Exploring learning how to learn in a team-based engineering education

Dirk Ifenthaler
Deakin University, Melbourne, Australia, and
Zahed Siddique and Farrokh Mistree
University of Oklahoma, Norman, Oklahoma, USA

Abstract

Purpose – In this paper, the authors aim to explore how students learn how to learn in a team-based graduate course Designing for Open Innovation using a theoretical framework that focuses on the cognitive functions of team-based processes and team performance.

Design/methodology/approach – An automated assessment methodology for the structural and semantic analysis of individual and shared knowledge representations serves as a foundation for the approach. A case study is presented that explores the development of individual mental models and shared mental models over the course.

Findings – An assessment of the mental models indicates that in this course three types of learning took place, namely individual learning, team-based learning, and learning from each other.

Originality/value – The automatically generated graphical representations provide insight into the complex processes of the learning-dependent development of individual mental models and shared mental models.

Keywords Students, Assessment, Teams, Experiential learning, Mental model, Engineering education, Shared mental model

Paper type Research paper

1. Introduction

With increasing globalization and twenty-first century trends such as the commoditization of technology, individuals are required to continuously refresh and adapt their competencies and keep their knowledge current. It is well documented that the changing environment and the diverse learning needs of individuals demand a change in the existing paradigm of engineering education (Mistree et al., 2012, 2014; Williams and Mistree, 2006). What is needed is a flexible, learner-centric paradigm that, among other things, instills in individuals the habit of becoming self-regulated, life-long learners (Azevedo et al., 2010; Ertmer and Newby, 1996; Ifenthaler, 2012b; Koper and Tattersall, 2004; Wilhelm and Beishuizen, 2003). A deep understanding of innovation-related competencies is required if we are to meet the needs of our...
graduates in preparing them for the challenges of the twenty-first century. In recent years development of competencies for innovation, especially in engineering, has received significant attention (Borrego et al., 2010; Diefes-Dux et al., 2013; Genco et al., 2012; Sullivan et al., 2001).

Moreover, teams are a critical and essential part in most organisations and companies because they combine different views, multiple skills, diverse experiences, analytical judgments and rich knowledge (Salas et al., 1992). Consequently, research in teams and learning has been a continuous endeavour in various scientific areas for more than 30 years. In general, a team is defined as a distinguishable set of two or more individuals who interact dynamically, interdependently, and adaptively toward a common and valued goal, who have each been assigned specific roles or functions to perform and who have a limited life span of membership (Salas et al., 1992).

Over the past few years at the University of Oklahoma a graduate course in engineering titled Designing for Open Innovation has been designed to address the requirements of a flexible and learner-centred learning environment as well as team-based activities. The course is designed to facilitate the development of competencies needed for the fast changing world and to empower students to take charge of their own learning. The approach fosters "learning how to learn" in a collaborative environment. The structure, assignments, and other details related to the course are presented in Mistree et al. (2013). In this paper, we explore the team-based components implemented in the graduate course Designing for Open Innovation and contribute to the emerging research in engineering education in three ways: first, it introduces a theoretical framework focussing on the cognitive functions of team-based processes and team performance. Second, it introduces an automated assessment methodology for the structural and semantic analysis of individual and shared knowledge representations. Third, it describes a case study exploring the development of individual mental models (IMM) and shared mental models (SMM) over the course of a semester and suggests theoretical as well as practical implications for teams, learning and assessment in engineering education.

