Farhangian, M., Purvis, M., Purvis, M., & Savarimuthu, B. T. R. (2015). The effects of temperament and team formation mechanism on collaborative learning of knowledge and skill in short-term projects. In F. Koch, C. Guttmann & D. Busquets (Eds.), Advances in social computing and multiagent systems: Communications in computer and information science (Vol. 541). (pp. 48-65). Cham, The Netherlands: Springer. doi: 10.1007/978-3-319-24804-2_4

The Effects of Temperament and Team Formation Mechanism on Collaborative Learning of Knowledge and Skill in Short-Term Projects

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Abstract. While collaborative learning has long been believed to hold a great value for organizations and classrooms, Modeling this learning in small, short-term project teams is a challenge. This paper describes the development of an agent-based modeling approach that can assist in understanding the collaborative learning of such project teams. A key aspect of the presented approach is our distinction between knowledge and skills required for the achievement of project goals. Both of these forms of intelligence need to be learned in the project context, but the rate of their expansion or enhancement may proceed differently, depending on the personality makeup of the team and the mechanism employed for team assembly. Based on reports from the theoretical and empirical literature, we derive a multi-agent computational model that characterizes how knowledge and skills may be learned among team members with varying personality attributes. Also, Group formation in virtual learning environments is either done voluntary or with the support from the system. In this connection, we studied two types of group formation mechanisms and the role of each mechanism in the collaborative learning and performance of teams.

Keywords: Knowledge · Skill · Collaborative learning · Multi-agent based simulation · Team formation

1 Introduction

Unlike traditional teams where employees learn and improve their performance through formal training, in many modern projects, collaborative learning within small teams often is undertaken and these teams may be assembled only for specific, short-term tasks. Some examples of these temporary teams include crowdsourcing platforms, scientific collaboration teams, open source software development teams, online games and so on. Also, there has been growing interest in the virtual learning communities where groups of students enhance their learning using Computer-Supported Collaborative Learning (CSCL) environments. How well these teams collaborate and fulfill, their missions will depend on the personalities of the individual team members and how well they can share their knowledge and skills. In this paper, we discuss how team formation mechanisms are involved in the acquisition and retention of skill and knowledge.

In the context of team learning, we believe that there is a significant difference between **knowledge** and **skill**. Knowledge, which can be characterized as "know-what", is articulable, i.e. it can be expressed in linguistic form and transmitted to others relatively easily. On the other hand, a skill, which can be characterized as "know-how", refers to a capability of effective interaction with the environment via a tight feedback loop. Skills, for example, the skill of riding a bicycle, are not easily put into words, since they involve tight feedback loops with the environment; and hence they are not as easily transferred when compared to knowledge. To learn a skill often requires close observation and collaboration with a master who already has the skill.

The goal is to construct a plausible simulation model to provide a prediction of knowledge and skill acquisition and retention in collaborative learning systems where temporary teams are formed for different tasks. This simulation tool could help researchers, managers and teachers to have a better understanding about the effect of group formation mechanisms on collaborative learning. The rest of this paper is organized as follows. In the following section, we review the relevant literature concerning the collaborative learning and team formation. Then, we describe the specifics of our model – both its conceptual elements and its computational aspects. Then, we describe how this model has been implemented algorithmically for agent-based simulation and report on some example results so far obtained.

2 Background

Collaborative learning is a learning method that helps people to retain, transfer, and receive knowledge and skill through intra-group collaboration and competition between groups [1]. The knowledge necessary for performing a task may be declarative, procedural, or a mixture of these two. Declarative knowledge represents factual information; procedural knowledge indicates task knowledge.

Today agent and agent-based services facilitate collaborative learning in crowdsourcing platforms and computer-supported Collaborative Learning (CSCL) environments. Agents can provide decision support for managers or teachers and assist them for some tasks, such as group formation. Designing a real multi-agent tool often entails high cost, time and effort. In this paper we simulate collaborative learning to analyze the effect of attributes such as the team formation mechanism and personality on the performance, knowledge, and skill growth of team members. The existing simulation models and tools such as [2–4] do not cover the personality along with knowledge and skill that are the main focuses of this paper.

ACT-R [5] is a cognitive structure that provides mechanisms representing procedural and declarative knowledge learning and forgetting. We chose to use ACT-R to represent employees or learners memory for acquisition and retention of declarative and procedural knowledge because other similar architectures such as Soar [6] and EPIC [7] are more restricted. Soar does not provide a forgetting mechanism, and EPIC does not provide a rule learning mechanism. A complementary approach to the cognitive approach, such as in the studies above, is to apply agent-based models to simulate human behavior instead of supporting this behavior [8].

Teams may benefit from the way they share information and collaborate, and this aspect of project team performance – how it evolves given the circumstances of personality makeup, skills, and knowledge – has not been explored much extent. In this paper, by employing ACT-R as architecture that deals with the emulation of human mental processes in conjunction with our proposed agent-based model, we describe and simulate our study in this area.

To pursue our examination along this course, one needs to have a reliable characterization of human personality. There are several schemes that have been developed over the years such as Five Factor Model (FFM) [9] however, we believe that the one for which there is the most accumulated data is the Myer-Briggs Type Indicator (MBTI) scheme [10]. This is based on a psychological type scheme originally developed by Carl Jung and modified by Myers [11] and has four personality dimensions: (a) iNtroverted-Extraverted, (b) Sending-iNtuitive, (c) Thinking-Feeling, and (d) Perceptual-Judgemental (the names representing extremal ends of each dimension).

