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ENaCT: An Action-based Framework for the Learning and Analytics of Critical Thinking

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Abstract: Critical thinking (CT) is an important 21st-century skill. In this paper we propose a new framework – Embodied Narratives of Critical Thinking (ENaCT) – to conceptualise the learning of CT, as well as analytics to assess CT, in a technology-enhanced environment. In the context of a CT activity, this position paper bridges the perspectives of embodied cognition, aligning actions that constitute learning, with learning analytics approaches, to measure and build embodied narratives of the learning process. We illustrate the components of this new framework through a preliminary interface design conceptualised for the learning of CT within an online reading platform. Applicability of the framework and future research agenda are discussed.

Keywords: Critical Thinking, Learning Analytics, 21st Century Skills, Embodied, 4E cognition

1. Introduction

Educators all over the world agree that critical thinking (CT) is one of the core 21st-century skills. Scholars conceptualise CT as either a skill (Paul & Binker, 1990; Paul & Elder, 2008) or a process (Jeevanantham, 2005). There exist several definitions of CT. For instance, according to Paul & Elder (2008), CT is characterised as the skill to analyse and evaluate thinking with a view to improve it; in other words, CT is self-directed, self-disciplined, self-monitored, and self-corrective thinking. Alternately, CT has been described as requiring high-order thinking and involving the processes of analysis, evaluation, reasonableness, and reflection (Jeevanantham, 2005). A well-cultivated critical thinker raises vital questions and problems, formulates them clearly and precisely, gathers and assesses relevant information, uses abstract ideas to interpret it effectively, comes to well-reasoned conclusions and solutions, and tests them against relevant criteria and standards. In addition, a critical thinker thinks open-mindedly within alternative systems of thought, recognising and assessing, as need be, their assumptions, implications, and practical consequences, and communicates effectively with others in figuring out solutions to complex problems (Paul & Elder, 2008).

Currently, CT is assessed using standardised tests or rubrics for open-ended activities. Some examples include the California Critical Thinking Skills Test (Facione, 1990), the Cornell Critical Thinking Tests (Ennis & Millman, 2005), the Ennis-Weir Critical Thinking Essay Test (Ennis & Weir, 1985), and the Watson-Glaser Critical Thinking Appraisal (Watson & Glaser, 1980). Researchers have also used rubrics in order to assess student performance on open-ended tasks or domain-specific measures of CT (Tiruneh et al, 2014; Mutakinati et al, 2018). Rubrics are designed based on the universal intellectual standards of Paul and Elder (2008).

Recently, researchers are also using learning analytics in order to measure and model complex thinking skills such as CT, engineering design, and decision making (Shum & Crick, 2012; Blikstein, 2011; Biswas et al, 2019; Vieira et al, 2016; Xing et al, 2019). Learning analytics can enhance, and be supported by, traditional educational data analysis methods. In particular, learning analytics methods employ learner trace data from learning environments to generate models of learners, predict learner performance, and adapt learning designs to better suit learning requirements (Biswas, et al., 2019; Moreno-Marcos, et al., 2020; Hernández-Leo, et al., 2019). However, in order to establish the reliability and validity of trace data analytics, and to make causal inferences about learning from these data, it is necessary to ground the analysis in the pedagogical theory of the domain (Winne, 2020) as well as cognitive accounts of the process of learning (Biswas, et al., 2019; Worsley & Blikstein, 2014). Such theoretically grounded learning analytics have not been done for critical thinking learning data.

In this work, we present an integrated conceptual and analytics framework which guides the evaluation and learning design for CT. This framework, informed by embodied accounts of thinking, cognition, and learning, will allow us to streamline learning analytics in order to measure theory-based markers of good CT performance from the collected data traces.

