Fairness in Student Allocation and Group Formation

Forshaw, Matthew; Alexadru, Cristina Adriana; Bentley, Caitlin; González-Zelaya, Vladimiro; Adjei, Joseph Kwame; Ajanovski, Vangel; Bikanga Ada, Mireilla; Brooks, Julian; Steenbergen, Merel; More Authors

DOI
10.1145/3724389.3731280

Publication date
2025

Document Version
Final published version

Published in
ITiCSE 2025 - Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education

Citation (APA)
Forshaw, M., Alexadru, C. A., Bentley, C., González-Zelaya, V., Adjei, J. K., Ajanovski, V., Bikanga Ada, M., Brooks, J., Steenbergen, M., & More Authors (2025). Fairness in Student Allocation and Group Formation. In *ITiCSE 2025 - Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education* (pp. 699-700). (Annual Conference on Innovation and Technology in Computer Science Education, ITiCSE; Vol. 2). ACM. https://doi.org/10.1145/3724389.3731280

Fairness in Student Allocation and Group Formation

Matthew Forshaw*
mforshaw@turing.ac.uk
The Alan Turing Institute
United Kingdom
Newcastle University
United Kingdom

Cristina Adriana Alexandru*
Cristina.Alexandru@ed.ac.uk
University of Edinburgh
United Kingdom

Caitlin Bentley*
caitlin.bentley@kcl.ac.uk
King's College London
United Kingdom

Vladimiro González-Zelaya*
carlos.gonzalez@newcastle.ac.uk
Newcastle University
United Kingdom

Joseph Kwame Adjei
jadjei@ashesi.edu.gh
Ashesi University
Ghana

Vangel Ajanovski
ajanovski@gmail.com
Ss. Cyril and Methodius University
North Macedonia

Mireilla Bikanga Ada
mireilla.bikangaada@glasgow.ac.uk
University of Glasgow
United Kingdom

Julian Brooks
j.brooks2@leeds.ac.uk
University of Leeds
United Kingdom

Joshua Burridge
josh.burridge@unimelb.edu.au
The University of Melbourne
Australia

Alex Chao
alexchao@ucsd.edu
University of California, San Diego
USA

Rutwa Engineer
rutwa.engineer@utoronto.ca
University of Toronto Mississauga
Canada

Olga Glebova
olga.glebova@uconn.edu
University of Connecticut
USA

Tasmina Islam
tasmina.islam@kcl.ac.uk
King's College London
United Kingdom

Mitsuka Kiyohara
mitsuka.kiyohara@mail.utoronto.ca
University of Toronto
Canada

Shao-Heng Ko
shaoheng.ko@duke.edu
Duke University
USA

Ellert Smári Kristbergsson
esm@tskoli.is
Reykjavik Technical College
Iceland

Svetlana Peltsverger
speltsve@kennesaw.edu
Kennesaw State University
USA

Seán Russell
sean.russell@ucd.ie
University College Dublin
Ireland

Maíra Marques Samary
marquemo@bc.edu
Boston College
USA

Merel Steenbergen
m.a.steenbergen@tudelft.nl
Delft University of Technology
The Netherlands

Carolin Wortmann
carolin.wortmann@uni-muenster.de
University of Münster
Germany

Abstract

Allocating students to projects is a commonplace task in computing education. These decisions underpin student-supervisor allocation, the formation of tutee and capstone groups, and pair programming. These allocations play a critical role for individual learner outcomes and the success of collaborative interventions. For example, imbalance in either gender, ethnicity, or nationality can negatively impact learner outcomes. Despite the critical importance of these allocation choices, we see little consensus on how these are implemented. The allocation task can be challenging and time-consuming for instructors of even moderately-sized classes, and the fairness implications can be difficult to assess. Inadvertently, an instructor may allocate in a way that amplifies existing biases or disproportionately harms those from disadvantaged or protected groups. From students' perspectives, a lack of transparency on the allocation process may also lead to issues of trust. The Working Group will undertake a study of allocation practices by bringing together educational and ML literature to develop and evaluate the fairness of allocation methods, and develop educator guidelines to promote pedagogically grounded allocation practices.