2. Theoretical background

2.1 Cognitive functions influencing team processes and team performance

A central concept of cognitive psychology is that individuals construct mental models in order to understand and explain experiences and events, process information and solve complex problems (Gentner and Stevens, 1983; Ifenthaler and Seel, 2011, 2013; Johnson-Laird, 1983). More precisely, the theory of mental models is based on the assumption that cognitive processing takes place in the use of mental representations in which individuals organize symbols or representations of experience or thought in such a way that they effect a systematic representation of this experience or thought, as a means of understanding it – or explaining it to others (Johnson-Laird, 1983). Hence, in order to create subjective plausibility the individual constructs an internal model that both integrates the relevant semantic knowledge and meets the perceived requirements of the situation (Ifenthaler and Seel, 2011, 2013). This internal model is referred to as an individual mental model (IMM) (Shute and Zapata-Rivera, 2008; Spector, 2010). Related theoretical concepts of mental representations stem from the system dynamics approach which uses representations in the form of causal loop diagrams and stock and flow models to support deeper understanding of complex, dynamic and probabilistic phenomena (Davidsen, 2000; Rouwette et al., 1996; Spector, 2000; Sterman, 1994).
System dynamic research has highlighted the value of involving several individuals for understanding and solving complex situations (Rouwette et al., 2002).

SMM are denoted as a shared representation of a team that includes overlapping domain and task knowledge, skills, attitudes, objectives, processes, components, communication, coordination, adaptation roles, relationships, behaviour patterns and interactions (Cooke et al., 2004; Klimoski and Mohammed, 1994; Mohammed and Dumville, 2001). It is evident that if team members share similar mental models they are more effective in their teamwork and perform better (Chung et al., 1999; Salas et al., 1992; van den Bossche et al., 2011). Several frameworks have been developed in order to describe these underlying cognitive processes of modelling, e.g. using the system dynamics approach (Luna-Reyes and Anderson, 2003; Vennix, 1999) and the mental model theory (Bierhals et al., 2007; Cannon-Bowers et al., 1993; Carley, 1997; Darabi et al., 2009).

This empirical investigation is based on an extended cognitive perspective of SMM and integrates and expands the theoretical assumptions from the above mentioned frameworks (Cannon-Bowers et al., 1993; Ifenthaler and Seel, 2013; Spector, 2000; Vennix, 1999). In Figure 1, the interaction of IMM and SMM and the influence on team processes and team performance is illustrated. The IMM of each team member integrates complex knowledge structures on declarative, procedural and metacognitive levels (Anderson, 1983; Clariana, 2010; Ifenthaler, 2011a; Jonassen et al., 1993; Spector and Koszalka, 2004). The overlap of the IMM is regarded as SMM. Cannon-Bowers and Salas (2001) identify two major components of SMM: task-related components and team-related components. As every team member shares a certain number of these components it is therefore possible for a team to develop a collective understanding of tasks, conditions and requirements that are needed to cope with the problem to be solved. However, this overlap is a result of complex interrelationships between individual declarative, procedural and metacognitive knowledge as well as shared task and team related knowledge (Cannon-Bowers and Salas, 2001). Team processes embody the
transformation of all inputs through social interaction among team members into results, such as critical perspectives, new ideas, decisions or material objects. Finally, the result of all actions reflect the team performance (Bierhals et al., 2007; Lim and Klein, 2006; Mathieu et al., 2000).

An important limitation regarding the above presented framework is that knowledge is internal and its representations are internal (Spector, 2010). Hence, it is not possible to assess these internal representations of knowledge directly (Ifenthaler, 2008; Seel, 1999a). Additionally, it is argued that different types of knowledge require different types of representations (Minsky, 1981). Hence, assessment of individual and team-based knowledge representation is always biased because of the necessary externalization of knowledge representation (Spector, 2010; Strasser, 2010). However, the possibilities of externalization are limited to a few sets of sign and symbol systems (Seel, 1999b) – characterized as graphical and language-based approaches. Still, externalizations are the only available artifacts for empirical investigations of individual and team-based knowledge representation. Such an externalization is always made by means of interpretation (Ifenthaler and Pirnay-Dummer, 2014).

2.2 Team-based components in the course design

The structure and organization of this course is different to typical graduate courses in engineering. First, the concept of Senge’s (1990) learning organization was emphasized throughout the lectures and the assignments. This allowed a fluent development of both competencies and learning objectives. Second, each lecture was focused on one or more questions for the day. These questions provided the rationale for covering the material on a particular day. When viewed at the end of the semester the questions represented a framework within which the course was orchestrated and a means for the students to frame their final semester learning essays.

