

# Group Formation in the Digital Age: Relevant Characteristics, Their Diagnosis, and Combination for Productive Collaboration

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**Abstract:** This symposium tackles a central topic in CSCL, group formation for productive collaborative learning with / in digital media. Traditional research on group formation has investigated mostly separate learner characteristics as preconditions of learning. Combinations of different learner characteristics and of learner characteristics with collaborative processes have been less in focus. Considering such combinations is necessary to represent the complexity of group interactions and learning. Despite the digitalization of learning, there has been only few attempts to investigate the diagnostic information that mining learner texts and learning processes can contribute to addressing this complexity for optimal group formation, and to assign groups automatically based on multiple parameters simultaneously. This symposium brings together a multi-disciplinary and international consortium of researchers who all focus on group formation for computer supported collaborative learning. They complement each other in investigating different combinations of learner characteristics, learning processes and automatic techniques for optimal group formation.

**Keywords:** group formation, learning processes, automatic diagnostic, optimal grouping

## Introduction

### Symposium focus and major issues addressed

Group formation for productive collaboration has been a central topic in the research agenda of CSCL for a long time. Early research shows that how a group of learners is formed principally influences collaborative learning, and most results favor heterogeneous groups (e.g., Webb, 1982). However, learners tend to self-form homogenous groups, which might not always foster learning (Bell, 2007). Learning success also strongly depends on group learning processes, which develop throughout collaboration (e.g. Weinberger & Fischer, 2006). The digitalization of society and the outspread of social media has emphasized the complexity of group interaction and learning. Productive interactions are becoming extremely important in the age of shallow processing of information and self-presentation, and need to be induced and sustained to warrant quality discussions (e.g., Greenhow, Robelia, & Hughes, 2009; Tsovaltzi, Puhl, Judele, & Weinberger, 2014). The research focus is, hence shifting towards identifying learner characteristics and processes that account for the complexity of interactions and can support transactive processes that emphasize communication with each other and can increase quality discussions

(Weinberger & Fischer, 2006; Fu, van Aalst, & Chan, 2016). Varying multiple learner characteristics for group formation simultaneously, and on the fly “spying” the development of learning processes may help represent the complexity of collaborative learning better. New technologies provide ways to form groups beyond one-dimensional distinctions: homogenous vs. heterogeneous. Still, research that investigates diagnostic and optimization techniques for online group formation (e.g. Konert, Bellhäuser, Röpke, Gallwas, & Zucik, 2016), or tests that against self-organized groups (Siqin, van Aalst, & Chu, 2015) is sparse. Systematic research on learning processes for group formation is also rare, and little research relates learning processes to group formation criteria (Fransen, Weinberger, & Kirschner, 2013).

This symposium looks at matching multiple learner characteristics through technological means and investigates process characteristics to tap on the complexity of group interactions for group formation. It raises the following questions: How do multiple learner characteristics need to be combined to leverage collaborative learning? What learning processes are most relevant, and how should we combine characteristics and processes: homogeneously vs. heterogeneously? Are there sequencing effects of homogenous and heterogeneous collaboration? How is the balance between productivity and learning opportunities of groups affected by the complexity of factors influencing group processes? What automatic techniques do we need to handle such combinations and to mine for relevant information to optimize learning processes for small and larger groups, or over longer periods of time?

### Significance of the contributions

Each individual contribution addresses several of the above general questions and formulates concrete research questions to test them empirically. They each contribute significantly to systematically addressing group formation to account for complex group interactions with scientific rigor.

Bellhäuser and colleagues look at forming groups automatically to optimize heterogeneity distribution. *How do homogenous and heterogeneous combinations of multiple learner characteristics distributed by a complex group-formation algorithm affect learning?* Measures of personality traits show main effects of heterogeneity on performance when extraversion and conscientiousness were manipulated in parallel.

Gijlers and colleagues examine learning processes in a jigsaw variant. *How does sequencing of homogeneous vs. heterogeneous grouping affect learning processes and outcomes?* They show that sequencing can cause procedural losses, but quality during homogenous collaboration relates to conceptually oriented contributions in later heterogeneous collaboration, which, in turn, influences learning outcomes.