*Working Group Co-Lead

ITiCSE 2025, Nijmegen, Netherlands

ACM ISBN 979-8-4007-1569-3/2025/06
https://doi.org/10.1145/3724389.3731280

ACM Reference Format:
Matthew Forshaw, Cristina Adriana Alexandru, Caitlin Bentley, Vladimiro González-Zelaya, Joseph Kwame Adjei, Vangel Ajanovski, Mireilla Bikanga Ada, Julian Brooks, Joshua Burridge, Alex Chao, Rutwa Engineer, Olga Glebova, Tasmina Islam, Mitsuka Kiyohara, Shao-Heng Ko, Ellert Smári Kristbergsson, Svetlana Peltsverger, Seán Russell, Maíra Marques Samary, Merel Steenbergen, and Carolin Wortmann. 2025. Fairness in Student Allocation and Group Formation. In *Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education V. 2 (ITiCSE 2025), June 27-July 2, 2025, Nijmegen, Netherlands.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3724389.3731280

1 Introduction and Motivation

Allocating students to projects and forming student groups are commonplace tasks in computing education. These decisions underpin student-supervisor allocation [7, 17], the formation of tutee and capstone [9] groups, and pair programming [8]. The quality of these allocations is known to play a critical role for individual learner outcomes [1], and the success of collaborative interventions. For example, imbalance in either gender [16], ethnicity [19], or nationality [18] can negatively impact learner outcomes.

Prior works focus on allocations to address issues of workload distribution [12] and complementarity of student skill-sets [10]. However, few consider the issue of fairness [11]. Furthermore, the considered fairness definitions deal with satisfaction level in the allocated project alone [4], missing key components such as the students' needs and the adversities they have had to overcome that could merit a preferential treatment.

Despite the critical importance of these allocation choices, we see little consensus on how these are implemented. Educators may rely on institutional norms, or develop their own solution for these problems – through Excel spreadsheets, Python scripts, or even by hand. For instructors of even moderately sized classes, the allocation task can be challenging and time consuming, and the fairness implications of their allocations can be difficult to assess. Inadvertently, an instructor may allocate in a way which amplifies existing biases, or disproportionately harms those from disadvantaged or protected groups. From the students' perspective, a lack of transparency on the allocation process may also lead to issues of trust.

There exists a mature literature base on *matching under preferences* [2]. This problem may be approached through graph theory algorithms that aim at finding an optimal matching [15]. However, these approaches lack the flexibility to constrain allocations, e.g., on demographic factors, or to express more advanced constraints, like gender parity or equal opportunity [6]. Alternative methods better suited to include fairness are mixed integer linear programming (MILP) [4] and lottery-based approaches [14]. Little has been done to consider socio-technical approaches that emphasise fairness for marginalised and underrepresented people and advocate for greater involvement by these students [3].

We have identified a critical gap between research and educational practice, where existing allocation methods lack the ability to capture pedagogic needs, and educational practice is not benefitting from existing research. This Working Group will undertake a multi-institutional study of allocation practices, and support the creation and adoption of pedagogically-informed allocation methods. We aim to answer these research questions:

RQ1: What are common approaches taken to student allocation and group formation in computing education practice?
RQ2: How can we formally define fairness in the context of student allocation and group formation?
RQ3: What are the fairness implications of allocation strategies? How is this impacted by the composition of cohorts?

2 Methodology

Our mixed-methods approach [5] – harmonised using *Concurrent triangulation* [5, 9] – begins with a systematic literature review, and a scoping review of existing tools. Qualitative expert interviews and focus groups explore student and educator perceptions and existing allocation practices. We address the disconnect between pedagogic and ML/AI fairness [13], by formalising theoretically- and pedagogically-grounded fairness definitions for student and group allocation. We implement existing allocation approaches, and evaluate their fairness across different cohort compositions. To address the research-practice gap, we publish an accessible infographic guide summarising pedagogic recommendations.