The pedagogical details and assignments embodied in Designing for Open Innovation are described in Mistree et al. (2013) and highlighted in Mistree et al. (2014). The relationship between the team organization and the course content is illustrated in Figure 2. The course content is centred on deliverables and lectures that are associated with dilemmas involving economy, society and environment. Each assignment and deliverable which was addressed in the class content was designed to support the team organization. Early in the semester students were given the question for semester (Q4S) in the context of their semester competencies they wished to develop along with their supporting learning objectives. There were lectures focused on higher-level topics related to learning how to learn along with content-based lectures focusing on bridging fuels and the wired and connected world of 2030. Lectures on cognitive constructs and tools to help frame and answer the Q4S through dilemma identification and management were also included. Finally, students reflected upon their semester learning through a semester learning essay. All of the class content was focused on dilemmas resulting from economical, sociological and environmental aspects that arise in energy policy and bridging fuels.

The team organization was supported through the class content and the assignments developed around this content. There were several levels of the team-based components. First, there were assignments early on in the semester designed for students to identify the competencies that they wished to develop throughout the semester (A0, A1, A2). This allowed for individual learning. Next, there were assignments that allowed students to get experience working in teams (A2, A3). Team assignments were designed
to support team-based learning through the use of technologies to address geographical differences (A3, A4). The Q4S was finally a compilation of A3 and A4 and the answer was compiled and submitted by each team. One of the unique aspects of this course was the team-based structure in which students worked in team settings in order to answer the Q4S. Students were asked to identify competencies needed to be successful at creating value in a culturally diverse, distributed engineering world.

2.3 The present study
In Fall 2012, an IRB approval from the University of Oklahoma was received to investigate the impact of IMM on the shared (team) mental model (and vice versa), how IMM change over the course of a semester and how students with different mental models prepare themselves to learn how to learn in an increasingly wired, interconnected and culturally diverse world. Overall, this initial study is exploratory and descriptive, rather than prescriptive. Specifically, the study is guided by the theoretical model (Figure 1) and the following research questions:

RQ1. How do IMM change over the course of a semester?
RQ2. How do SMM change over the course of a semester?
RQ3. Do IMM have an impact on the shared mental model?

3. Method
3.1 Participants and design
Nine students who enrolled in Fall 2012 in AME 5740 Designing for Open Innovation were invited to participate voluntarily in this study. Based on the response to
assignment 0 and assignment 1 the course instructor assigned students to teams to work on assignment 2 (Figure 2). Each team had three students. The demographics are as follows:

- **Team alpha.** Doctoral student (industrial engineering, Iranian, female), exchange student (aerospace engineering, German, male), undergraduate (mechanical engineering, permanent resident of Iranian origin, female).

- **Team beta.** Doctoral student (mechanical engineer, working full time in industry, US citizen, male), MS student (aerospace engineer, working full time in industry, US citizen, male), undergraduate (industrial engineer, working full time in industry, US citizen, male).

- **Team gamma.** MS student (mechanical engineer, working full time in industry, US citizen, male), MS student (mechanical engineering, Indian, male), MS student (industrial engineering, Indian, male).

The final sample for this study consisted of participants from team alpha (one male and two females ages 23-32). All three participants described themselves as non-Hispanic white and two participants declared themselves as international students.

The case study included assessment of learner characteristics ($O_{LCH}$), individual mental models ($O_{IMM}$), shared mental models ($O_{SMM}$), team process ($O_{TPR}$), and team performance ($O_{TPE}$) evaluation at significant course deliverables during the semester that are represented as $X_1, X_2,$ and $X_3$; see Figure 3. $O_{LCH}$ and $O_{IMM}$ are assessed at the start of the semester to get a base-line. $O_{IMM}, O_{SMM}, O_{TPR}$ and $O_{TPE}$ are then assessed from assignments and deliverables to determine change in participants’ individual and team learning processes.

