Learning Sciences Beyond Cognition: Exploring Student Interactions in Collaborative Problem-Solving with a Multimodal Approach

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Abstract

The meaning and measurement of intelligence remain open to question. Standardised definitions and tests that focus on purely cognitive aspects of intelligence can make Intelligence sound like something we either have, or do not have, at any particular moment in time. However, intelligence beyond purely cognitive aspects is not static and changes over time, it is not an all or nothing concept. In this chapter, we argue that constructivist pedagogies such as collaborative problem-solving (CPS) should be acknowledged as dynamic combinations of skills, abilities, and knowledge. Therefore, when they are explored as a process rather than a means to reach certain cognitive learning outcomes, they should be evaluated with a suitably wide ranging approaches beyond standardised cognitive assessments. Investigations of these dynamic processes require approaches that can provide insights into processes across multiple social planes (individual, group, classroom), multiple resources (people, tools), and multiple spaces (physical, digital, hybrid). Hence, they require a multimodal approach. Here, we discuss Multimodal Learning Analytics as one potential example of such an approach. We also present our results from two case studies investigating student interactions with their contexts and with each other during CPS processes to interpret group differences beyond cognition. We conclude the chapter with some suggestions for practice and current challenges against the more prevalent use of multimodal technologies in the learning sciences.

Introduction

In a radio show discussing his life, the eminent neuroscientist Henry Marsh reflected on his voluntary work in the Ukraine and comments that to be a good neuroscientist, or indeed medic of any kind, you have to care deeply about your patients, you have to be compassionate. Clearly, you do need strong emotions and sophisticated emotional intelligence to be a good neuroscientist. And so, it is with learning and teaching. Learning is the holy grail of success and it is about a great deal more than cognitive processing, it is a whole body and mind initiative (Luckin, 2018). The Learning Sciences have produced a great deal of research about how and when we are best able to learn, to apply our knowledge, to synthesise what we know in order to solve problems, to communicate, make decisions, think and to integrate our experiences in the world with this process of synthesized cognitive knowledge construction.

Today, as educators and as learners, we are faced with many challenges. For example: an increasingly automated and AI augmented world in which children will experience a very different life to that of their parents (Siraj, 2017). We must prepare for the much-anticipated upheaval through ensuring that our education and training is tuned to the new demands of the workplace and society (Tucker, 2017). We must chart a course through a potentially bumpy landscape (Walsh, 2017). Fundamental to success in this endeavour will be putting the findings of the Learning Sciences to work in the way that we design our intelligent technologies to support our intelligent human teachers and learners.

For example, the Learning Sciences have demonstrated that Collaborative Problem Solving (CPS) can be an extremely effective means of learning (Luckin, Baines, Cukurova, & Holmes, 2017). But it is not an easy pedagogy for educators to adopt and its positive outcomes for learning are not always consistent (Slavin, 2014). The current understanding of CPS as a generic skill acknowledges it as a complex skill set (Scoular, Care & Hesse, 2017); as "a bundle of skills, knowledge and abilities that are required to deal effectively with complex and dynamic non-routine situations in different domains" (Funke et al., 2018). We argue that educational technologies designed to make meaning through multiple modalities can help both educators and learners to achieve better results when using CPS. And that Multimodal Learning Analytics (MMLA) is a valuable example in this respect. MMLA can provide insights into learning processes that happen across multiple contexts between people, devices and resources, both physical and digital, and can reflect learners' progress in terms of their synthesized integrative knowledge construction beyond the purely cognitive.

In this chapter we discuss, all too briefly, the richness of human learning, understanding, engagement, curiosity, motivation and knowledge construction. We consider this discussion within the frame of human intelligence. We reflect the manner in which the learning sciences can help us to expand our framework for describing human intelligence beyond the merely cognitive processing of information. We discuss evidence from work investigating student activity in CPS situations beyond cognition and their potential value to learning scientists. Building upon these investigations, we explore the potential of MMLA to help us track the richness of human intelligence as it develops beyond the routine cognitive processes that are often the subject of learning and its assessment.

Human Intelligence

The term intelligence is broad and embraces a number of concepts pertaining to knowledge, ability, reasoning and cognition. Its meaning has been discussed since Socrates' time, fuelling many academic discussions, such as those arising from Spearman's 'g factor' (1904) in which intelligence reflects a broad mental capacity, Gardner's multiple types of intelligence (1983) distributed across a number of areas including both abstract and concrete thought and practice, and Sternberg's Triarchic Theory (1985), which argues that analytic skills should also be incorporated into such a model, and that context is significant. The significance of context is also a feature in recent studies in evolutionary biology that suggest the social and environmental context is key to the effective development of intelligence (see for example, Laland et al., 2014, Clark, 2015)

Not only is the meaning of intelligence contested, but the way that intelligence could and should be measured has also been the subject of much research, including the Simon-Binet IQ test (1905), designed to determine which children might need additional help at school, to the less culturally specific Wechsler Scales (1939), the Bayley Scales of Infant Development (1969), and the less US-centric British Ability Scales (1979). The meaning and measurement of intelligence remain open to question, and interest in their study has been renewed by the advent of AI applied at scale. The nature of the connection between intelligence and education is also increasingly challenged (Roth et al., 2015), with discussions exacerbated by the increasing role of AI in the workplace and the accompanying demands for changes to education, training, and assessment (Luckin, 2017). In parallel, there are calls for AI to be developed with greater attention to be more "human-centred" that reflects "the depth that characterizes" human intelligence (Fei Fei, 2018).