2. Related Work

2.1 Critical Thinking

The literature on teaching-learning of CT predominantly comprises contributions from three different schools of thought - Philosophy, Psychology, and Education (Lai, 2011). While there are significant differences between the three on what constitutes CT, they agree on three key ideas related to CT - the need for personal dispositions, the key abilities to be exhibited by the learner, and the importance of background knowledge (Ennis, 1985; Halpern, 1998; Bailin et.al., 1999; Facione et al, 2000). Dispositions are broadly defined as attitudes or habits of mind, whereas the abilities involve actions that require learners to use higher-order thinking (e.g. analysing arguments or claims, making inferences, judging or evaluating situations, making decisions, or solving problems). Domain-related background knowledge is considered essential to CT as evaluations and decisions one makes will have a strong bearing on the domain. Paul and Elder's (2001) 'Elements of Thought' provides an objective framework for investigating CT skill and underlying processes. According to Paul and Elder's model, all thinking consists of eight basic structures (elements of thought). These include, an understanding of, and an ability to, formulate, analyse, and assess: (i) the purpose (or significance) of a problem/activity, (ii) the questions at issue, (iii) presented/available information with respect to the context, (iv) problem-relevant concepts, (v) (one's own) interpretations of the above and inferences based thereupon, (vi) one's assumptions, (vii) implications and consequences of the output of the activity, and (viii) one's point(s) of view (Figure 1). An uncritical thinker, according to this model, has less command on these elements of thought (Paul & Elder, 1999).

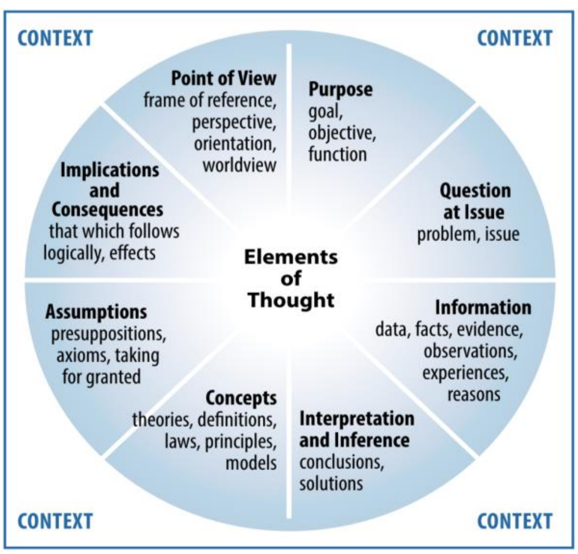

Figure 1. Elements of thought, reproduced from Paul & Elder (2019)

Existing assessments of CT skills are broadly reliant on standardised tests or rubrics for assessing open-ended activities. The California Critical Thinking Skills Test (CCTST), for instance, was devised to assess the development of CT as a part of an academic curriculum designed to improve CT among undergraduate students (Faicone, 1990). The Cornell Critical Thinking Tests collection is another example of multiple-choice tests that measure "general" CT abilities (Ennis, 1993). The Ennis-Weir Critical Thinking Essay Test (Ennis & Weir, 1985) and the Watson-Glacer Critical Thinking Appraisal (Watson and Glacer, 1980) are short-answer or essay type assessment questions. The Halpern Critical Thinking Assessment (HCTA; Halpern, 2010) consists of both multiple-choice and short-answer questions, and has a total of 25 everyday scenarios that respondents analyse and critique. HCTA measures five subcategories of CT skills: (i) verbal reasoning skills; (ii) argument analysis skills; (iii) skills in thinking as hypothesis testing; (iv) skills to utilise the concepts of likelihood and uncertainty; and (v) decision-making and problem-solving skills.

While all of these assessments are administered after CT learning-teaching interventions as post-tests, there are other subjective methods such as rubrics for more open-ended activities that help measure a learner's CT skills. For instance, Mutakinati et al. (2018) utilise a four-level rubric, with four distinct criteria for evaluating open-ended assignments in a project-based learning setting. The authors also used this rubric to classify thinkers into six categories. The rubric is based on Paul and Elders' (2001) framework of CT.