### 3.2 Instruments

#### 3.2.1 Individual mental model assessment

The individual mental model assessment ($O_{IMM}$) focused on declarative, procedural, and metacognitive knowledge. Three prompts asked the participants to write three paragraphs with at least 350 words each.

#### 3.2.2 Shared mental model assessment

The shared mental model assessment ($O_{SMM}$) focused on the participant’s contribution to the team and the other team members’ contribution to the team. Two prompts asked the participants to write two paragraphs with at least 350 words each.

#### 3.2.3 Team assessment and diagnostic measure

The team assessment and diagnostic measure (TADM) instrument measures team-related knowledge (Johnson *et al.*, 2007). TADM consists of 17 items forming six factors (team knowledge, communication, attitudes, dynamics and interactions, resources and environment, satisfaction/frustration). The questions were answered on a five-point Likert scale (1 – strongly disagree; 2 – disagree; 3 – not sure; 4 – agree; 5 – strongly agree).

#### 3.2.4 Attitudes towards engineering

The 44 questions focusing on attitudes towards engineering were answered on a five-point Likert scale (1 – strongly disagree; 2 – disagree; 3 – neutral; 4 – agree; 5 – strongly agree).

Figure 3.

Longitudinal research design
3.2.5 Self-concept. The participant’s self-concept was measured with the confidence scale (Bandura, 2006) consisting of eight items which were answered on a five-point Likert scale (Cronbach’s $\alpha = 0.87$). Four items focused on the participant’s confidence for performing in the course (CPC) and four items focused on their confidence for performing on their first engineering job after graduation (CPJ).

3.3 Procedure
At the start of the semester, demographic data (5 minutes), learner characteristics (beliefs, self-concept; 10 minutes), and a pre-assessment of attitudes towards engineering (15 minutes) were collected. During the semester, three waves of data collection were administered as follows: individual mental model (three paragraphs – 350 words – focusing on declarative, procedural, and metacognitive knowledge; 30 minutes), shared mental model (two paragraphs – 350 words – focusing on self and other participant’s contribution to the team; 20 minutes), (TADM; 5 minutes), self-concept (5 minutes). The last wave of data collection additionally included a post-assessment of attitudes towards engineering (15 minutes).

3.4 Data analysis
The short essays were analysed with automated knowledge visualization and assessment (AKOVIA). The AKOVIA tool allows an automated analysis of verbal re-representations (Ifenthaler and Pirnay-Dummer, 2014). The re-representation process is carried out in multiple stages including several parsing heuristics. The automated analysis generates seven measures including four structural and three semantic measures (Ifenthaler, 2010b; Ifenthaler and Pirnay-Dummer, 2014). The seven measures are quantified as follows: $0 \leq s \leq 1$ (where $s = 0$ is complete exclusion and $s = 1$ is identity). Table I provides a description of the seven measures.

Recent studies using the analysis functions of AKOVIA show a high practicability for multiple research questions and good overall test quality (Al-Diban and Ifenthaler, 2011; Ifenthaler, 2012b; Pirnay-Dummer and Ifenthaler, 2010; Pirnay-Dummer et al., 2010). The reliability scores range from $r = 0.79$ to $r = 0.94$ and are tested for the structural and semantic measures separately and across different knowledge domains (Ifenthaler, 2010b). Convergent and divergent validity has been tested using several criteria. Ifenthaler (2010a) reports a validity study using a declarative knowledge test as an outside criterion. The study demonstrates convergent (declarative knowledge correlates significantly with the semantic measure, $r = 0.355$) and divergent validity (no significant correlation between declarative knowledge and structural measures). Another validation study showed convergent validity among structural (e.g. SFM and GRM, $r = 0.79$; SFM and STM, $r = 0.63$; all correlations are significant) and among semantic (e.g. CCM and PPM, $r = 0.68$, PPM and BSM, $r = 0.91$; all correlations are significant) measures (Ifenthaler, 2010b).

