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Comparing homogeneous and heterogeneous ability grouping in collaborative computational lab activities in Financial Mathematics

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Abstract
Collaborative learning is an engaging methodology to captivate students in problem-solving activities and inclusive computational lab practices and to foster sensemaking. The knowledge co-construction process can be influenced by group composition. This study aims to investigate how group composition affects knowledge co-construction in student-led computational lab activities in Financial Mathematics. This was done by comparing two different group compositions working within a Computer-Supported Collaborative Learning environment, in two consecutive academic years, namely AY 2020/2021 with internally homogeneous ability groups and AY 2021/2022 with internally heterogeneous ability groups. 572 student responses to a weekly survey were included in the analysis and the adapted Interaction Analysis Model was used to investigate peer interactions.

Keywords: *Collaboration; computational thinking; grouping; mathematics education.*

1. Introduction

Socio-constructivist theories support the idea that knowledge is co-constructed through social interactions, shared experiences, and the exchange of points of view (Lave, 1991). In the context of mathematics education, collaborative learning is useful to effectively engage students in problem-solving activities and to apply theoretical concepts to real-world scenarios. Specifically, introducing collaboration into computational thinking practices is beneficial to promote sensemaking (Odden & Russ, 2019) and facilitate understanding of models and algorithms. This study aims to investigate the knowledge co-construction process within an undergraduate Financial Mathematics (FM) module dealing with mathematical models for finance and computational techniques for pricing financial derivatives, namely the Advanced

Computational Finance module (ACM30110) offered by the School of Mathematics and Statistics at University College Dublin (UCD). In this research, we focus on the collaborative student-led lab activities timetabled in this module and analyse the impact of group composition (homogeneous vs heterogeneous ability groups) in the knowledge co-construction process in two different academic years, i.e. 2020/2021 and 2021/2022. This paper is organized as follows: Section 2 outlines the theoretical framework; Section 3 covers the research context, data collection, and analysis methods; Section 4 presents the results and explanations; the final section concludes with potential future research directions.

2. Theoretical framework

In recent years, there has been increasing focus on Computational Thinking (CT) and related practices. Wing (2017) defines CT as a skill not restricted to computer science but one that - when integrated into education - fosters problem-solving, critical thinking, and sensemaking (Odden & Russ, 2019). Recognizing its importance, CT is now part of curricula at all levels. Weintrop et al. (2016) outlined how to effectively embed CT in STEM through a taxonomy with four main categories. Indeed, integrating coding and CT practices requires careful consideration of which computational practices to introduce and how to use them. In mathematics education, computational practices extend beyond algorithm manipulation; they include leveraging tools to enhance scientific understanding. These align with the concept of *inclusive computational practices* (Caballero & Hjorth-Jensen, 2018) and underscores the role of technology in STEM subjects. CT practices also support collaboration, enhancing knowledge co-construction (Resta & Laferrière, 2007). Research highlights that collaborative learning is more effective than individual learning for CT development (Chen, Wang & Li, 2022). Technology-enhanced collaborative activities fall under Computer-Supported Collaborative Learning (CSCL), where interactions between peers shape learning (Zabolotna et al., 2023).

To investigate the knowledge co-construction, models like the Interaction Analysis Model (IAM) (Gunawardena et al., 1997) have been developed. The IAM, with its 5 phases and 21 sub-phases, is widely used for analysing online discussions and has been adapted to various contexts (Lucas et al., 2014). Barana, Boetti et al. (2023) modified IAM for Financial Mathematics, structuring it into 6 phases and 16 sub-phases to analyse collaboration in lab activities where CT is a core practice. We refer to this paper for a deeper description of the 6 phases. A key factor in collaborative learning is group composition. While research comparing homogeneous and heterogeneous ability groups is limited, findings suggest that both have advantages. Wyman and Watson (2020) found that students in homogeneous groups performed slightly better, though not significantly so. Homogeneous groups promote equal involvement, enhancing performance (Ge et al., 2018), while heterogeneous groups may benefit low-achieving students but risk turning into peer tutoring (Briggs, 2020). Murphy et al. (2017) found that heterogeneous groups achieved better comprehension, yet low-achieving students were less engaged. Mesghina et al. (2024) suggest that low-achieving students benefit from cooperative learning regardless of group composition, with learning gains being statistically similar between homogeneous and heterogeneous groups.