However, definitions and tests can make intelligence sound like something we either have or don't have at any particular moment in time, but Intelligence is not static, it is something that changes over time. An early alternative conceptualisation of intelligence opposing to its commonly promulgated static nature was offered by Lev Vygotsky (1980). His evaluation of human activity was that it is much more than the external performance celebrated by the behaviourist thinkers who were prevalent at the time of Vygotsky's research, such as Thorndike (1911; 1914), Watson (1926), and Skinner (1991; 1957). Vygotsky proposed that children's development was the result of their interactions with other people, which formed the building blocks for the psychological processes through which the intellect of that child was constructed.

Human Intelligence and Social Interaction

Vygotsky's work introduced a developmental approach in which the higher psychological processes, such as creative imagination and rational thinking, are specific to humans and cannot be explained in the same fashion as the elementary processes that we share with other animals. The key difference being the social, inter-personal activity that is essential to advanced human thinking and the foundation of our human intelligence. These advanced human thinking processes evolved as we learnt to use gesture and spoken or written language to communicate with each other, to work together collaboratively, and to think beyond our physical interactions in the world: to think and talk abstractly.

In this sense, to conceptualise intelligence and progress in purely cognitive terms is to ignore the social history of an individual's interactions. This narrow conceptualisation gives too much weight to individual psychological processes, biological maturation, or genetic inheritance and it misses the important embodied, emotional, and social human perspective. In order to bring in arguments for the dynamic nature of intelligence and its broader conceptualisations beyond cognition, let us start from the dynamic nature of our knowledge and understanding about the world and about knowledge itself, or in other words, epistemic cognition.

Looking Beyond Cognition

Epistemic Cognition

Knowledge is concerned with our relationship to the world. As our world constantly changes and evolves so must we in our probing and evaluating of our own relationship to that world. We must constantly test what it means for us to know something about the world, to make sense of the world and to construct our personal and communal knowledge of the world, both as an abstraction and as an observable, experiential reality. Through this probing and evaluating we can come to 'know' something about the world. However, more important than knowing something, is our ability to understand what knowledge is, and where it comes from. This is our *epistemic cognition* and we must nurture it in ourselves and in people we educate. The term *epistemic cognition* is a generic term that is used to refer to people's understanding about the nature of knowledge, it implies some level of reflection on our part upon our thinking about knowledge.

Learning Scientists have grappled with the issue of epistemic cognition across the areas of psychology and education, as well as philosophy. A seminal piece of work conducted by William Perry (1968) with Harvard undergraduate students outlined nine different positions that people could adopt towards the nature of knowledge, ranging from: naïve understanding (knowledge is derived from authority), to a sophisticated understanding (knowledge is self-constructed, context relative and evidence-informed). This and later research (Hofer, & Pintrich, 1997) demonstrate that most people have a fairly naïve, unsophisticated personal epistemology. We also know that epistemic cognition varies when people engage in different subject areas, that it is not coherent and that it varies between contexts. Based on decades of research on epistemic cognition and its related concepts *such as* epistemological beliefs, reflective judgment, ways of knowing, epistemological reflection, and personal epistemology, there is little evidence that we are the consistent, rational humans that we might like to think that we are. Yet, most of the rationalisation in our thinking happens retrospectively. We lack sophistication, are inconsistent and incoherent in our beliefs, our knowledge and our certainty about how and what we know. However, we do have the capacity to be sophisticated. For example, we are easily able to interact effectively across a wide range of contextual changes. We can use this 'contextual intelligence' to help us to refine and enhance our knowledge construction and synthesis. With the right support, we can increase the sophistication of our understanding and our epistemic cognition. Humans are also capable of developing a rich understanding of themselves as thinkers: a knowledge of their own knowledge and thinking; a knowledge about how they are feeling; a knowledge of their personal context. This self-knowledge takes us beyond cognition, to meta levels of cognition and emotions.

Metacognition

Cognition is the process through which we develop our knowledge and understanding of the world. It encompasses both our experiential and our algorithmic minds (Kahneman, 2011). Effective cognition requires that we engage our: attention, memory, problem solving, and our evaluative abilities. Our fascination with our ability to know and regulate our own thinking: our metacognition, dates back to Aristotle, and has grown into a substantial area of study in the Learning Sciences. Countless empirical studies have shown that metacognition is a key component of the way that successful people operate in the world. As a concept, metacognition has undergone much refinement. Its complexity is summarised well in a 2011 book by Pina Tarricone (2011), who has produced an excellent 20-page taxonomy of metacognition. However, despite the size of the subject, the term metacognition can be broadly defined as *our knowledge and control of our own cognitive processes*. Early researchers like Flavell (1979) differentiated between our knowledge of our cognitive processes and the processes that we use to monitor and regulate these cognitive processes. The latter include the executive functions of planning, mental resource allocation, monitoring, checking, error detection and correction, for example.