4. Results
The change of participants’ confidence for performing in the course (CPC), confidence for performing on their first engineering job after graduation (CPJ) and their evaluation of team-related knowledge (TADM) during the semester (five measurement points; x-axis) is illustrated in Figure 4. Clearly, at the beginning of the semester participants reported low confidence towards their performance on their first engineering job
<table>
<thead>
<tr>
<th>Measure (abbreviation) and type</th>
<th>Short description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface matching (SFM) Structural indicator</td>
<td>The surface matching compares the number of vertices within two graphs. It is a simple and easy way to calculate values for surface complexity</td>
</tr>
<tr>
<td>Graphical matching (GRM) Structural indicator</td>
<td>The graphical matching compares the diameters of the spanning trees of the graphs, which is an indicator for the range of conceptual knowledge. It corresponds to structural matching as it is also a measure for structural complexity only</td>
</tr>
<tr>
<td>Structural matching (STM) Structural indicator</td>
<td>The structural matching compares the complete structures of two graphs without regard to their content. This measure is necessary for all hypotheses that make assumptions about general features of structure (e.g. assumptions which state that expert knowledge is structured differently from novice knowledge)</td>
</tr>
<tr>
<td>Gamma matching (GAM) Structural indicator</td>
<td>The gamma matching describes the quotient of terms per vertex within a graph. Since both graphs that connect every term with each other term (everything with everything) and graphs that only connect pairs of terms can be considered weak models, a medium density is expected for most good working models</td>
</tr>
<tr>
<td>Concept matching (CCM) Semantic indicator</td>
<td>Concept matching compares the sets of concepts (vertices) within a graph to determine the use of terms. This measure is especially important for different groups that operate in the same domain (e.g. use the same textbook). It determines differences in language use between the models</td>
</tr>
<tr>
<td>Propositional matching (PPM) Semantic indicator</td>
<td>The propositional matching value compares only fully identical propositions between two graphs. It is a good measure for quantifying semantic similarity between two graphs</td>
</tr>
<tr>
<td>Balanced semantic matching (BSM) Semantic indicator</td>
<td>The balanced semantic matching is the quotient of propositional matching and concept matching. Especially when both indices are being interpreted, balanced propositional matching should be preferred over propositional matching</td>
</tr>
</tbody>
</table>

Table 1. Description of the AKOVIA measures

Figure 4. Change of participants’ confidence (CPC, CPJ) and team-related knowledge (TADM)
(measurement point 1; M = 3.00; SD = 0.90), whereas their confidence increased significantly towards the end of the semester (measurement point 5; M = 4.58; SD = 0.52), \( \chi^2(4) = 9.56 \ p = 0.049 \). The change of confidence for performance in the course (CPC; \( \chi^2(4) = 2.04 \ p = 0.729 \)) and the evaluation of team-related knowledge (\( \chi^2(3) = 6.60 \ p = 0.086 \)) did not change significantly.

4.1 Change of IMM

The RQ1 investigated how IMM change over the course of a semester. In order to describe the diversity and variability of students’ mental model, we used the automated visualization function of AKOVIA (Ifenthaler and Pirnay-Dummer, 2014). The visualization function creates an association net based on the semantic text produced by the students at various points during the semester in response to the assignments.

The initial representations of participant’s declarative knowledge are illustrated in Figures 5 and 6(a). Clearly, the most important concepts used by the participants focused on the tools introduced during the first class meetings as well as the collaborative setting of the course (Figures 5 and 6(a)). The dashed lines indicate strong association between most frequently used concepts in the written assignment and blue lines indicate weak associations between concepts. One strong association of participant MM07F was found for collaboration – developers. Strong associations of participant MF06F were found between tools – collaboration, tools – communication, tools – use, share – videos.