2.2 Embodied accounts of cognition and thinking

Traditional approaches to analysing the processes of thinking and reasoning (collectively, thinking skills) in technology-enhanced learning environments are predominantly grounded in the information processing theories of cognition (Majumdar et al., 2014; Pande & Chandrasekharan, 2017; Reynders et al., 2020). These approaches assert that a learner first engages in extraction of information from the content embedded in the learning environment (e.g. text, representations, models); the learner performs thinking or reasoning about 'using' this extracted information. Further, the 'act' of thinking or reasoning about is understood by these approaches as (i) symbolic transformation or translation performed on the extracted information, (ii) as taking place entirely inside the brain/skull, and (iii) as separate or dissociated from the actual content presented in the learning environment, as well as the actions/interactions one performs on this content. The learner's body, and bodily actions (e.g. movements, gestures, interaction with the surroundings), in these approaches, are treated as a product of information-based thinking.

Newer approaches to cognition and learning (e.g. 4E cognition; Menary, 2010; Newen et al., 2018), however, treat actions as a critical part of the thinking process, and not merely as a product of thinking. For instance, distributed cognition-based investigations of problem-solving processes have shown how spontaneous (assumedly information seeking) actions in virtual environments (e.g. constantly rotating the incoming shapes through all possible orientations in Tetris) help offload parts of thinking (e.g. matching shape orientations and contours with increasing speed and accuracy), and the underlying cognitive processes (e.g. mental rotation), to elements in the external environment (e.g. controller keys, computer screen displaying the game as one plays it in real-time; Kirsh & Maglio, 1994; Kirsh, 2010). Empirical evidence also suggests that actions (e.g. highlighting text, sketching - processes traditionally deemed as outputs of thinking) facilitate the emergence/occurrence of newer ideas and insights during the processes of problem-solving and scientific discovery (Aurigemma et al., 2013). This indicates that actions feed back into, and reorganise and refine, thoughts.

Going one step further, embodied and enactive cognition approaches regard ones' thinking, their actions, and the environmental elements being interacted with, as *coupled* together (Pande, 2020). For instance, Landy et al (2014) show, in the context of a technology-enhanced learning environment designed to support embodied learning of mathematical concepts, how mathematical symbols, the physical operations one performs on symbols, and the visible forms of relationships between those symbols, together constitute one's mathematical thinking (for work on perceptual learning, also see Kellman & Garrigan, 2007; Landy & Goldstone, 2007; Pande & Chandrasekharan, 2020). In summary, these new approaches in cognitive science show that elements of (technology-enhanced) learning environments, and one's bodily actions on those elements are not dissociated from thinking, as initially considered, but rather are a part of the thinking and reasoning processes.

This revised understanding of thinking as an action-based or embodied activity has implications to designing for, and analysing, learning in interactive technology environments. Modern technologies allow diverse ways of presenting target content/concepts and/or their representations. These diverse presentations in turn afford novel body-based interactions between the learner and the elements of the learning environment. Given that body and actions affect thinking (by constituting it; e.g. Landy et al., 2014), technology-enhanced learning environments could be designed to include novel affordances (and related interactions) to facilitate more 'desired' forms of thinking (e.g. CT or its components) among learners. Similarly, learner actions/interactions within such environments in relation to their affordances could be analysed to understand and/or generate models of the thinking processes, and learners, as well as to investigate the effectiveness of the learning environment designs.

2.3 Learning Analytics

Recent research in learning analytics aims to model and analyse complex 21st-century competencies in order to support traditional educational data analysis (Shum & Crick, 2016). The goal is to model student behaviour as they do complex thinking tasks such as decision making, programming, and engineering design, in technology-enhanced learning environments, in order to improve assessment and performance prediction, as well as to provide feedback to learners (e.g. Blikstein, 2011; Biswas et al, 2019; Vieira et al, 2016; Xing et al, 2019). In this approach, learners' actions in learning environments (such as their use of certain resources, artefact creation, reading, typing) are captured. Machine learning methods are then applied to the captured action-data in order to identify sequences or clusters of actions, and correlate these patterns with student performance on tasks. These patterns and correlations help build a learner model. The learner model can then be used to make predictions and adapt instruction. The underlying assumption here is that the action patterns of a learner say "something" about their performance on the task.