Erkens and colleagues use text mining to form knowledge-heterogeneous groups and to support group awareness: *How can automatically diagnosed knowledge influence processes and outcomes of heterogeneous groups?* They report promising results on automated grouping and recommend which method should be used for the additional visualization of co-learners' heterogeneity.

Lara Schmitt and colleagues study collocated collaborative embodied learning with tablets and additional cognitive support. *To what extent does heterogeneity of bodily processes influence cognitive processes and learning outcomes?* They point to differential effects of bodily and cognitive process heterogeneity that exemplify the need investigate such processes heterogeneity and their interaction.

Sankaranarayanan and colleagues combine automated methods to support transactive processes in collaborative work settings. They investigate conditions of balancing productivity while allowing possibilities for learning to take place within a group. *Can technological supporting scrutiny of processes and transactivity cater for a good balance of productively working together and learning from each other?* They are finding positive results that transfer between different contexts.

### Collective contribution towards the issues raised

Together the contributions disentangle a central topic in the learning sciences, group formation for collaborative learning. They tackle the question from technological and psychological perspectives. They use a broad range of learning contexts and methods. All studies use innovative grouping variables and designs. They utilize either automatic group formation, or technology-based communication, or both. They indicate best candidates of information that group-formation algorithms can draw upon to deliver optimal grouping, i.e. types of learner characteristics and productive learning processes, and of potent heterogeneous vs. homogenous combinations. The contributions, hence, present a wide spectrum of research while sharing a cutting edge focus to foster quality discussion in complex collaborative interactions through on the fly evaluation of processes and group formation.

The discussion will attempt a synthesis of the presented research, while maintaining a critical eye to pinpoint weaknesses and gaps that still need to be addressed before a comprehensive account on the topic can be claimed. This will be a source of inspiration for further research, but also for collaboration possibilities among and beyond the contributors. The discussant, Jan Van Aalst, is a leading researcher in the learning sciences

enjoying a broad overview of the developments in the field through his editorial work. He is currently publishing research, cited here, in group formation. He is, therefore, aptly suited to provide insightful, productive critiques, lead the discussion and help us advance our common approach. Other researchers can profit and orient their own future research around the proposed further possibilities. Presentations will be 12 min. long, including an introduction to the topic. A 20 min. discussion will follow, which will also be opened up for the audience.

## **Birds of a feather learn well together? An experimental study on the effect of homogeneous and heterogeneous learning group composition on satisfaction and performance**

Henrik Bellhäuser, Adrienne Müller, Johannes Konert, and René Röpke

Collaborative learning is an effective learning strategy, well-established in research, and frequently implemented in academic learning settings. However, one aspect of collaborative learning that has received only little attention from both researchers and practitioners is the question of composition of learning groups: Which participants should form a group together so that all of them profit the most from the group? Group composition is particularly important because when students are free to form groups by themselves they tend to form homogeneous groups (Hinds, Carley, Krackhardt, & Wholey, 2000). This phenomenon, often called homophily, can lead to undesirable outcomes because heterogeneous groups tend to perform better than homogeneous groups (Bell, 2007).

In our approach, we focus on two personality traits as grouping criteria that have been investigated the most in literature on group composition effects: Extraversion and conscientiousness. For extraversion, researchers have postulated that heterogeneous distribution within each learning group should be beneficial (Kramer, Bhawe, & Johnson, 2014). It is argued that extraverted persons often engage in leadership behavior and that conflicts may arise when too many group members exert leadership. For conscientiousness, one hypothesis is that homogeneous distributions should lead to better outcomes (Prewett, Walvoord, Stilson, Rossi, & Brannick, 2009). The presumed mechanism is that group members with the same level of conscientiousness can easily agree on a common goal for the group work (e.g. high achievement goals for highly conscientious groups).

One important point of critique towards these hypotheses is that they were derived solely based on correlational studies. Experimental approaches, that would allow for causal effects, are still missing in the literature. Experimental variation of group formation requires complex algorithms. In our interdisciplinary approach, we therefore developed a software that is capable of randomly splitting the population into several subpopulations in which different predefined criteria can be applied for group formation. Data is collected via questionnaires to diagnose extraversion and conscientiousness for each person. The algorithm then optimizes the formation of groups respecting homogeneity for conscientiousness and heterogeneity for extraversion.