The representations of participant MF06F’s declarative knowledge at a later stage of the semester are illustrated in Figure 6(b). Here, a clear shift is discerned towards a more elaborate understanding of the subject domain of the course. However, some concepts (and propositions, i.e. concept – link – concept) are not well connected to the overall understanding (e.g. organizations, techniques).

**Figure 5.**
Mental model representation of student’s MM07F declarative knowledge at beginning of the semester

**Note:** The dashed lines indicate strong association between most frequently used concepts in the written assignment and blue lines indicate weak associations between concepts.
An in-depth qualitative analysis of the mental models, using AKOVIA, suggests that participants gained declarative, procedural, and metacognitive knowledge over the course of the semester. This is evident through a clear shift from basic concepts linked to tools used for the course to more elaborated concepts linked to the problem’s domain of the course. However, the strongest gain was found on the declarative knowledge level (Figures 5 and 6). Additional descriptive analyses of the quantitative measures, using AKOVIA, suggest that participants have moved forward significantly in collaborative, team dynamics, communication, etc. which are metacognitive knowledge (Figure 7).

4.2 Change of SMM

The RQ2 investigated how SMM change over the course of the semester. For this analysis individual responses are aggregated into a shared knowledge representation, using the aggregation function of the AKOVIA (Pirnay-Dummer and Ifenthaler, 2010).
The aggregated representation is developed based on common knowledge the individual participants share. Figure 8 illustrates how the SMM change over the course of the semester. For example, in-depth qualitative analysis of the representations indicate a shift from being aware of meta-competencies earlier in the course, and then developing these competencies at a higher level of cognition, along with a more domain oriented declarative knowledge (e.g. alternatives, fuel, economy, etc.).

Figure 7. Mental model representation of student’s MF06F metacognitive knowledge at a later stage of the semester

Figure 8. Aggregated mental model representation of shared declarative knowledge at (a) beginning of the semester, (b) middle of the semester and (c) end of the semester (A0EOS)
4.3 Impact of IMM on SMM

The RQ3 investigated if IMM have an impact on the shared mental model (SMM). Using the quantitative comparison measures of AKOVIA (Ifenthaler and Pirnay-Dummer, 2014), we calculated similarities between the aggregated SMM and the IMM. The comparison results between IMM and SMM for declarative, procedural, and metacognitive knowledge representations are shown in Table II.

For the declarative knowledge, we found equal influence of all participants at measurement point one (Table II). The contribution of the individuals to the shared knowledge gained in the middle of the semester. However, at the end of the semester we found that participant MF06F contributed 80 per cent and participant IF04F contributed 54 per cent of declarative knowledge to the shared mental model while participant MM07F only contributed 23 per cent to the shared mental model. On procedural knowledge, we found equal contribution of all participants on the shared mental model throughout the semester. However, on metacognitive knowledge we found a major contribution of participant MF06F on the shared mental model (except for the first measurement point, see Table II).

5. Discussion

Typically, graduate engineering design courses are a continuation of the content and structure found in undergraduate courses. However, the structure of graduate engineering courses need to be designed to allow students learn how to be independent thinkers and to take charge of their own learning. With globalization, courses offered in the traditional format do not always prepare individuals to be competitive, and consequently may have little value or relevance to students after they graduate. Hence, we have advocated the mass customization of courses (Williams and Mistree, 2006) that will allow students to identify and develop selected competencies.

In this course, learning was achieved at three levels: individual learning, team-based learning, and learning from each other. This structure was systematically developed using specific assignments. Initially, the assignments were focused on the individual to help each student identify his/her own learning objectives. The teams were core to developing an answer to the question for the semester (Q4S) and an important component of the end of semester deliverables. In addition to the team answer to the Q4S at the end of the semester, each student submitted two reports, namely, an end of semester assignment 0 and a semester learning essay.