When these analyses are grounded in a theoretical framework of the domain, such as the above-described embodied accounts of thinking, wherein bodily actions are constitutive of thinking, these clusters or sequences can be used to make causal inferences about learner performance on tasks (Winne, 2020). The theoretical grounding increases the validity and reliability of learning analytics. However, there is a dearth of research into building embodied or action-based learner models, especially for CT tasks. Therefore, a primary goal of our work is to develop an integrated conceptual framework that brings together learner modeling and CT acquisition, within the theoretical framework of embodied cognition.

3. ENaCT Framework

We propose a framework that integrates the process of acquisition of CT (the learning aspect), and the process of data-based modelling of a critical thinker or a CT learner (analytics aspects). As discussed earlier, most conceptual and analytics approaches to CT, being implicitly or explicitly grounded in the information processing accounts of mind, tend to treat CT as dissociated from one's bodily actions, and one's tendencies or patterns of navigation through a (task) context/environment. To address this major limitation, we focus on an individual's actions performed during learning or problem solving, in the context of CT. For this new action-based (embodied) framework, we use Paul and Elder's (2019) 'elements of thoughts' model (see figure 1 in section 2.1), which provides a comprehensive set of possible (cognitive) tasks involved in executing or learning CT.

Figure 2 shows the new Embodied Narratives of Critical Thinking (ENaCT) Framework. As indicated earlier, our framework has two components: a conceptual component modelling how artefacts in one's environment, and the bodily interactions one has with those artefacts, relate to learning and execution of a skill (e.g. CT); and an analytics component modelling how artefacts and actions could help generate assessments or models of the learner. In the first conceptual component, we consider that problem solving or learning happens when an individual interacts with the given system affordances, and executes actions. Learning scaffolds are specific sets of affordances either embedded within the learning environment or provided externally. Scaffolds are primarily designed for assisting the process of learning. The system affordances should be designed with inputs from the specific thinking task model that outlines how different (bodily) actions of an individual constitute the application or execution of one or more elements of thought. In addition to interacting with the environment (e.g. a technology-enhanced learning environment), an individual can also create artefacts anytime during or at the end of the learning or problem-solving process. Such artefacts created at an intermediate stage of a process can themselves generate newer affordances, which can be further incorporated in the individual's action space as one proceeds through problem solving, and/or support learning. Thus, as one keeps interacting with the affordances within that action space, different individuals can follow different pathways of problem-solving or learning. Through time, one may also further adapt themselves to incorporate newer pathways such as those generated by newer artefacts, in turn facilitating richer skill execution and learning (hence the bi-directionality of the connection in Figure 2).

In the second learner modelling component of the framework, the action space is logged as learner interactions in the learning environment together with learner generated artefacts. Similar to system affordances, learning analytics should also be informed by the specific thinking task model. The level of acquisition of the skill, and related behaviors, can be used to develop a learner model collectively based on the interaction and artefact generation log data.

Our approach thus does not consider one's bodily actions in the environment and generated artefacts as products of critical thinking, particularly as we believe that the generated artefacts also generate newer affordances (and hence thinking possibilities) for the learner/problem solver. In this framework, one's bodily actions, and the artefacts they generate, constitute CT similar to how a learner's actions in 'Graspable Math' (Landy et al, 2014) constitute mathematical thinking. Moreover, we consider actions/interaction patterns as a part of one's observable behaviour that could be linked to CT; however, in the conceptual components of the model, we deem actions as part of the critical thinking process - which is why observing them to model thinker/learner behaviour makes all the more sense.