- **Extraversion** vs. **Introversion**– an introverted keeps more to him or herself or faces and an extraverted outer social world.
- **iNtuition** vs. **Sensing**– An intuitive type is more abstract and understands according to his or her inner compass, while a sensor gathers information that is in concrete, objective form.
- **Thinking** vs. **Feeling**– A thinker makes decisions based on logic and demonstrable rationality, and a feeler is more empathetic and attempts to see things from given perspectives a.
- **Judgmental** vs. **Perceptive**– A judger wants things settled and organized, and a perceiver is flexible and spontaneous.

In the following section, we describe our agent-based model that incorporates personality type along with the knowledge and skill levels for each agent. The personality type is assumed to be fixed while the knowledge and skill levels are dynamic.

3 The Model

Figure 1 shows a schematic diagram of an individual agent that works on a project team. It has personality, skill, and knowledge components. Within the knowledge, the component is the "Knowledge Credibility" subcomponent, which stores the confidence in which knowledge sources and interactive partners are held.

The goal is to use this as a modifiable template for the examination of dynamic knowledge and skill influences on individual and team performance via simulation experiments. Agents are seeded with various personality types, knowledge, and skills (as described below), and then simulations are run to examine collaborative learning. For each simulation cycle, agents team up and start working on a task. They exchange what knowledge they have with teammates and update their Knowledge-Credibility values with respect to their teammates. They also improve their skills by observing and imitating their teammates' behaviours.

In the following subsections, further details concerning the operation of these agent components are provided.

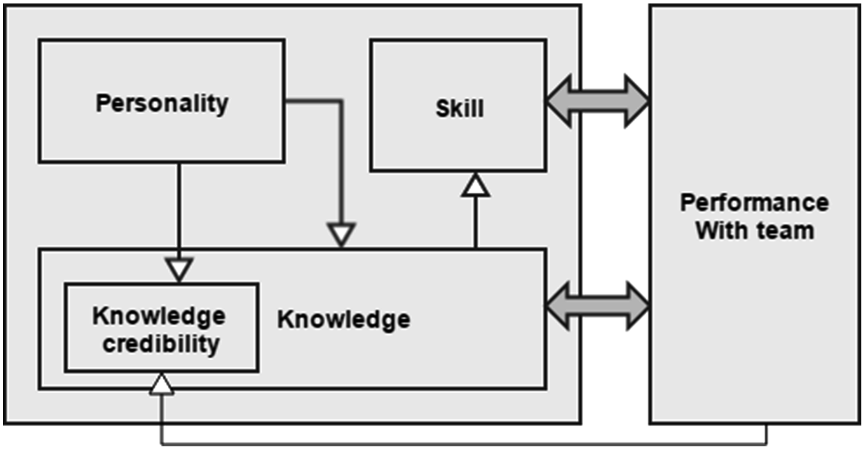

Fig. 1. Model components' overview.

3.1 Task Performance

In our model, each group task needs a set of knowledge and skills. *TASK* is a set of tasks that we have in the system.

$$TASK = \{task_1, task_2, \ldots, task_n\} \tag{1}$$

And each $task_b$ is a vector of *l*- dimensions; each dimension represents the requirements for that task. And each *task* requires a vector of skill requirements:

$$REQ_b = \{requirement_{b1}, requirement_{b2}, \ldots, requirement_{bn}\} \tag{2}$$

For example, we have a task that is about analyzing health economy data in New Zealand. It requires a set of skill requirements as presented as follows:

$$REQ_1 = \{RProgramming, presentation\} \tag{3}$$

Completing a task requires two sets of knowledge (general knowledge and skill-related knowledge). Before the acquisition of one skill, one needs to learn a knowledge set related to that skill: Here K_{rvb} represent the knowledge matrix related to skills for task *b*.

$$K_{rvb} = \begin{bmatrix} \mathrm{k}_{rb11}\mathrm{k}_{rb12}\ldots\mathrm{k}_{rb1n} \\ \mathrm{k}_{rb21}\mathrm{k}_{rb22}\ldots\mathrm{k}_{rb2n} \\ \cdot \\ \cdot \\ \cdot \\ \mathrm{k}_{rbm1}\mathrm{k}_{rbm2}\ldots\mathrm{k}_{rbmn} \end{bmatrix} \tag{4}$$

In our example, we need some knowledge about R programming and also about presentation. The first row of the matrix K_{rvb} indicates the knowledge about R programming and each $\mathrm{k}_{rb11}, \mathrm{k}_{rb12}, \ldots, \mathrm{k}_{rb1n}$ represents a fact. For example, k_{rb11} represents this knowledge: microbenchmark library in R provides infrastructure to accurately measure and compare the execution time of R expressions.

