Using a Bayesian Modelling Approach, *Res. High Educ.*, 2018, vol.59, pp. 133–155.

[6] M. Fritts and F. Cabrera, AI recruitment algorithms and the dehumanization problem, *Ethics and Inf. Tech.,* 2021, vol. 23, pp. 791–801.

[7] L. Halim, E. Shahali, and Z. Iksan, Effect of environmental factors on students' interest in STEM careers: The mediating role of self-efficacy, *Res. Sci. & Technol. Edu.*, 2021, pp. 1–18.

[8] P. R. Lewis, *et al.*, *Self-aware Computing Systems: An Engineering Approach*, Springer, 2016.

[9] J. Rohmer, Uncertainties in conditional probability tables of discrete Bayesian Belief Networks: A comprehensive review, *Eng. Appl. Artif. Int.*,2020, vol. 88, issue 103384, pp. 1–14.

[10] J. Sjaastad, Sources of Inspiration: The role of significant persons in young people's choice of science in higher education, *Int. J. Sci., Edu.*, 2012, vol. 34, no. 10, pp. 1615–1636.

[11] M. Tamtik and M. Guenter, Policy Analysis of Equity, Diversity and Inclusion Strategies in Canadian Universities – How Far Have We Come?, *Canadian J. Higher Edu.*, 2019, vol. 49, no. 3, pp. 41–56.

[12] A. Turkyilmaz, L. Temizer, and A. Oztekin, A causal analytic approach to student satisfaction index modeling, *Ann. Oper. Res.*, 2018, vol. 263, pp. 565–585.

[13] K. Varner, L. Mey, T. Mentzel, G. Glazer, B. Tobias, and T. Seiple, Pulse Check: Underrepresented Minority Health-Care Student Recruitment and Retention at the University of Cincinnati, *J. College Student Retention: Res., Theory & Practice* 2018, vol. 20, no. 3, pp. 388–405.

[14] P. Verma, S. K. Sood, and S. Kalra, Student career path recommendation in engineering stream based on three-dimensional model, *Comput. Appl En. Educ.*, 2017, vol. 25, pp. 578–593.

[15] M. Virtic and A. Sorgo, Lower secondary school experiences as predictors of career aspirations toward engineering, and production and processing occupations, *Eur. J. Eng. Edu.,* 2022, vol. 47, no. 5, pp. 833–850.