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Team formation instruments to enhance learner interactions in open learning environments

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ABSTRACT

Open learning environments, such as Massive Open Online Courses (MOOCs), often lack adequate learner collaboration opportunities; they are also plagued by high levels of drop-out. Introducing project-based learning (PBL) can enhance learner collaboration and motivation, but PBL does not easily scale up into MOOCS. To support definition and staffing of projects, team formation principles and algorithms are introduced to form productive, creative, or learning teams. These use data on the project and on learner knowledge, personality and preferences. A study was carried out to validate the principles and the algorithms. Students ($n = 168$) and educational practitioners ($n = 56$) provided the data. The principles for learning teams and productive teams were accepted, while the principle for creative teams could not. The algorithms were validated using team classifying tasks and team ranking tasks. The practitioners classify and rank small productive, creative and learning teams in accordance with the algorithms, thereby validating the algorithms outcomes. When team size grows, for practitioners, forming teams quickly becomes complex, as demonstrated by the increased divergence in ranking and classifying accuracy. Discussion of the results, conclusions, and directions for future research are provided.

1. Introduction

Open learning environments, such as Massive Open Online Courses (MOOCs), currently attract large bodies of learners. Initially these environments were envisioned to provide learning settings based on the pedagogical vantage point of networked learning, with a strong emphasis on learner self-direction and learner contribution. Downes (2006) and Siemens (2004) coined the term “connectivism” to label such learning settings. In parallel a different kind of MOOC rose to attention, one that builds on behaviourist, rather than social-constructivist educational principles. Reports, however, from both learners and MOOC providers indicate that drop-out rates from both kinds of MOOCs are massive, and that in particular the latter kind offers limited opportunities for learner collaboration (Daniel, 2012; Edinburgh University, 2013; McGuire, 2013; Morrison, 2013). While there are many reasons for drop-out rates to be high, these effects can at least partly also be explained by learning settings that do not motivate learners. In the up till now small-scale connectivist MOOCs learners are expected to be self-directing, which can present learners with difficulties related to insufficient task structure (Kop, Fournier, & Mak, 2011). In the large-scale behaviourism-based MOOCs, scaffolding, teacher-learner contacts and collaborative learning opportunities are limited, which leads to sub-optimal learning (Daniel, 2012; Edinburgh University, 2013). Some MOOCs (NovoEd, 2014; Stanford University, 2012) address this by allowing self-selection into teams or by providing relatively simplistic grouping criteria such as by proximity of geographic location or by language(s) mastered.

In general, collaborative learning processes in open learning environments can take shape as suggested in the theoretical computer-supported collaborative learning (CSCL) framework of Stahl (2006). Stahl describes that, in a cyclic process, individuals express problems, collaborate with peers to develop shared understanding, use and create learning materials, which are then again used by others to learn from. While learning can be instigated by individuals and whole communities can benefit from its outcomes, Stahl places the actual learning process in the context of the small group. However, with regard to implementing the framework, Stahl (2013) also notes it: “… needs appropriate CSCL technologies, group methods, pedagogy and guidance to structure and support groups to effectively build knowledge …”. In this article we investigate a particular approach to forming teams for collaborative

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learning in open learning environments. We surmise this is a specific operationalisation of Stahl's framework. Hence we ensure that (i) learner problem statements are related to the learning settings in which they are made, (ii) collaboration takes place in teams with suitable knowledgeable peers only, (iii) only knowledge sources are available that fit the learners needs, (iv) the interactions between learners are structured, not fleeting and shallow.

Our approach promises to unleash the powers of constructivist learning and to implement the well-researched team-based learning settings of project-based learning (PBL; Blumenfeld et al., 1991; Davies, de Graaff, & Kolmos, 2011) in MOOCs (Sloep, Berlanga, & Retalis, 2014). Implementing PBL provides several well-known benefits. First, it improves the learners' motivation, so that learners are more inclined to deal with hard, complex problems and spend more time studying (Johnson, Johnson, Stanne, & Garibaldi, 1990; Marin-Garcia & Lloret, 2008). Second, and related to improving motivation, PBL plays a role in learner retention (Dahms & Stentoft, 2008; Fisher & Baird, 2005). Third, PBL blends learning and working, thereby creating realistic (inter-professional) learning experiences (Felder, Felder, & Dietz, 1999; Springer, Stanne, & Donovan, 1999), which prepare learners for real-life working conditions (Haines, 2014). Forth, generally speaking, collaboration between learners as envisioned in PBL has been shown to lead to an increase in learning outcomes compared to individual learning (Hsiung, 2010). Fifth, it can prevent knowledge sharing issues learners encounter when trying to use e.g., social media as open learning environments. Ma and Chan (2014) found that in social media only a tiny proportion of users engage in a type of knowledge exchange that is ultimately beneficial to them.