3. Setting and Methods

In this study, we aim to answer the following research question: "How does group composition - homogeneous versus heterogeneous ability grouping - affect the co-construction of knowledge in collaborative student-led lab computational activities in Financial Mathematics?". The setting of the research study is the tailored student-led lab designed for an Advanced Computational Finance module (ACM30110, formerly ACM30070), fully described in Perrotta (2021) and Perrotta & Dolphin (2021). The module is offered by the School of Mathematics and Statistics at UCD as a core module for stage 3 students enrolled in the BSc in FM and as an optional for stage 3 students in the BSc in Applied and Computational Mathematics (ACM). The study was conducted in Spring 2021 and Spring 2022. Specifically, in Spring 2021 the module was delivered as a 5-credits module online, due to COVID-19 restrictions, while in Spring 2022 it was redesigned and delivered as a 10 credits face-to-face module. A typical week consists of theoretical lectures, tutorials, and student-led lab activities. While lectures and tutorials were slightly affected by the 2022 redesign, lab materials and assessments were heavily modified. Leveraging on the analyses of 2021 lab practices (Barana, Marchisio, et al., 2023) and the change of the teaching setting from online to face-to-face, activities were adjusted to foster collaboration and tackle student challenges. Specifically, tailored computational practices, such as collaborative debugging (Andersen, 2022) and collaborative coding, were introduced to enhance meaningful collaboration and foster in-depth sensemaking. The computational component, as a pillar of the subject, was further emphasized. Within this context, we investigate the knowledge co-construction process by comparing homogeneous and heterogeneous ability groups in CT practices in FM, focusing on lab activities in Spring 2021 (homogeneous groups) and Spring 2022 (heterogeneous groups). In Spring 2021, the 50 attending students (15 ACM and 35 FM) were divided into 7 internally homogeneous groups, labelled from A to G. Each group consisted of 7 students, except for group D, which had 8 students. Students were grouped according to their grade point average (GPA) to form level groups. Groups A, B, and C consisted of high-achieving students with average GPAs of 3.96, 3.64, and 3.45, respectively. Groups D and E consisted of intermediate-level students with average GPAs of 3.26 and 3.04, respectively. Finally, Groups F and G consisted of low-achieving students with average GPAs of 2.79 and 2.43. Actually, the reported averages exclude two students, which were removed from the dataset: one - initially in group E - who never attended labs, and an Erasmus student in group D. The presence of ACM and FM students was balanced within the groups, and gender and possible minorities were balanced. In Spring 2022, 23 students (3 ACM and 20 FM) enrolled in the module, but only 22 actually attended it, and they were split into 5 internally heterogeneous groups, labelled from A to E. Groups A and B had 5 components, while groups C, D, and E had 4 students each. Since it was not possible to assign one ACM student to each group, the grouping was solely based on students' GPA. Students were assigned to heterogeneous groups based on GPA: each group had a similar GPA on average, ranging from 3.51 to 3.67. To balance the groups' competences and keep heterogeneity, the two groups with 5 students have a wider dispersion of GPAs around their average (Group A has components whose individual GPAs range from 2.62 to 4.04 and Group B has GPAs ranging from 2.9 to 4.2), while the other three groups were composed of students whose individual GPAs were close to the group average. Similar studies have not reported any difference in sex/gender in the design or analysis phases unless this was needed for the purpose of the research. In our case, data is not analysed according to the sex variable. However, particular attention was given to the sex/gender balance in group composition in this research study. To avoid any sense of discomfort, there were at least two females in each group. Only group D had one female, who freely chose to be the only female student in that group instead of being assigned to another one. As seen in Table 1, the groups in Spring 2021 have a lower standard deviation for the internally homogeneous GPA between students, while in Spring 2022 the standard deviations are higher because the students in the groups have different GPAs. The composition of Spring 2022 groups D and E, featuring intermediate students for ensuring internal heterogeneity, mirrored that of the Spring 2021 groups.