Apart from these related-knowledge skills, for each task, some general knowledge is required that is represented with K_{gb}.

$$\mathrm{K}_{gb} = \left[\mathrm{k}_{gb1}, \mathrm{k}_{gb2}, \ldots, \mathrm{k}_{gbm}\right] \tag{5}$$

In our example, we need some piece of information about health economy in New Zealand, each $\mathrm{k}_{gb1}, \mathrm{k}_{gb2}, \ldots, \mathrm{kb}_{gbm}$ represents a fact. For example, k_{gb1} represents the knowledge that there is a correlation between diet nutrition and income in the New Zealand. In our model, each employee has a set of skills,

$$skill_i = \{skill_{i1}, skill_{i2}, \ldots, skill_{in}\} \tag{6}$$

Each element in the $skill_i$ vector represents the qualification of employee. For example, for employee 1, $skill_1$ represents his vector skill that each one represents a specific skill. And $skill_{11}$ represents R programming is 0 and $skill_{12}$ represents that represents MATLAB programming is 5. The competency of members in skills is calculated as follows:

$$Sk_{il} = 1 - \min\{0, |skill_{il} - requirement_{bl}|\}/skill_{il} \tag{7}$$

Sk_{il} indicates the competency of employee i in domain l; $skill_{il}$ indicates the level of skill of employee i in domain l; and $requirement_{bl}$ indicates the level of skill requirement in domain l in task b We used this formula to avoid giving credit to the employees' over qualifications. The sum of the competency of employee i in task b is calculated by the sum of his competency in all the domains as follows:

$$Sk_{ib} = \sum\nolimits_{l=1}^{m} Sk_{il} \tag{8}$$

Sk_{ib} represents competency of employee i in task b, and m represents the number of domains in the task b for employee i.

Also, each employee has some knowledge vectors for each skill that is represented as following matrix:

$$K_{evi} = \begin{bmatrix} \mathrm{k}_{ei11}\mathrm{k}_{ei12}\ldots\mathrm{k}_{ei1n} \\ \mathrm{k}_{ei21}\mathrm{k}_{ei22}\ldots\mathrm{k}_{ei2n} \\ \cdot \\ \cdot \\ \cdot \\ \mathrm{k}_{eim1}\mathrm{k}_{eim2}\ldots\mathrm{k}_{eimn} \end{bmatrix} \tag{9}$$

K_{evi} represent the knowledge vector related to each skill for employee i.

Apart from knowledge related to skill, each employee has two other knowledge vector including general knowledge and knowledge about other people.

$$\mathrm{K}_{gi} = \left[\mathrm{k}_{gi1}, \mathrm{k}_{gi2}, \ldots, \mathrm{k}_{gim}\right] \tag{10}$$

K_{gi} represents the general vector of employee i. And K_{ij} in the following vector represents the knowledge of employee i about knowledge credibility of employee j.

$$\mathrm{K}_{ij} = \left[\mathrm{k}_{i1}, \mathrm{k}_{i2}, \ldots, \mathrm{k}_{ij}\right] \tag{11}$$

The final performance of the employees in the tasks is related to their skill competency and general knowledge competency. In our example skills in R programming and presentation and also knowledge about health economy improve the task performance. Knowledge competency is calculated as follows:

$$KK_{gib} = \max\{0, \mathrm{K}_{gb} - \mathrm{K}_{gi}\} \tag{12}$$

As having both of these factors, is critical for the performance a task, following the formula is suggested:

$$Pe_b = \left(\sum\nolimits_{i=1}^{n} W_{si} * Sk_{ib}\right) * \left(\sum\nolimits_{i=1}^{n} W_{ki} * KK_{gib}\right) \tag{13}$$

Pe_b indicates the performance of a team in task b, Sk_{ib} indicates the competency of agent i for task b, and Kk_{gib} indicates the general knowledge competency of agent i for task b. Also, W_{si} indicates the importance of skill i and W_{ki} indicate the importance of knowledge i.

In the rest of the paper, we argue that skill and knowledge improve over time and demonstrate how personalities of employees make a difference in employees' leaning and teams' performances.

3.2 The Influence of Personality

In our model, there are three personality dimensions (as specified by the MBTI scheme) that come into play. Associated with these three personality dimensions, six assumptions are considered and as explained as follows. These assumptions are based on studies reported in the literature about MBTI and team behavior [12–16].

- 1st assumption: Compared to Feeling types, a Thinker's relationship with a person is more sensitive to their knowledge of that person.
- 2nd assumption: Sensors record the result of their satisfying or unsatisfying team experiences as facts more than iNtuitive types do.
- 3rd assumption: Sensors have a higher rate of gathering knowledge from others compared to iNtuitive types.
- 4th assumption: iNtuitive types have a higher rate of self-learning knowledge compared to the Sensors.

- 5th assumption: It is more likely for extraverted types to share their knowledge compared to introverted types.
- 6th assumption: Introverted types have a higher self-learning rate compared to Extraverted types.

A number represents the degree of personality in each dimension is presented as follows:

- Introverted/Extraverted (IE): (range 0–0.5 → *Introverted* 0.5 – 1 → E*xtraverted*)
- iNtuitive/Sensing(NS):(range 0−0.5 → *Intuitive* 0.5 – 1 → S*ensor*),
- Thinking/Feeling (TF):(range 0–0.5 → *Feeler* 0.5 – 1 → *Thinker*),
- Perceiving/Judging (PJ): (range 0–0.5 → *Perceiver* 0.5 – 1 → J*udgers*).

Apart from personality variables, some other non-personality variables affect decisions and behaviour. These factors are discussed in the following sections. These factors include task performance, knowledge credibility, knowledge growth, skill growth and forgetting (of both knowledge and skill).