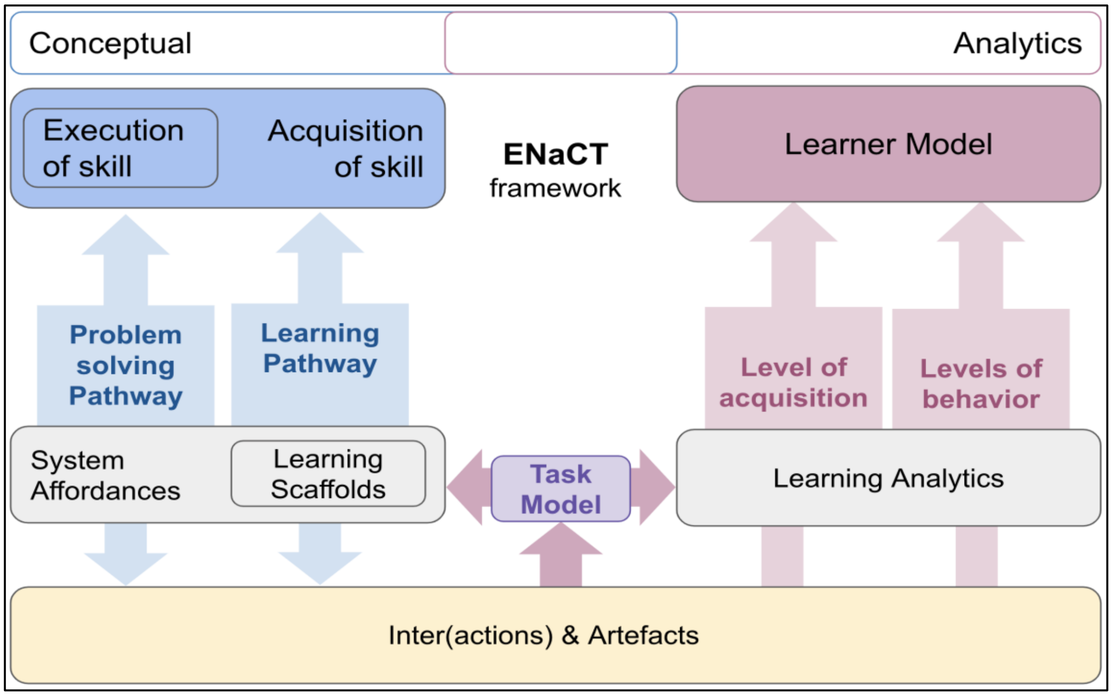

Figure 2. Embodied Narratives of Critical Thinking (ENaCT) Framework

4. Instantiation of the framework for a CT Task

In this section, we elaborate on the ENaCT model with reference to the following CT task:

> *"As you already know, the novel coronavirus has spread all over the world, and different governments have given guidelines and rules for containing the spread of the virus. The school and policymakers in your region are discussing whether schools should run in a regular mode (all the students on campus/in the classroom), or hybrid mode (50% students attend physically, while the remaining attend via internet) or completely online mode. If you were the policymaker, what mode would you propose, and why?"*

We envision that this task would be performed within a software environment with affordances designed as sub-tasks based on Paul and Elder's Elements of Thought (Paul & Elder, 1999). The environment will provide learners the opportunity to explicitly 'act on' and practice each of these elements. Further, the environment would include information and conceptual resources in the form of interactive graphs, text, and videos which learners can use as they need while doing the task. The environment would be open-ended - no predetermined order/sequence of activities (pathway) would be imposed, and learning scaffolds would be available on demand. Within such an environment, the task model for critical thinking could be as shown in Figure 3.