Implementing PBL in traditional educational settings requires expertise from teachers for defining project tasks and staffing them. However, as in large scale MOOCs staff time expenditure needs to be kept low, we propose that learners themselves play an active role in defining projects for PBL. Learners who are enabled to *self-define tasks* develop a motivating sense of ownership and responsibility for their learning processes. At the same time, however, *self-selection of teams* ought to be discouraged. Fiechtner and Davis (1985), Oakley, Felder, Brent, and Elhajj (2004) hold that for teams to be effective, team formation should be performed by experts. These experts use knowledge of the project tasks and of the prospective team members to form teams (Graf & Bekele, 2006; Martín & Paredes, 2004; Obaya, 1999; Slavin, 1989; Wilkinson & Fung, 2002). In large-scale MOOCs however, a complicating factor is that these experts will most probably not be available. Therefore we argue that if large groups of learners in MOOCs are to be enabled to self-define project tasks and to receive effective team formation suggestions, we need to develop automated support services. These mimic expert behaviour in assessing whether projects relate to the MOOC's learning materials and form teams based on task and team member characteristics (beyond language and geographical location). The services provide intelligent team formation principles, for which we build on extensive preparatory research. In this research we inferred several *team formation principles* from team formation literature and developed the corresponding *team formation algorithms* (Spoelstra, Van Rosmalen, & Sloep, 2014; Spoelstra, van Rosmalen, van de Vrie, Obreza, & Sloep, 2013). It is our future goal that our instruments will be able to assess whether suggested projects qualify for execution inside MOOCs and to form effective project teams. In this article, however, we focus on the *validation* of the set of team formation instruments we developed, based on important factors in team formation, such as knowledge, personality, and preferences. First, we aim to validate the team formation principles we inferred. Second, we aim to validate their implementation in algorithms, using real-world learner data for their input. This validation will be based on practitioner agreement with the team formation principles and by comparing practitioner outcomes on team formation tasks to the outcomes of the computer algorithms. The remainder of the article is structured as follows: In Section 2 we present a team formation model, which uses learner knowledge, personality and preferences to suggest teams fit for executing a project. In Section 3, we present the research questions and hypotheses, on the basis of which we aim to validate the team formation instruments. Section 4 describes the materials and methods we used to test the hypotheses. In Section 5, the results are presented. Sections 6 provides an extensive discussion of these results, while in Section 7 we draw conclusions and suggest future research.

2. A team formation model

The automated service builds on earlier work in which we introduced a team formation model for use in open learning environments, as well as in more traditional learning settings. The model was constructed based on a review of PBL and team formation literature. It aims to mimic the behaviour of team formation experts (i.e., use knowledge on task and team members to form teams fit for various tasks) (Spoelstra et al., 2013). An updated version of the model is presented here, which explicitly adds the assessment of fit of a project in a knowledge domain. It also puts the assessment of learner preferences logically before the assessments of knowledge and personality (see Fig. 1).

The model describes the definition of a project (a task addressing multiple topics carried out by multiple learners) in a knowledge domain. This definition is assessed for fit in the knowledge domain. Next, learner preferences (such as available time slots or languages spoken) are compared to the project characteristics (such as duration, preferred number of team members, preferred language). This comprises the *first* step in the chronology of the team formation process, which limits the number of learners from which teams can be formed. In the *second* step, the assessment of knowledge is used to match the knowledge required for executing the project to the knowledge the prospective team members can provide. The assessment of personality is aimed at predicting team member performance (George & Zhou, 2001; Jackson et al., 2010; Barrick, Mount & Strauss, 1993). For this, personality can be represented by the personality trait "Conscientiousness", which can be assessed with e.g., the Big Five personality test (Barrick & Mount, 1991). In the *third* step the resulting data are combined, based on

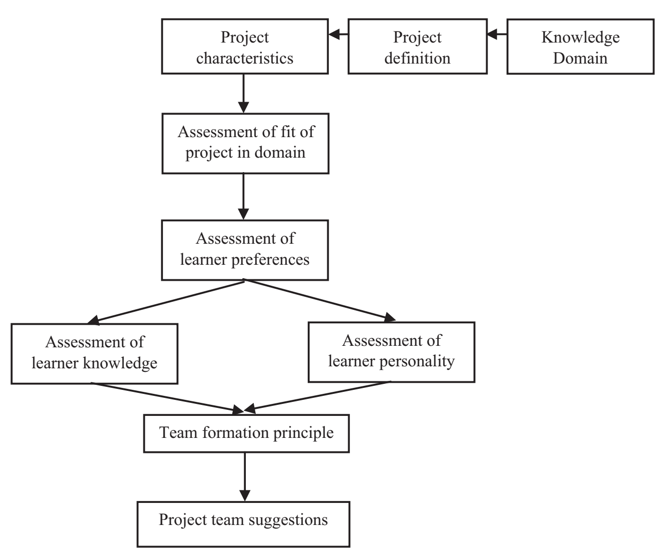

Fig. 1. The team formation model.