3.3 Knowledge Sharing

Knowledge can be shared through communication. In our knowledge-sharing model, two main factors including having a common goal (being in one group) and desire to have connections with others (extraversion) can cause more knowledge sharing.

As mentioned in the *5th assumption*, extraverted types are more likely to share their knowledge compared to introverted types, who limit their social activities to a few people. So the probability of sharing knowledge with another agent is related to two factors. IE_i (Level of Extraversion of agent) and In_i (in-group factor that is a binary value if agent j is in same group, $In_j = 1$, or if an agent is in another group, $In_j = 0$). The probability of sharing knowledge calculated as follows:

$$Sh_{ij} = \frac{w_{IE} IE_i + w_{In} In_j}{w_{IE} + w_{In}} \tag{14}$$

Where Sh_{ij} is agent i probability of sharing knowledge with agent j. And weights w_{IE} indicates w_{In}, indicate the importance of Extraverted personality, In-group factor respectively. The willingness to accept shared knowledge is related to Knowledge-credibility (trust), and it is explained in the next section.

3.4 Trust (Knowledge Credibility)

Trust is **a crucial** part of knowledge sharing [17]. The knowledge-sharing process entails two different socio-cognitive decisions [18]:

(1) a decision to pass or not pass on a piece of knowledge
(2) a decision to accept or reject a given piece of knowledge.

The degree of confidence that one has in the integrity and competence of the organizational environment is essential for both of these decisions [17].

Although trust can take different forms, we assume in our organizational context here that trust refers to the degree to which a person can have confidence in the information that he or she may receive from a coworker; and we call it knowledge-credibility. There are three principal routes by which we can acquire information relevant to team performance: team success, direct interaction, and indirect interaction:

(1) ***Team success:*** This parameter reflects the history of previous team successes.
(2) ***Direct Interaction:*** agents gather information from the expertise of another agent who shares his knowledge.
(3) ***Indirect interaction:*** each agent gathers third parties' attitudes about other agents. The average of these attitudes determines the general reputation of the agent.

As a result overall the Knowledge-credibility of agent i on agent j is calculated as follows:

$$Kc_{ij}(t) = \frac{(w_{Id}Id_{ij}(t) + w_{Re}Re_{ij}(t) + w_{Ts}Ts_{ij}(t))}{w_{Id} + w_{Re} + w_{Ts}} \tag{15}$$

Kc_{ij} refers to Knowledge-credibility of agent i to agent j at time t This knowledge-credibility is affected by three factors: Ts_{ij} (team success), Id_{ij} (direct interaction), and Re_{ij} (indirect interaction or reputation). Weights w_{Id}, w_{Re}, w_{Ts} determine the importance of direct trust, indirect trust and team success, respectively. These three factors are explained in the following sections.

3.4.1 Team Success

Team success reflects agents' past team experiences with other agents and represents the total number of satisfying and successful group tasks.

If the performance of the task is less than the threshold, θ_1 the task is unsatisfying. Otherwise it is satisfying. Agents update their belief about team members after each task by this formula:

$$Ts_{ij}(t) = \begin{cases} Ts_{ij}(t-1) + e^{NS_i w_{NS}} Pe_{ijb}/100 & \text{if } Pe_{ijb} > \theta_1 \\ Ts_{ij}(t-1) - \frac{e^{NS_i w_{NS}}}{100 Pev_{ij}} & \text{otherwise} \end{cases} \tag{16}$$

$Ts_{ij}(t)$ indicates the belief of agent i about past experience with agent j. NS_i represents the sensing personality of agent i, and Pe_{ijb} represents the performance in task b where agent i and agent j are team members. As mentioned above in the *2nd assumption,* for people with a Sensing personality, what happened in the past is a more important factor compared to iNtuition types, and w_{NS} indicates the importance of the Sensing personality on team success factor on Knowledge-credibility.

3.4.2 Direct Interaction

Over the course of time, agents update their beliefs about other agents' expertise and develop their Knowledge-credibility. If agent j shares some knowledge with agent i, agent i develops his belief on (confidence in) the expertise of agent j as described in the following formula:

$$Id_{ji}(t) = \begin{cases} Id_{ji}(t-1) - w_{TF}(1 - TF_i) & K_j = 0 \textit{ and } K_i = 1 \\ Id_{ji}(t-1) + w_{TF}(1 - TF_i) & \textit{if Agent i accept } K_j \\ Id_{ji}(t-1) & \textit{otherwise} \end{cases} \tag{17}$$

$Id_{ji}(t)$ indicates the direct trust of agent j on agent i; TF_i indicates the degree of feeling personality of agent i; and $(1 - TF_i)$ determines thinking of this agent. And w_{TF} indicates the weight of thinking-feeling dimension. In this formula we face 3 scenarios which are based on the *1st Assumption* (above):

(1) If agent j expresses his opinion about a topic on which he does not have any knowledge (i.e. $K_j = 0$, then it would have a negative effect on agent i'*s* opinion who knows that's j is wrong. Agent i decrease his value of Knowledge-credibility based on his thinking-feeling personality. People with thinking personality make judgements based on empirical verification, so it makes them more sensitive to false knowledge.
(2) Agent i may accept the knowledge from agent j. The details about accepting knowledge are explained in the knowledge sharing section.
(3) Agent i may receive knowledge from agent j and without knowing whether the knowledge is true or false. In this case it will not have any effect on agent *j's* Knowledge-credibility.