Assignments that had the potential to add value to the learning of others were shared as “best practices” with the entire class. Often “best practices” from former students

<table>
<thead>
<tr>
<th>Time of semester</th>
<th>Participant</th>
<th>Beginning</th>
<th>Middle</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td>Declarative knowledge</td>
<td>MF06F</td>
<td>0.43</td>
<td>0.68</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>MM07F</td>
<td>0.45</td>
<td>0.66</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>IF04F</td>
<td>0.44</td>
<td>0.66</td>
<td>0.54</td>
</tr>
<tr>
<td>Procedural knowledge</td>
<td>MF06F</td>
<td>0.69</td>
<td>0.48</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>MM07F</td>
<td>0.50</td>
<td>0.67</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>IF04F</td>
<td>0.56</td>
<td>0.59</td>
<td>0.51</td>
</tr>
<tr>
<td>Metacognitive knowledge</td>
<td>MF06F</td>
<td>0.11</td>
<td>0.65</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>MM07F</td>
<td>0.59</td>
<td>0.30</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>IF04F</td>
<td>0.34</td>
<td>0.47</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Table II. AKOVIA comparison measures (concept matching – CCM) between individual and SMM
of the course were also discussed in class or presented on the course web site. This aspect of the presented approach enabled team-based and collective learning; students learn from and about each other, get inspired and can build on others work to develop new knowledge, which is reflected in the results of this case study (e.g. change of IMM, change of SMM). A positive side effect is also the incentive to be recognized as the author of a “best practice” in the full knowledge that it will be read by others in the class.

5.1 Implications

Our approach is focused on students developing competencies needed in a world in which change is the order of the day. The differences between our approach and the traditional approach found in many engineering programs are shown in Table III. The restructuring of this design course has transformed the hierarchical structure of a traditional course into one that facilitates collective learning. To address these differences, students develop competencies by using a method which fosters learning how to learn by placing students in a team-based environment, which many will experience in academia and industry once they graduate. We focus on students learning how to learn by providing them with an opportunity to learn how to identify and manage dilemmas (Koedinger and Aleven, 2007). One of the main differences between this course and that of a traditional nature is how the assignments were used to scaffold student learning and team formation.

As highlighted in our results of the case study (e.g. impact of IMM on SMM), a successful team typically possesses an informational advantage over individuals (Mesmer-Magnus and DeChurch, 2009). Therefore, students were introduced the concept of team-based learning by working in teams whose membership was determined by assignment 1 submissions. Yet, not all teams are capable to take full advantage of these benefits. Some teams may even fail on their tasks. Therefore, to ensure that each member contributed equally, team contracts anchored in the learning organization construct were required in assignment 2. However, as highlighted in our results, not all team members contributed in an equal portion to the team’s performance. Nevertheless, results of this case study indicate that SMM are a significant factor for successful team processes and team performance (van den Bossche et al., 2011).

The outlined approach may also be implemented in larger classes which would result in a greater number of teams. As we develop the automated team-based assessment methodology further, this may help to overcome labour intensive manual analysis of team-based outcomes and provide opportunities for near real-time interventions. AKOVIA has been successfully implemented for the analysis of team-based performance with over 50 teams (Ifenthaler, 2014).

Given the recent developments in educational data mining and learning analytics (Long and Siemens, 2011), the automated assessment and analysis function of AKOVIA could be used to inform ongoing learning process. Results of these assessments could

<table>
<thead>
<tr>
<th>Traditional courses</th>
<th>Collective courses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structure</td>
<td>Hierarchical</td>
</tr>
<tr>
<td>Focus of course</td>
<td>Content</td>
</tr>
<tr>
<td>Learning mode</td>
<td>Student are told what to learn</td>
</tr>
<tr>
<td>Evaluation</td>
<td>Students are evaluated</td>
</tr>
</tbody>
</table>

| Key differences between traditional courses and the collective courses approach |

Table III.
then be utilised to create meaningful interventions. Feedback into the ongoing learning could be explicit by using results of the automated assessment and analysis as well as convergence towards a reference solution (Ifenthaler, 2014).