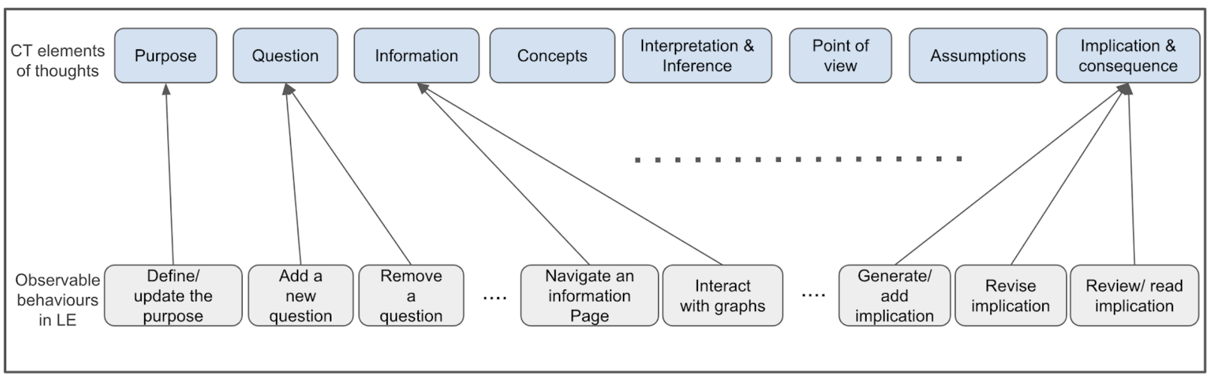

Figure 3. Task model for critical thinking activity

From observable behaviours within the software learning environment, we could assess learner performance on the task and acquisition of CT skills. For instance, adding/modifying entries in the 'Purpose' sub-task is one of the actions that is constitutive of the element of thought of "Purpose". By identifying patterns in learner behaviour, such as "viewing graphs" followed by "modifying purpose", we can gauge the level of learner behaviour. Further, by assessing the quality of generated artefacts (e.g. entries in the "Purpose" sub-task), we can assess one's progress of learning (level of acquisition) of CT. Together, these analytics would help us build the learner model. The ENaCT framework adapted to this CT task model is shown in Figure 4.