3.4.3 Indirect Trust (Reputation)

Agents not only compute Knowledge-credibility based on expertise and team success, but also, they collect recommendations from other agents. When agent l interacts with agent i and transfers his attitude towards a third party, agent j, he is building agent j's reputation for agent i. So the reputation of agent j is calculated as follows:

$$Re_{ij}(t) = Re_{ij}(t-1) + Kc_{il}(t) * Kc_{lj}(t) \tag{18}$$

$Re_{ij}(t)$ indicates the reputation of agent j for agent i at time t. $Kc_{il}(t)$ indicates the knowledge credibility of agent i to agent l, and $Kc_{lj}(t)$ indicates the knowledge credibility of agent l to agent j. The way, which people exchange information about other agents is similar to knowledge sharing that is explained in Sect. 3.4.

3.4.4 Knowledge Acceptance

As mentioned earlier the willingness to accept shared knowledge is related to Knowledge-credibility (trust). This is relevant to sensing personality as mentioned in the *3rd assumption*. When agent i share his knowledge with agent j, the probability that agent j accepts the knowledge is related to his Knowledge-credibility and Sensing personality. In the MBTI scheme, people with Sensing personalities are more willing to gather facts compared to iNtuition types.

The probability that knowledge is accepted by agent j is calculated as follows:

$$a_{ji} = \left(w_{Kc}e^{Kc_{ji}}/10 + w_{NS2}NS_j\right)/(w_{KC} + w_{NS2}) \tag{19}$$

a_{ji} is agent j willingness to accept knowledge from agent i that is related to two factors: Kc_{ji} (the Knowledge-credibility of agent j for agent i) and NS_j (the level of Sensing in agent j). Where weights w_{Kc}, w_{NS2} indicate the importance of Knowledge-credibility and the Sensing personality in accepting knowledge, respectively.

3.5 Self-learning Knowledge

In addition to learning skill from others, we cover the effect of self-learning. In each time step, people increase their knowledge at a rate that is related to the Introverted and iNtuition components of their personalities. Introverted types have a higher self-learning rate than Extraverted types (*6th assumption*), and iNtuitive types can generate new knowledge by interpreting their past knowledge (*4th assumption*).

This probability is calculated as follows:

$$Sl_i = \frac{\theta_5(w_{IE2}(1 - IE_i) + w_{NS3}(1 - NS_i))}{w_{IE2} + w_{NS3}} \tag{20}$$

where Sl_i indicates the probability of self-learning of agent i. Again, this probability determines the likelihood of a knowledge topic's value getting set to a value of 1. IE_i reflects where the agent lies along the Introverted-Extraverted personality dimension, and NS_{i_i} indicates where along the Sensing-iNtuition dimension (values are from 0 to 1). w_{IE2}, w_{NS3} indicate the importance of Introverted and iNtuition personality types, respectively, and θ_5 shows the rate of self-learning knowledge growth.

3.6 Skill Learning

Employees not only learn the knowledge by interacting with other agents; they can also improve their skills or procedural knowledge by observing others' behavior. Observational learning is an effective method of collaborative learning that is commonly used by both human and computer models [19]. In observational learning, people need a model to imitate the behavior. In our model, agents improve their skills by observing and imitating another agent who is using the same skill in their team. Two factors affect the improvement of skill – the difference between the skills of people who are performing the task and the amount of relevant knowledge that the learner has. In our simulation model, skill improvement of an agent is calculated as follows:

$$skill_{iv}(t) = skill_{iv}(t-1) + K_{evi}\theta_2(skill_{iv}(t-1) - skill_{-iv}(t-1)) \tag{21}$$

Skill improvement is affected by K_{evi} which represents the sum of knowledge related to $skill_{iv}$. And $skill_{iv}(t)$ indicates the skill v of agent i in time t, and θ_2 shows the growth rate of skill.$skill_{-iv}$ indicates the skill v of other members in the team.

3.7 Forgetting

People forget their knowledge and skills if they stop using them, but the degree of forgetting differs in knowledge and skill. In order to model how people learn and forget knowledge and skill, we used declarative and procedural memory that is presented in the ACT-R cognitive architecture [20]. In this model, declarative knowledge represents factual information, and procedural knowledge indicates task knowledge.

In ACT-R, a declarative memory item is dependent on how often (frequency) and how recently (recency) the item is used. Also in the higher stages of learning, the strength of declarative memory increases by practicing. However, when knowledge is stored in procedural memory, it will not easily decay with time.

In our model, we assume that knowledge is stored in the declarative memory and skill is stored in the procedural memory. The forgetting rate in knowledge is faster than skill but also depends on the competency of agents in that skill. So, skill deterioration (when employees are not using that skill) is calculated as follows:

$$skill_{iv}(t) = skill_{iv}(t-1) - \theta_3 e^{-(skill_{iv}(t))} skill_{iv}(t-1) \tag{22}$$

$skill_{iv}(t)$ indicates the skill v of agent i in time t, and θ_3 shows the forgetting rate of the skill.

In addition to frequency and recency, which are mentioned for skill forgetting, the competency in the skill related to that knowledge reduces the forgetting rate of knowledge [21].