### **Method and results**

In the present study, N=430 students in an online mathematics preparation course were randomly assigned to one of nine conditions in a completely balanced 3x3 design, with extraversion and conscientiousness each distributed homogeneously, heterogeneously, or ignored for group formation (in the latter condition, the algorithm did not apply restrictions for this criterion, hence groups in this condition could be either homogeneous, heterogeneous or in between). This design allows for the analysis of the two main effects of heterogeneity of extraversion and conscientiousness, and of the interaction effect between the two variables. To increase test power, we intentionally included conditions that were hypothesized to be maleficial. As results of the voluntary mathematics preparation course did not have implications for the subsequent university courses, this experimental design was considered acceptable from an ethical point of view. Students enrolled voluntarily in the preparation course to recapitulate mathematics school knowledge before the actual university lectures began. The preparation course was carried out completely online and included a large collection of instructions and self-tests to work with individually. Additionally, participants were asked to complete three weekly group assignments with complex modelling tasks that allowed for different approaches towards the solution. The groups of four members each were free in their choice of communication channel; the majority chose online communication (forum posts, video chat) due to distance between places of residence. As outcome measure, participants rated their satisfaction with the quality of group collaboration on a 6-point Likert scale and retrospectively estimated their time investment for the group assignments. Furthermore, quantity of assignments handed in (0 to 3) and respective quality (rated by tutors on a 10-point Likert scale) was collected as measures of performance.

For the 3x3 ANOVA, we found no significant main effects for any of the dependent variables, but instead several significant interaction effects that were difficult to interpret. For a deeper insight into the data, we therefore split up the design in three separate parts: Part 1 included the two conditions where conscientiousness was ignored,

thereby using extraversion as the sole grouping criterion (homogeneous vs. heterogeneous). Inversely, part 2 included those two conditions where extraversion was ignored and conscientiousness was used as the sole grouping criterion (homogeneous vs. heterogeneous). Lastly, part 3 included those four conditions where both criterions were manipulated simultaneously (each of them either homogeneously or heterogeneously).

For part 1, consistent with our hypothesis, we found positive effects for heterogeneous extraversion on performance, but no effects on time investment and satisfaction. For part 2, also consistent with our hypothesis, positive effects for homogeneous conscientiousness were shown on performance and satisfaction, with no effect on time investment. However, when both variables were manipulated simultaneously in part 3, results partly contradicted our hypotheses: We found positive main effects for heterogeneous extraversion and for heterogeneous conscientiousness on performance, satisfaction, and time investment. Thus, whether conscientiousness should be distributed homogeneously or rather heterogeneously seemed to be dependent on whether extraversion is manipulated simultaneously or not. These findings will be critically evaluated in the light of a replication study that was conducted recently. Preliminary analyses from the second study seem to support parts of the results of the first study. Implications for future research and application in teaching settings will be discussed.

## **Knowledge exchange of students using the differentiated Jigsaw approach**

Hannie Gijlers, Elise Eshuis, and Tessa Eysink

Active participation is an important factor related to successful collaborative learning. Students with different ability levels might not benefit equally from group work (Tomlinson et al., 2003). We can compose homogeneous and heterogeneous ability groups, each with their own advantages and drawbacks. Homogeneous ability groups make it possible to adjust the material, and level of scaffolding to the needs of the students (Lou et al., 1996). Research indicates that homogeneous grouping is effective when combined with tailored instruction and scaffolding (Kulik & Kulik, 1991). Within homogeneous groups, students are more likely to build on their partner's contribution because students have access to comparable knowledge and skills, and discussions are based on equality. Without appropriate support, below average students in homogeneous groups might have insufficient knowledge and skills to complete the task. In heterogeneous groups, below average students might benefit from high ability peers because they might receive help and feedback (Saleh, Lazonder, & de Jong, 2005). The tutee, tutor relation is more likely to occur between below average and above average peers, average peers might be left out of these tutoring conversations (Lou et al., 2006). The jigsaw is a collaborative learning technique that is often used to promote participation in collaborative learning tasks. By requesting students to study different parts of the material that are required to complete the final group task interdependence between group members is created. Each learner can make a unique contribution. In the STIP approach (Dutch Acronym: Samenwerken tijdens Taak-, Inhoud- en Procesdifferentiatie), working in homogeneous and heterogeneous ability groups is combined in a so called differentiated jigsaw (Eysink, Hulsbeek, & Gijlers, 2017). In this approach, students first construct knowledge in homogeneous groups, with materials and instruction tailored to the students' ability level. Subsequently, students exchange their knowledge in heterogeneous groups in order to complete a group assignment. Different subtopics are available for the homogeneous phase to ensure that students can provide a unique contribution to the heterogeneous group.