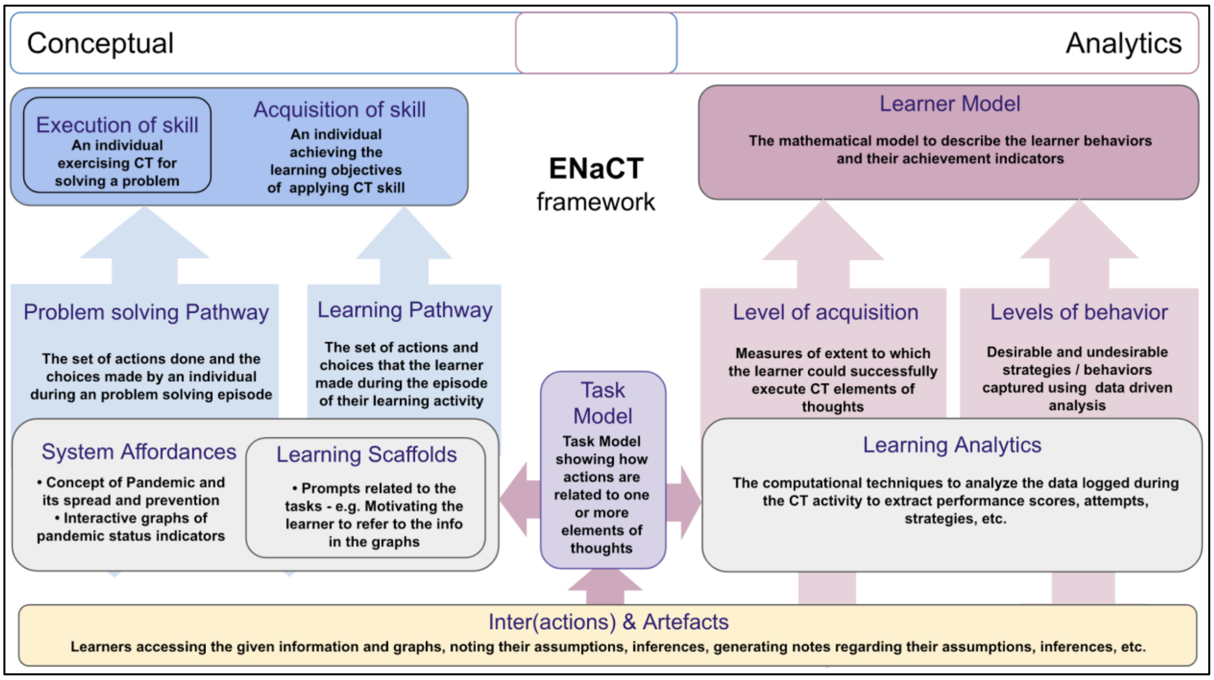

Figure 4. Instantiation of ENaCT Framework for a task

5. Implications and contribution

5.1 Approaches to the development of CT

As learners navigate through the software learning environment and do CT tasks, they use the affordances to solve problems and scaffolds to learn various aspects of the CT skill. From the embodied accounts of cognition and thinking, it follows that one's (bodily) action patterns are representative of their level of performance on CT tasks, as well as their level of acquisition of CT skills. By measuring one's performance using an independent CT test and rubric, and classifying the behaviours of good and poor critical thinkers, we can identify behavioural markers of good performance and learning on CT tasks. Further, these behavioural markers could be utilised to build a narrative of learning pathways/trajectories, possibly as a constitutive or causal account of how certain behaviours relate to one's observed performance and learning (Rahaman et al, 2017).

5.2 Learning and Educational Technology Design

In section 4, we propose one possible instantiation of a technology-enhanced learning environment for CT. The ENaCT framework can be utilised for revising the design of learning activities and environments based on learning analytics. An individual's performance scores and engagement, for instance, with individual elements of thought help in tracking their competencies on each aspect of CT, whereas individual scores aggregated together at any time can provide the level of overall CT skill acquired by a learner. These scores and the interaction behaviours of a learner help in further updating the learner model. The learner model generated in a specific context at a given time could be used to predict one's task performance and engagement. Subsequently, interventions can be designed for adaptively (or intelligently) scaffolding the learning activity. For instance, by characterising the productive and unproductive behaviours of critical thinkers as described in section 5.1, we could adaptively present personalised scaffolds to learners based on whether their behaviours are productive or unproductive. If a learner is showing unproductive behaviours, we could provide them additional scaffolds to shift their behaviours towards being productive as done in adaptive tutoring systems (Chen et al, 2019).

5.3 Pedagogical Implications

We aim to design an online environment to foster learner CT skills by giving the learner a specific task context. Having a technology framework and model to extract data regarding skill acquisition behaviors could collectively inform teachers, facilitators and other stakeholders about the learner, and the process of learning. A valid and reliable indicator can thus help formatively assess the learner. Such an objective indicator would also serve as a self-assessment tool for the learner. Teachers can be supported in classroom orchestration of learning activities using dashboards that show (possibly, also real-time) performance indicators of students, which they can use to modulate their teaching by, for instance, initiating collaborations, personalising interventions, and debriefing (Holstein et al, 2020).

6. Conclusion

In this paper, we proposed a framework for building embodied accounts of CT, based on Paul and Elder's (1999) CT task model. We proposed an approach to tracing CT skill as enacted within an online learning environment. In our conceptualisation, we explicitly considered the bodily actions that a learner performs, together with affordances of the online system as constitutive of the learner's CT. Such a theoretical lens is missing in the CT learning and assessment literature. Our framework helps re-analyse the learning of CT in an interactive online learning environment. While our theoretical basis for the different aspects of the framework is solid, currently we have not conducted empirical studies to validate it. Our immediate future work involves implementing the instantiation described in section 4 and gathering data to validate/revise our framework. We hypothesise that such an intervention would lead to the development of an embodied narrative of the learning as well as learning analytics of critical thinking.

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