Each time that a person uses knowledge; this knowledge is refreshed and is saved from forgetting. The probability that a person loses his knowledge is related to the strength of skill related to this knowledge. So, the probability of forgetting knowledge is calculated as follows:

$$P_{fk} = \theta_4 e^{-(skill_{iv}(t)))} \tag{23}$$

P_{fk} indicates the probability of forgetting knowledge, $skill_{iv}(t)$ indicates the competency in the skill related to knowledge, and θ_4 indicates the rate of knowledge forgetting.

4 Simulation

The proposed mathematical model was translated into an agent-based model and implemented in Repast [22]. In this model, self-organizing teams perform a task in the context of a temporary project. Each temporary project consists of two tasks, and each task is related to a single skill, and two people are required to work on a task. So, a temporary project needs four employees.

Initial setup of the experiment comprised 100 employees and 25 tasks, with each task requiring four employees. Each individual has some initial properties, such as a vector of skills, a matrix of knowledge related to these skills, and a knowledge credibility vector of other employees. In each cycle, individuals team up and start a task. Each task takes 100 time-steps. In each time, step agents develop their trust of each other and knowledge that is explained in detail in Sect. 4.1 by communicating and updating their skills by observation. In this paper, two task allocation mechanisms are studied: based on trust (knowledge credibility) and skill.

(1) **Knowledge credibility:** In the first scenario, employees form a team based on their knowledge credibility. We assume one employee starts a task and asks three other members with the highest knowledge credibility to join that task.

```
Initialization: Group formation mechanism and inputs such as task
and team members' characteristics
For each task
    FOR time step < current-time step + 100 DO
      FOR each time step
        FOR each agent i
          With probability Sh_ij (formula 12):
              Share knowledge with agent j
          IF receive a knowledge from agent j
              With probability of a_ij (formula 14):
                  Accept the knowledge
                  Update direct interaction Id_ji(t) (formula 8)
          END IF
          IF receive information about agent k
                  Update Re_ik(t)          (formula 10)
          END IF
          With probability Sl_i (formula 15):
              Update knowledge
           When agent i using same skill as agent j
           AND they are in same team:
                Improve skill ΔSk_ij       (formula 17)
          WHEN agent i stops using skill v: forget (formula 18)
          WHEN agent i stops using knowledge k : forget
          (formula 19)
          END FOR
        END FOR
      END WHILE
      Calculate team performance Pe_b (formula 3)
      IF agent j is in the same team
        Update team success trust Ts_ij(t) (formula 9)
Next task allocation
```

Fig. 2. Pseudo code of the agent simulation model.

(2) **Skill competency:** In the second scenario, people are assigned to a task based on their competency. Managers assign a combination of employees with the highest skill as explained in Formula 7.

Initially for each of the four MBTI personality dimensions, we established a scale between 0 and 1 and assigned values for each employee. In our initial settings, a vector contains 10 knowledge items assigned to each skill. In addition to that knowledge, we have a general vector of knowledge that contains 100 elements. We assume each project needs a maximum of 50 units of this knowledge.

The values assigned 1 for the weight parameter and number 100, 0.1, 1, 10, 1 to the parameters θ_1, θ_2, θ_3, θ_4, *and* θ_5 respectively and we receive the results of 100 model runs for the model analysis. We ran two types of experiments: firstly, we compared two task allocation mechanisms and their differences in knowledge learning, skill learning, and team performance by assigning a random personality to the agents. Then, we compared the effects of different types of employees (in terms of personality) and their roles in the team performances in two task allocation mechanisms (Fig. 2).

Also, we are developing a proposed simulation tool to help managers and teachers identify how changes in knowledge, skill, and the performance of group m embers appear due to their attributes such as personality, skill, knowledge, task requirements, and also the task allocation mechanism. A schematic representation of this tool is illustrated in Fig. 3.

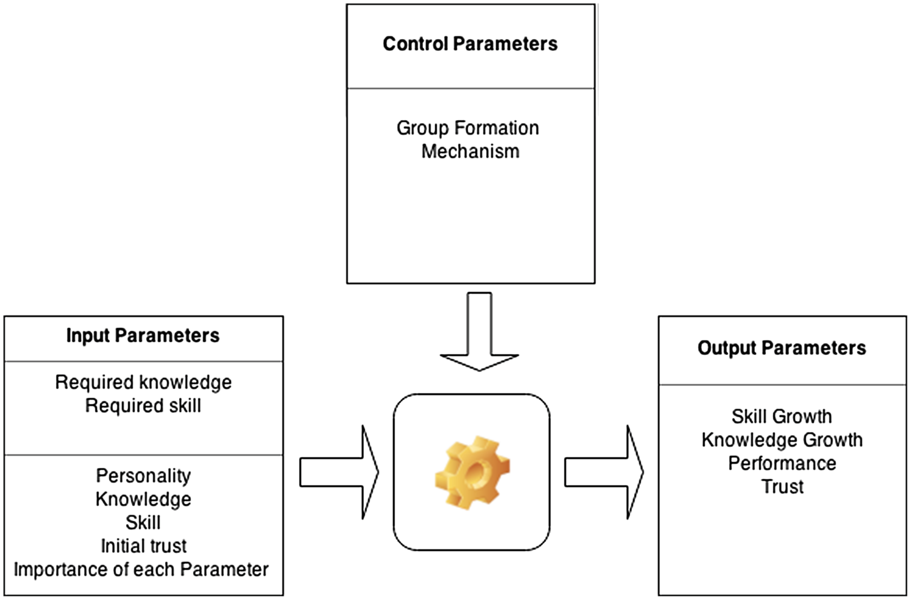

Fig. 3. Input-output and control parameter of proposed simulation tool

5 Results

In our computer simulation, we compared knowledge growth, skill growth, and performance while performing 10 tasks (1000 time steps) using two task allocation mechanism. Figure 4 compares the average knowledge of employees (an average over 100 runs) for both team-formation mechanisms (based on knowledge credibility and skill). Figure 5 shows a comparison of the average skills of employees (averages over 100 model runs) for both team-formation mechanisms – based on credibility and skill-based team formation after 10 tasks (1000 time steps). Figure 6 compares the average team performances (averaged over 100 model runs) for both team formation mechanisms based on credibility and skill-based team-formation after 10 tasks.