Table 1. Group composition in Spring 2021 and Spring 2022 in terms of GPA mean.

Spring 2021				**Spring 2022**			
Group	N	GPA Mean	St. Dev.	Group	N	GPA Mean	St. Dev.
A	7	3.96	.17	A	5	3.51	.58
B	7	3.64	.13	B	5	3.62	.50
C	7	3.45	.13	C	4	3.63	.35
D	7	3.26	.10	D	4	3.67	.15
E	6	3.04	.08	E	4	3.67	.08
F	7	2.79	.15				
G	7	2.43	.36				

For our study, we analysed the answers to a weekly survey that students attending the module in Spring 2021 and Spring 2022 completed after each lab, with a total of 572 responses (396 for Spring 2021, 176 for Spring 2022). The survey contains both Likert-scale and open questions, which asked students to reflect on the effectiveness of inclusive computational practices and collaboration on improving their understanding. The survey can be found in (Barana, Boetti, et al., 2023). We performed a qualitative analysis of those answers using the IAM framework in its adapted version to the FM context (Barana, Boetti, et al., 2023), classifying them in accordance to the 6 phases, i.e. (0) no evidence of interaction; (1) sharing and comparing of information; (2) the discovery and exploration of dissonance or inconsistency among ideas, concepts or statements; (3) negotiation of meaning/co-construction of knowledge; (4) testing and modification of proposed synthesis or co-construction; (5) agreement statement(s) / applications of newly constructed meaning. We analysed the students' responses, trying to understand how they moved iteratively through the phases of the knowledge co-construction process, considering that each phase builds on the previous one, and thus trying to identify the final one they were able to reach. We then collected the results in a contingency table and carried out statistical analyses, such as the Fisher-Freeman-Halton exact test based on 10000 tables sampled according to the Monte Carlo method, to investigate possible relationships between the composition of the groups and the phase of the knowledge co-construction process reached.

4. Results and discussion

In Table 2, the results of the qualitative analysis using the adapted IAM phases are shown. We can see that lower phases indicate less interaction and collaboration in the knowledge co-construction process. For both Spring 2021 and Spring 2022, the highest percentages are highlighted in bold. In both years, phase 1 is the most common, which is in line with the other studies, but Spring 2021 resulted in a higher percentage of phase 5 than Spring 2022. As stated in (Barana, Boetti, et al., 2023), it is interesting to observe that in Spring 2021 the three higher phases of the knowledge co-construction process, (3, 4 and 5), occurred in groups with lower GPAs. This means that groups with lower-performing students showed higher engagement in co-construction of knowledge and deeper understanding, whereas high-achieving students in groups tended to be less cooperative, preferring their comfort zone and avoiding pushing their boundaries or challenging themselves. In Spring 2022, the highest phases occurred in groups A, C, and E, which are heterogeneous groups composed respectively of high-low students, medium high-medium low students and intermediate students.

Table 2. percentage of phases occurrence considering the adapted IAM. For each phase and for each Spring semester, the groups registering the highest percentages are highlighted in bold.