In the present study we focus on the effect of the STIP-approach on the learning processes and knowledge gains of students with different ability levels. Resulting in three research questions:

- 1) What is the effect of the STIP approach on the knowledge gains of students?
- 2) Are there differences in knowledge exchange processes between heterogeneous groups and are they related to individual knowledge gains of the students?
- 3) Are students' learning outcomes of the homogenous phase related to their learning process and learning gains of the heterogeneous phase?

## **Method and results**

A comparison was made between the STIP condition ( $N = 95$ ) and a control condition ( $N = 149$ ) (grade 4, 9-10 years old). Heterogeneous groups consisted of one below average student, three average students and one above average student. Students participated in 6 STIP modules, each consisting of 2 lessons) about STEAM related topics like the weather. Students in the STIP condition worked in homogeneous groups during the first lesson and heterogeneous groups during the second lesson. Heterogeneous groups consisted of one below average student, three average students and one above average student. In the present study we focus on the sixth and final module

(about the weather). Teachers in the control condition taught the same content but used their regular teaching approach (business as usual).

Student products from the homogeneous and heterogeneous groups were scored as indicators of performance in these groups. Furthermore, an individual knowledge pre- and posttest was administered. Group work was recorded with digital cameras, students' contributions to the overall discussion and more specifically their exchanged knowledge was coded to provide information about the amount and nature of students' contributions to the group work.

With respect to the learning outcomes it was found that students in the control condition reached higher learning gains compared to students in the STIP condition ( $F(1, 242) = 22.84, p < .001$ ). Although the total time of the lessons was shorter in the control condition, the time students actively engaged with learning material was higher in this condition. Video analysis revealed that in the STIP condition a lot of time was needed to organize seating arrangements, collect materials students created in the homogeneous phase etc. Zooming in on the results of the STIP condition, we found a positive relation between the amount of contributions made by individual students and their individual learning gains ( $r = .649, p < .001$ ). Moreover, the quality of the outcomes of the homogeneous group was positively related to the number of conceptual oriented contributions in the heterogeneous groups ( $r = .588, p < .001$ ). The quality of the results of the heterogeneous collaboration was positively related to students' individual learning gains on the knowledge tests ( $r = .222, p < .047$ ). The first results of the video analyses and products of the heterogeneous groups shows that students engage in a high amount of coordinative activities. A first exploration of the data suggests that in the knowledge exchange phase no significant differences were found in the amount knowledge exchange related utterances made by students from varying competence levels ( $F(2, 25) = 2.50, p = .102$ ). At the moment, coding of the process data is fine-tuned and further analysis is performed to gain insight in the participation levels of students with different ability levels.

## **Impact of text-mining based group formation and group awareness on learning in small groups**

Melanie Erkens, Sven Manske, H. Ulrich Hoppe, and Daniel Bodemer

Small group learning is a powerful educational approach, if collaborating students are a good match and know enough about each other's knowledge to use the group beneficially. One measure to ensure that the characteristics of participants are distributed across groups in a favorable way is to form groups of students with heterogeneous knowledge (cf. Dillenbourg & Jermann, 2007). In particular, learners with complementary knowledge are expected to learn by compensating for gaps in individual knowledge through explaining missing concepts to each other (Ploetzner, Dillenbourg, Preier, & Traum, 1999). However, it is difficult for learners to find out about knowledge levels and knowledge differences on their own. Cognitive group awareness tools provide learners with such information by collecting, transforming, and visualizing socio-cognitive variables and feeding them back to the group, frequently allowing the learners for comparison (cf. Bodemer, Janssen, & Schnaubert, 2018). Thereby, these tools support learners discovering gaps and expertise in knowledge, which can improve knowledge exchange and knowledge acquisition. It thus seems reasonable from a learner's and teacher's view to combine knowledge-complementary group formation with group awareness support. However, if teachers want to support their students with both measures in class, this is a burden for them as they have to collect information on the students' knowledge, enabling them to form appropriate learning groups and to provide feedback to students about their knowledge. A facilitation of both could lie in automated technologies such as text-mining methods that allow the efficient formation of groups of learners with a magnitude of text dissimilarities and to support group awareness by visualizing degrees to which learners wrote on specific topics (Erkens, Bodemer, & Hoppe, 2016; Manske & Hoppe, 2017). We investigated the suitability of text-mining methods in two studies. The first study examined the research questions: Do text mining-based group formation and group awareness visualizations have an effect on knowledge acquisition? In the second study, we were interested in optimizing the feedback and investigated the research question: Which text-mining method provides the most accurate group awareness visualizations?