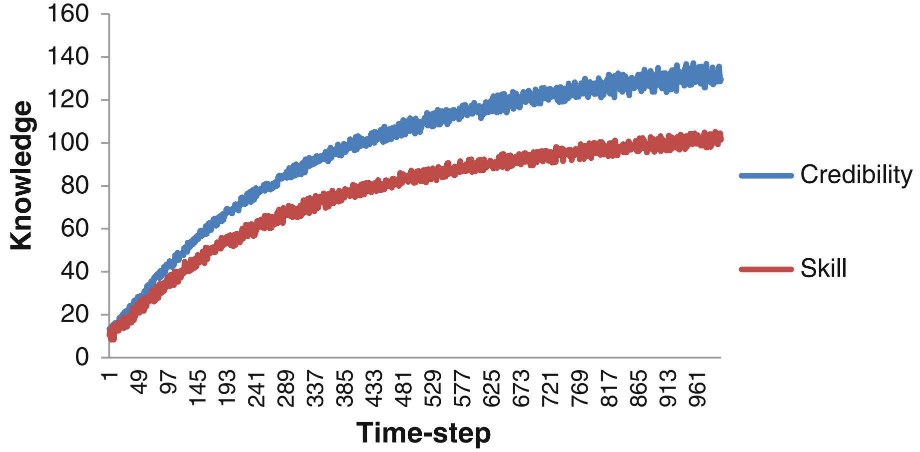

Fig. 4. Knowledge growth for credibility-based teams and skill-based teams.

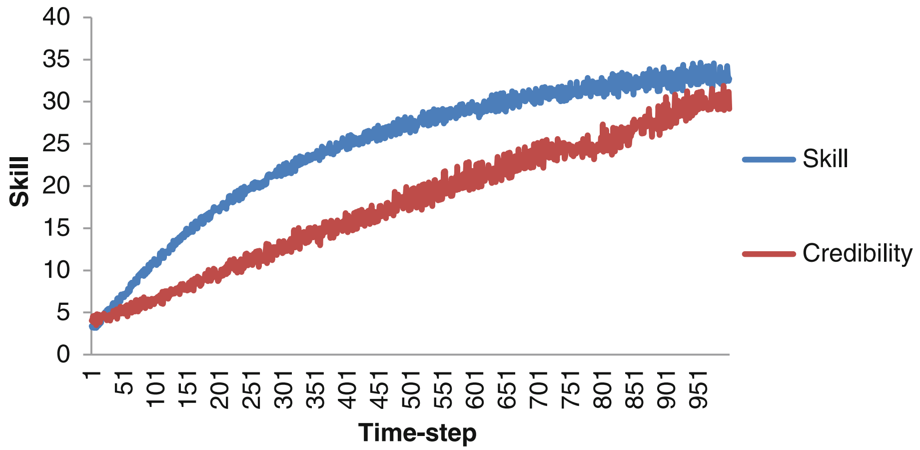

Fig. 5. Skill growth for credibility-based teams and skill-based.

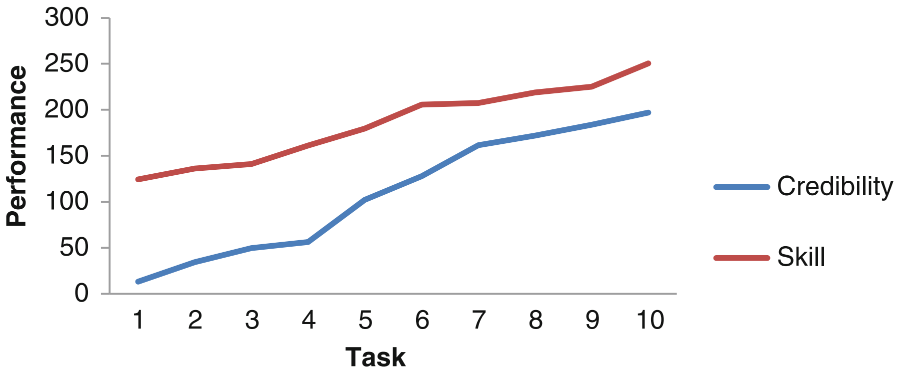

Fig. 6. Performance for credibility-based teams and skill-based teams.

The simulation results showed the average performance of teams in skill mechanisms had better performance compared to the credibility mechanism. However, the gap between the two results shrank over time. Despite this gap in the performance, the average knowledge in teams based on knowledge credibility is much higher than teams based on skill. Skill growth in teams with the skill-based formation is faster than the credibility-based team formation scenario; however, the results show that the average skill was almost sustained over the long term.