	Group	Phase 0	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5
Spring 2021	A	**6.3%**	27.0%	**15.9%**	33.3%	3.2%	14.3%
	B	**7.0%**	38.6%	5.3%	35.1%	0.0%	14.0%
	C	3.0%	**59.1%**	6.1%	19.7%	3.0%	9.1%
	D	0.0%	**50.8%**	10.2%	30.5%	3.4%	5.1%
	E	4.5%	29.5%	9.1%	**40.9%**	**6.8%**	9.1%
	F	0.0%	26.0%	**14.0%**	**38.0%**	0.0%	**22.0%**
	G	1.8%	45.6%	**14.0%**	21.1%	1.8%	**15.8%**
	Total	3.3%	40.4%	10.6%	30.6%	2.5%	12.6%
Spring 2022	A	0.0%	34.2%	18.4%	26.3%	**10.5%**	10.5%
	B	**7.3%**	**56.1%**	9.8%	22.0%	2.4%	2.4%

	C	0.0%	34.4%	9.4%	37.5%	3.1%	**15.6%**
	D	**9.7%**	**51.6%**	16.1%	16.1%	3.2%	3.2%
	E	0.0%	29.4%	**23.5%**	**44.1%**	0.0%	2.9%
	Total	3.4%	41.5%	15.3%	29.0%	4.0%	6.8%

The Fisher-Freeman-Halton exact test results for Spring 2021 and Spring 2022 provide a statistical foundation to argue that the composition of student groups, whether homogeneous or heterogeneous, significantly influences collaborative learning dynamics. In Spring 2021, when students were divided into homogeneous ability groups, the test value of 48.292 ($p=0.005$) indicates a strong and statistically significant association between group composition and the knowledge co-construction process. The test value for Spring 2022 was lower at 30.499 ($p=0.021$), but still significant, pointing to a meaningful impact of group composition even with heterogeneous groups. Therefore, we cannot say that the difference in group composition is the only statistically significant factor in stimulating the process of knowledge co-construction, but there are some considerations to make. Firstly, due to the pandemic, the collaboration was online in Spring 2021. With the return to in-person teaching in Spring 2022, in-class observations indicated increased students' motivation to work with peers. Secondly, in Spring 2021, the computational practices were calibrated in such a way that during the lab activities the students could discuss tasks and codes they had already worked on individually prior to the lab. In Spring 2022, being returned to in-person teaching, individual coding followed by collective discussion was replaced by collaborative coding and collaborative debugging: this inevitably led to different and more active ways of collaborating. Finally, students in Spring 2022 were, on average, slightly higher achieving than students in Spring 2021 and the levels between them were more similar. Indeed, the average GPA of the class was 3.23, with a standard deviation of 0.52 in Spring 2021, versus 3.61, with a standard deviation of 0.37 in Spring 2022. Spring 2021 students' GPAs ranged from 1.76 to 4.16, with around 33% of students having a GPA below 3. Spring 2022 students' GPAs ranged from 2.2 to 4.2, with around 9% of students having a GPA below 3. These inherent variations in the labs' characteristics (teaching delivery, practices design and class composition) between the two years likely had a significant effect on the ways students interacted and co-constructed knowledge, regardless of group composition, and should therefore be factored into the evaluation of the results.

5. Conclusion

In this research study, we investigated how group composition affects the co-construction of knowledge in collaborative student-led computational lab activities in Financial Mathematics. We considered two different academic years, i.e., 2020/2021 and 2021/2022, and two different group compositions, respectively internally homogeneous and heterogeneous groups, by considering students' GPAs. By using the adapted IAM (Barana, Boetti et al., 2023), we analysed peer interactions in the knowledge co-construction process. Our analysis found no statistically significant differences based on group composition. However, changes in teaching settings and redesigned lab practices over the two years might have influenced collaboration. For this reason, we have further investigated the effect of the setting and the lab redesign in the knowledge co-construction process, and we have identified some factors which are responsible for the improvement of collaborative knowledge construction in 2022 (Barana et al., submitted). Thus, we now plan to compare the Spring 2022 and Spring 2024 groups since, in 2024 the groups were homogenous like in 2021, while the lab activities and the teaching environment were the same of 2022 (face-to-face and same inclusive CT practices). Since this study is limited by its use of weekly survey responses instead of direct observation, future work will make use of video recordings and discussion transcripts.

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