5.2 Limitations

Though the findings may not be generalizable, case studies such as this allow researchers to hypothesize and theorize relationships that may otherwise remain covert (Hartley, 1994). The promising findings of this case study guide the further development of future research projects focussing on team-based learning in engineering education. Currently, a follow-up study is being conducted with a similar sample size which will be used for validating the preliminary results.

Another limitation refers to the assessment of knowledge. As knowledge is internal and its presentations are internal, it is not possible to measure IMM and SMM directly. Additionally, it is argued that different types of knowledge require different types of representations (Johnson et al., 2011). Therefore, it is necessary to identify economic, fast, reliable, and valid techniques to elicit and analyse knowledge representations (Ifenthaler, 2008, 2010b). Advanced databases and network technologies contribute an especially wide variety of applications for an efficient assessment of individual and team data. However, numerous capabilities remain unused because standard assessment tools do not facilitate these technological features. Future studies shall enable the investigation of strengths and weaknesses of valid techniques for the elicitation and analysis of knowledge representations (Al-Diban and Ifenthaler, 2011; Clariana, 2010; Johnson et al., 2009).

A further limitation refers to the sample which included a select group of participants from one university all enrolled in a specific course, thus prohibiting generalisations of results. This fact clearly limits the external validity of our findings (Campbell and Stanley, 1963). Accordingly, future studies shall include various levels of difficulty, task type and dispositions of participants within and across different subject domains.

6. Closing remarks

The initial results of this case study suggest that it is worth to follow this line of investigation in a larger setting in order to gain insight into the complex processes of the learning-dependent development of IMM and SMM. Teams have many advantages in complex environments (Cannon-Bowers et al., 1993; Johnson et al., 2007). But not all teams are able to take full advantage of those benefits.

Designing and creating learning environments which empower engineering students to learn how to learn is not an easy task. When students enter learning environments, most learners want quick answers to questions they already have (Ifenthaler, 2012a; Pirnay-Dummer et al., 2012). Thus, students tend to like to be provided with simple recipes and scripts – because they seem to be of more practical value at the time. Our approach to learning environments violates this quasi-need because we aim to bring about conceptual change (Vosniadou, 2007). Clearly, we need to explore further the effectiveness of scaffolding and feedback of learning.

Studies have shown that it is very difficult but possible to influence individual and SMM by providing specific forms of scaffolds and feedback (Ifenthaler et al., 2011). Ifenthaler and Seel (2005) argue that it is important to consider how scaffolds
and feedback are provided to the learner at specific times during the learning process. Feedback on mental-model construction, such as the use of mental maps has been investigated and discussed controversially in education research (Azevedo and Bernard, 1995; Bangert-Drowns et al., 1991; Mayer, 1989; Narciss, 2008; Pirnay-Dummer and Ifenthaler, 2011; Shute, 2008). One promising form of automatically generated feedback are mental maps, i.e. graphical representations of IMM or SMM (Ifenthaler, 2011b). These graphical representations highlight the most important objects and associated causal relations of the phenomenon in question. New developments in computer technology enable us to dynamically generate mental maps and expert representations, leading to the possibility of using mental maps to generate direct responses to the learner’s interaction with a learning environment. Such a form of feedback is defined as model-based scaffolds (Ifenthaler, 2009), which is generated purposively and individually to student-constructed responses to the learning environment (Ifenthaler, 2009). Such dynamic and timely scaffolding can promote the learner’s self-regulated learning (Zimmerman and Schunk, 2001) as well as team-based learning.

We have developed an assessment method based on mental maps to longitudinally track students’ and teams mental model progression. In future we will investigate further the effectiveness of model-based feedback to support the development of twenty-first century competencies in the context of engineering education.

References


**Corresponding author**
Dirk Ifenthaler can be contacted at: dirk@ifenthaler.info

To purchase reprints of this article please e-mail: reprints@emeraldinsight.com
Or visit our web site for further details: www.emeraldinsight.com/reprints