In addition, we analyzed the effects of personality on team performance and the differences of these effects on the two task allocation mechanisms. In this connection, we conducted new simulations and instead of assigning random values to personality, specific personality values assigned to all employees for a team.

We conducted experiments over different scenarios with different personality value setting and measured the average performance after performing 10 tasks. These scenarios were measured for two self- rized in Fig. 5, which shows a heat map, with each value of a matrix representing a different color. Rows represent the dimensions of personality in both mechanisms, and the columns represent the value of each dimension.. These results represent the performance value of each scenario. For example, the first row from the bottom (I-E-C) shows a particular distribution of Introverted-Extraverted (I-E) personality with respect to the Knowledge-credibility mechanism (C). The number 0.1 in the Personality axis indicates that 0.1 is assigned to the I_E personality dimension of all the agents. In this scenario, the average performance of teams in 10 tasks is equal to 10. The second row from the bottom (I-E-S) shows the Introverted-Extraverted (I-E) personality with respect to the skill mechanism (S) and the first number is a scenario for which the number 0.1 assigned to that particular personality trait of the employees, and the average performance was 8. By comparing these two values, we observe the difference between team performances based on team formation mechanisms.

The results reveal that, there is a relationship between personalities of employees and the overall performance. Results show Extraverts have a positive effect on performance for both team assembly mechanisms based on trust and skills. However, a balance of Introverts and Extraverts led to a better result compared to the scenarios for which all members are very Extraverted. The observed behavior showed increasing Extraversion had a positive effect in the Skill-based scenarios compared to the Knowledge-credibility-based scenarios. In the other words, if team members are skillful, some teams' member with a particular (such as being Extraverted) could end up with more knowledge-sharing and consequently improved performance.

Sensing-iNtuition personalities have almost opposite effects on the two team-formation mechanisms, and they follow different patterns. Intuition is a more important factor in Knowledge credibility-based teams compared to skill-based teams. A simple, approximate explanation of this behavior is as follows. First, in a system where all the employees are Sensors, they are eager to gather additional knowledge. Since teams are formed based on credibility, this virtue assists them for a high knowledge sharing rate. When team formation is based on skill and employees are intuitive, they do not share their knowledge and this phenomenon results in negative learning and consequently poor performance.

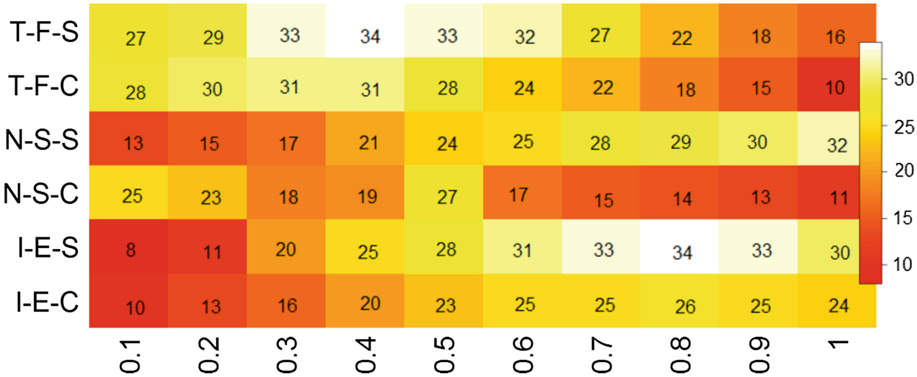

Fig. 7. performance and personality in credibility-based teams and skill-based teams.

Having a high Thinking personality was shown to be better in our simulations than having a high Feeling type of personality in most of the cases. The Thinking personality had more advantages for team formation based on knowledge credibility compared to team formation based on skill. This reflected the effect that when people have thinking personalities and team formation is based on knowledge credibility; they eventually find better teams to work with. When people are feelers they might trust in wrong persons and give them the credit that they do not deserve that but in a world with thinking people these mistakes less likely occur.

6 Discussion and Future Work

The growth of collaborative learning in crowdsourcing platforms and CSCL systems suggests that a simulation environment could provide better understanding of group formation and learning process. In this paper, we have developed a model that shows how people in collaborative learning systems may grow their knowledge and skill via collaborative learning. Group formation in virtual learning environments is either done voluntary or with the support from the system. We investigated how a group formation mechanism might affect the collaborative learning and team performance. So, we compared the results of two group formation mechanisms: based on skill and based on knowledge credibility.

The results of our simulations showed that although team assembly based on skill ended up with good performance, they are not necessarily successful in collaborative learning. In particular, knowledge increased more in the credibility-based team-formation mechanism. We also investigated the effects of temperament (personality) on team performance for both team-assembly mechanisms, and we observed several interesting results as summarized in Fig. 7.

Implication derived from the simulation environment could provide a low cost tool for managers, teachers and researchers to have a better understanding of the impacts of different scenarios on teams' collaborative learning and performance.

There are several interesting research issues that we will consider in our future work. So far, we have investigated the roles of personality, trust, knowledge, and skills in team performance. However, another dimension that we intend to investigate includes motivation and amount of effort that individuals put into their group tasks.

We wish to emphasize again that what we are presenting here as a contribution is not so much the specific simulation results, but a modelling and simulation approach that can demonstrate interesting emergent effects for collaborative learning and project team performance. The parameterization can be set for specific contextual circumstances to examine sensitivities in this area.

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