References

[1] Cristina Adriana Alexandru. 2025. Group Assignments and Support Aimed to Develop Student Teamwork Skills and a Positive Attitude Towards Teamwork in Computer Science Higher Education. In *Computing Education Practice.* 9–12.
[2] Arif A Anwar and AS Bahaj. 2003. Student project allocation using integer programming. *IEEE Transactions on Education* 46, 3 (2003), 359–367.
[3] Caitlin Bentley, Chisenga Muyoya, Sara Vannini, Susan Oman, and Andrea Jimenez. 2023. Intersectional approaches to data: The importance of an articulation mindset for intersectional data science. *Big Data & Society* 10, 2 (2023).
[4] Marco Chiarandini, Rolf Fagerberg, and Stefano Gualandi. 2019. Handling preferences in student-project allocation. 275, 1 (2019), 39–78.
[5] John W Creswell and J David Creswell. 2017. *Research design: Qualitative, quantitative, and mixed methods approaches.* Sage publications.
[6] Irene E De Pater, Annelies EM Van Vianen, and Myriam N Bechtoldt. 2010. Gender differences in job challenge: A matter of task allocation. *Gender, Work & Organization* 17, 4 (2010), 433–453.
[7] Yuanyuan Fan, Ana Evangelista, and Hadi Harb. 2021. An automated thesis supervisor allocation process using machine learning. *GJEE* 3, 1 (2021).
[8] Isabella Graßl and Gordon Fraser. 2024. Equitable Student Collaboration in Pair Programming. In *Proceedings of the 46th CSEE&T.* 274–285.
[9] Sara Hooshangi, Asma Shakil, Subhasish Dasgupta, Karen C Davis, Mohammed Farghally, KellyAnn Fitzpatrick, Mirela Gutica, Ryan Hardt, Ellie Lovellette, Steve Riddle, et al. 2024. Experiences of Instructors Who Teach Capstone Courses in Computing Fields. In *Proceedings of ACM ITiCSE 2024.* 759–760.
[10] Dmitry Krass and Anton Ovchinnikov. 2006. The University of Toronto's Rotman School of Management uses management science to create MBA study groups. *Interfaces* 36, 2 (2006), 126–137.
[11] Tai Le Quy, Gunnar Friege, and Eirini Ntoutsi. 2023. Multi-fair capacitated students-topics grouping problem. In *PAKDD.* Springer, 507–519.
[12] Jeffrey A Miles and Howard J Klein. 1998. The fairness of assigning group members to tasks. *Group & Organization Management* 23, 1 (1998), 71–96.
[13] Shira Mitchell, Eric Potash, Solon Barocas, Alexander D'Amour, and Kristian Lum. 2021. Algorithmic fairness: Choices, assumptions, and definitions. *Annual review of statistics and its application* 8, 1 (2021), 141–163.
[14] Parag A Pathak. 2006. Lotteries in student assignment. *Unpublished mimeo, Harvard University* (2006).
[15] Lyle Ramshaw and Robert E Tarjan. 2012. On Minimum-Cost Assignments in Unbalanced Bipartite Graphs. (2012).
[16] Sukhada Samudra, Cynney Walters, Destiny Williams-Dobosz, Aarati Shah, and Peggy Brickman. 2024. Try before you buy: are there benefits to a random trial period before students choose their collaborative teams? *CBE LSE* 23, 1 (2024).
[17] Victor Sanchez-Anguix, Rithin Chalumuri, Reyhan Aydoğan, and Vicente Julian. 2019. A near Pareto optimal approach to student–supervisor allocation with two sided preferences and workload balance. *Appl. Soft Comput.* 76 (2019), 1–15.
[18] James B Shaw. 2004. A fair go for all? The impact of intragroup diversity and diversity-management skills on student experiences and outcomes in team-based class projects. *Journal of Management Education* 28, 2 (2004), 139–169.
[19] Reyn Van Ewijk and Peter Sleegers. 2010. Peer ethnicity and achievement: A meta-analysis into the compositional effect. *Sch. Eff. Sch. Imp.* 21, 3 (2010).