### **Method and results**

Regarding the first research question, we assumed that the effect of text mining-based support on knowledge acquisition becomes larger the greater the heterogeneity of a dyad is. This hypothesis was tested in a collaborative classroom scenario with 54 dyads discussing the topic of climate change that were either formed of students with high knowledge heterogeneity and provided with awareness information (supported group) or of students with random knowledge heterogeneity and without awareness information provided (unsupported group). A moderation model with group membership (supported / unsupported) as independent variable, text dissimilarity as moderator and knowledge acquisition as dependent variable explained 21 % of the variance of knowledge

acquisition caused by the discussion ( $R^2 = .21$ ,  $F(3, 50) = 4.53$ ,  $p = .007$ ). However, since there was no significant effect of the interaction term, we included only the main effect terms into the analysis. This model explained 20 % of the variance of knowledge acquisition caused by the collaboration ( $R^2 = .20$ ,  $F(2, 51) = 6.40$ ,  $p = .003$ ) with both group membership ( $\beta = .327$ ,  $t(53) = 2.61$ ,  $p = .012$ ) and dissimilarity ( $\beta = .279$ ,  $t(53) = 2.21$ ,  $p = .031$ ) significantly predicting knowledge acquisition. Regarding the second research question, we used texts created by 22 students in a similar collaboration to compare the quality of automatic semantic extraction approaches compared to a correct (manual) classification. To assess the quality of the text analysis approaches, we used recall ('true positive rate'), precision ('true positive accuracy') and the F-measure (a weighted harmonic mean of precision and recall) on the sets of extracted concepts of each method (automatic extraction) compared to the set of relevant concepts from a manual coding. The text analysis approaches used are network text analysis ('NTA'), ontology-enriched NTA and DBpedia Spotlight. The ontology-enriched NTA uses an ontology created by domain experts in order to increase the accuracy of the NTA. The ontology encodes the domain knowledge structured as synonym-term-category triplets in the domain of the learning context. DBpedia Spotlight is a semantic extraction method, which spots keywords in a text using an ontology based on Wikipedia. The results indicate that the ontology-enriched NTA performed best in precision (84.4%), recall (44.2%), and F-measure (56.6%).

Overall, text mining-based support seems suitable to collect, transform, and visualize cognitive information from educational data for supporting teachers in their challenging task to form knowledge-heterogeneous groups and to visualize co-learners' cognitive information for better group awareness. Regarding knowledge acquisition, the results show that text-mining generated knowledge heterogeneity is positively related to learning, either with or without additionally supported group awareness. In addition, the results illustrate that group awareness support can increase knowledge acquisition. Regarding the visualization of information, it was shown that collecting cognitive information by using ontology-enriched NTA provided the most accurate values.

## Effects of process heterogeneity in collaborative embodied learning with tablets

Lara Schmitt, Dimitra Tsovaltzi, and Armin Weinberger

Learner characteristics may affect learning processes and outcomes in collaborative settings. Learner prior characteristics, like prior knowledge and attitude to collaborative learning (Harrison, Price, Gavin, & Florey, 2002; Webb, 1982), have been tested extensively. Heterogeneous combination of these characteristics influence cognitive processes, but results are inconsistent. They seem to heavily depend on the development of cognitive processes during collaboration (Cheng, Lam, & Chan, 2008), but also in interaction with bodily processes (Niedenthal, Barsalou, Winkielman, Krauth-Gruber, & Ric, 2005). However, little is known about heterogeneous combinations of embodied processes, i.e. mixed cognitive and mixed bodily processes. Process heterogeneity may impact the further development of learning processes in co-located collaborative settings where bodily expression is innate. We investigate process heterogeneity to inform automatic group formation in embodied learning.

Besides shallow cognitive processing, bodily expression of emotion and gesturing are crucial in describing spatial elements of a situation accurately, which is described as deep processing. Notwithstanding learner prior characteristics, task conditions like technological affordances, verbalization prompts and group processes, may lead to deep processing (Niedenthal et al, 2005). When the task representation is explained to a partner to reach a common embodied action, deep embodied processing and learning are promoted. Explaining may be especially necessary when partners are heterogeneous with regard to their bodily expression and cognitive processing and cannot assume a common ground. Previous studies on proportional thinking with tablets, tested the effects of embodied processes using the 'Proportion' app (Rick, Kopp, Schmitt, Weinberger, 2015). Users directly manipulated two bars to bodily experience their proportional relation. A pedagogical agent, a wise owl, provided *verbalization prompts* to elicit explanations about physical actions in the app, and foster abstraction from embodied experiences. The studies highlighted a high potential of heterogeneous embodied processes for learning (Rick et al, 2015), and showed learning gains from embodied learning. Verbalization prompts increased cognitive processes (quality of discussions), and bodily expression of emotion (Schmitt & Weinberger, 2018).

Here, we test the effects of heterogeneous bodily processes on the quality of cognitive processes, as well as the effects of heterogeneous bodily processes and of heterogeneous cognitive processes on performance.

## Method and results

A sample of  $n=80$  participants (around 10 years old) learned collaboratively for 40 minutes with 'Proportion'. They physically manipulated proportional quantities and received verbalization prompts requesting them to explain, summarize, and generalize their actions to prompt deep embodied processing of the task representation. Heterogeneity was observed in group processes. Pre- and a post- math tests as well as surveys were applied

individually. We analyzed embodied processes (bodily expression of emotions), and cognitive processes (epistemic quality, transactivity, off-task behavior). Coding schemes with sufficient inter-rater reliability were used to measure emotions and off-task behavior, focusing on gestures and gaze, as well as epistemic quality and transactivity, focusing on content of discussions and on co-constructing explanations. Regarding performance variables, we analyzed knowledge outcome and knowledge convergence (math tests), and efficiency (number of solved problems). Variables were aggregated at dyad level. Process heterogeneity and knowledge convergence were determined with the Coefficient of Variation (CoV, Weinberger, Stegmann, & Fischer, 2007). We split the sample into two sub-groups: homogeneous (lower ~50% of CoV), vs. heterogeneous (upper ~50% of CoV).

MANOVAs showed a large overall significant effect of **heterogeneity of bodily processes on quality of cognitive processes**:  $F(3,26)=4.732, p=.009, Pillai's Trace=.353, \eta_p^2=.353$ . A large negative effect on transactivity just missed significance:  $F(1,28)=3.796, p=.061, \eta_p^2=.119$ . Consistent with theoretical claims about the interaction of bodily and cognitive processes, heterogeneity of bodily processes influences cognitive processes, but rather groups with homogeneous bodily processes were more cognitively transactive by trend. Possibly, homogeneity in bodily expression frees space up for shared cognitive processing. There was also an overall significant effect of **heterogeneity of bodily processes on performance**:  $F(3,31)=3.858, p=.019, Pillai's Trace=.272, \eta_p^2=.272$ . As expected, there was a large significant effect on efficiency,  $F(1,33)=9.179, p=.005, \eta_p^2=.218$ , but an effect on knowledge outcomes could not be found. Heterogeneous groups with regard to bodily processes tended to solve more problems in the embodied learning app. This deep embodied learning did not transfer to cognitive knowledge outcomes in the posttest, which aligns with situated cognition. Regarding **heterogeneity of cognitive processes**, we found a large significant effect of **heterogeneity of epistemic quality on performance**:  $F(3,30)=3.096, p=.042, Pillai's Trace=.236, \eta_p^2=.236$ . A medium negative effect on knowledge outcomes just missed significance,  $F(1,32)=4.025, p=.053, \eta_p^2=.112$ , and there was a large negative effect on knowledge convergence,  $F(1,32)=8.120, p=.008, \eta_p^2=.202$ . There were no effects of transactivity or task focus on performance. Unexpectedly, homogeneous groups with regard to epistemic quality tended to learn more, which increases the possibility for more similar knowledge scores within groups. The results surprisingly showed some negative effects of embodied heterogeneous processes, bodily and cognitive. Investigating heterogeneity of embodied processes may help to avoid false assumptions on group formation for collocated collaboration.

## CSCS Gets to Work: Towards Collaborative Learning with Working Professionals

Sreecharan Sankaranarayanan, Cameron Dashti, Chris Bogart, Xu Wang, Majd Sakr, Michael Hilton, and Carolyn Rosé

Automation is blamed for the projected loss of 5 million jobs by 2020 as argued by the World Economic Forum. As educational technologists however, we adopt a more optimistic view of its place in the workplace, even as automation in terms of group formation and support for collaboration gets cast in a dystopian light (Rummel et al., 2016). The ultimate aim of our work is to inject learning opportunities in work settings with particular focus on technical fields like software development. We start by investigating how technology can support the correct balance between productivity and learning in project-based learning contexts. Group formation figures into this with the idea that the extent to which working groups provide an environment that is conducive to learning is related to the plethora of personal and contextual factors discussed within the contributions to this symposium. If technology is effective in placing individuals into project groups that bring out the best in them, that assignment can lead to advantages, both in terms of learning and productivity. Our own work on team assignment has been developed and tested in lab studies and real instructional contexts (Wen et al., 2016). In our past work, observed exchange of transactive conversational contributions in one context when used as an indicator of collaboration potential in order to form teams in a second context resulted in significant improvements to group products and processes over randomly assigned teams (Wen et al, 2016). In this contribution, we focus on a new paradigm for collaborative learning which we call Online Mob Programming (OMP) in which group work is conducted online where the collaboration can be instrumented to support team assignment, role taking, and work structuring.

Learning in the context of group work is a concern both in industry and in the more familiar confines of formal learning in project courses. While collaborative project based learning provides opportunities to foster needed teamwork skills, it also exposes other difficulties such as management overhead and conflict, among others. These challenges are exacerbated online and at scale, two contexts that have become more prominent in computer science education. In industry, the conflict is even more keenly felt, and the pressures of productivity frequently undercut parallel efforts to provide training opportunities for employees. The challenge in our work is

to create a context in which learning and productivity can be jointly optimized within group work and the emerging trend from industry we build on is Mob Programming (Zuill, 2016).

## Method and results

We have begun formal investigation of the OMP paradigm in the context of a 6-week free online Cloud Computing course offered to working professionals in the summer of 2018. We thus first ensure that the industry-inspired paradigm can be cast in a pedagogical setting to simultaneously prioritize productivity and learning. The instrumentation enables instructors to check on group processes and progress, but also allows for automated forms of support for group learning such as Conversational Agents (Wang et al., 2017). OMP involves students assuming and rotating through distinct roles responsible for brainstorming potential ideas, deciding on a path forward and implementing the selected path thus providing the benefit of a structured collaboration that manages group processes for relatively large groups of 4-6 students. Within this paradigm, automated group assignment could be used to place students in teams that bring out the best in them based on the prediction of collaboration potential from observed exchange of transactive contributions in a class discussion forum (Sankaranarayanan et al., 2018).

In an instructional context, we cast OMP as a form of collaborative learning where 4-6 participants assume different roles to collectively contribute a solution to a programming challenge. In this way, cognition is distributed, and group members with differing abilities are able to contribute in different roles while benefiting from the support of the group.

Results from the study show evidence of success with students following the structure of OMP and the mob setup scaling to groups having 3 to 6 participants. Further, subjective feedback from students indicate that they are teaching and learning from their peers and shifting from focusing solely on productivity to a combination of productivity and learning. The success of the paradigm in this context has prompted us to further investigate OMP in the undergraduate computer science context where it will be offered as a part of a semester-long project-based Cloud Computing course. We are now conducting an experimental study where we compare the OMP paradigm with automated transactivity based team assignment with OMP and randomly assigned teams and an individual condition as a control. At the symposium we will present an experience report that summarizes our key takeaways allowing instructors and other researchers to use these pedagogically valuable insights as well as join us in further investigating and adopting the paradigm for their classrooms.

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