Sophisticated metacognition, with good self-regulation skills, helps people to fulfil their potential. Many scholars have explored the relationship between metacognition and our intellectual performance. Jerome Bruner (1996), for example, described the way in which our metacognitive awareness can increase processes such as attention, problem-solving and intelligence. Scholars such as Marzano (1998), have demonstrated that our metacognitive skills and abilities can increase the learning outcomes that we measure in our education systems, particularly those that relate to problem-solving. Goos and her colleagues (2002) have given us the evidence that successful students are continually evaluating, planning and regulating their progress, thus helping them to learn and to increase their deep level processing. We also know that the development of executive metacognitive processes is associated with enhanced cognitive performance. However, as Kornell (2009: p12) puts it so succinctly, a person's metacognition is not a case of 'turning an inward eye on their memories and somehow analyzing them directly'. To believe that reflection in and of itself is sufficient for metacognition is to fail to appreciate the sophistication of our metacognitive processing. We need to appreciate the complexity of our metacognitive skills, and we need to appreciate that they are highly interconnected to other elements of our human intelligence.

Emotional Intelligence (meta-emotions)

As one might expect, there are a substantial number of theories about how are emotions impact upon if, when and how we learn. For example, in the 80s, Ortony and his colleagues (1988) came up with a theory that has been popular with researchers in the learning sciences. Ortony's team saw emotions in purely cognitive terms, as functions determined by someone's goals and attitudes. This assumes, of course, that the achievement of a goal is something that is important to us, which is over simplistic. On the other hand, much recent research into the relationship between our emotions and our learning has focused on motivation.

Motivation is the way that our emotions drive our actions to increase our knowledge and understanding of the world. When we talk about motivation, are we referring to some physiological process that influences our desire to behave in a particular way, or are we merely referring to the reasons why we do something (Bergin *et al.,* 1993; Ryan, & Deci, 2000)? There are theories that can help us answer both these questions. In an epic piece of research at the start of the 21st-century, Pintrich (2000) attempted to integrate the research about motivation to learn. His work incorporates a range of theories and identifies three core integrated components of motivation to learn:

1. The *expectancy component*: which is concerned with our beliefs about our ability to complete a learning action. Investigations into this expectancy component can be broadly subdivided into our belief about the extent to which we have control over the outcomes of a learning action and its environment, and beliefs about how effective we are likely to be if we attempt to complete the proposed learning action.
2. The *value component*: which refers to our beliefs about the value of the learning action under consideration. It reflects our perceptions of the importance of the learning action that will be influenced by our personal interest in the learning action and our perceptions of its utility for the future.
3. The *affective component:* which accounts for our emotional or affective reactions to the learning action in question. This is particularly complex. It is not the case that being in a positive motivational state will necessarily increase our inclination to complete a particular learning action.

The goal orientation component of Pintrich's value component has typically been defined in terms of two broad orientations, although this conceptualisation varies (see, for example, Ames, 1992; Boekaerts, 2003; Dweck and Leggett, 1988): an orientation towards increasing competence (mastery orientation); or an orientation toward increasing performance relative to others (performance orientation). Within the performance orientation there is a further differentiation between our approach towards achieving high-performance, or our avoidance of low performance. An approach performance orientation has been linked to high achievement and learning, whereas an avoidance performance orientation has been linked to low learning outcomes (see, for example, Harackiewicz *et al*., 1998). Interestingly, our orientation towards a goal impacts on our social attitudes too. Mastery-oriented learners have been demonstrated to be more likely to be supportive in collaborative interactions with peers and more likely to engage in 'creative risk-taking' (Damon, & Phelps, 1989).

The extent to which we adopt an orientation is not fixed and can be manipulated by contextual and dispositional factors (Harris *et al*. 2008). There is also a close connection between motivation and metacognition. The two are interweaved, each having a bidirectional impact on the other, and they are closely related to the concept of self-efficacy.

Perceived Self-efficacy

In 1982, Stanford professor Albert Bandura (1982) wrote in the *American Psychologist* journal that:" perceived self-efficacy is concerned with judgements of how well one can execute courses of action required to deal with prospective situations." (p 201). In this article, he provided evidence that *higher levels of perceived self-efficacy were related to higher levels of intellectual performance*. He observed that people avoided activities if they believed they were not capable of coping with them, but performed with confidence in those tasks they believed they were capable of coping with. This means that the development of our perceived self-efficacy is extremely important.

Perceived self-efficacy is not a concept whose importance is limited to students. Teachers' perceptions of their self-efficacy are also important. Teachers' perceptions of self-efficacy have been shown to influence their instructional practices, enthusiasm, commitment and teaching. Positive and accurate perceptions of self-efficacy in teachers have also been related to higher levels of student achievement and student motivation (Skaalvik, & Skaalvic, 2007; Woolfolk Hoy, & Burke Spero, 2005; Wolters, & Daugherty, 2007; Klassen *et al*., 2009).

It is important to emphasise that these constructs described should be considered as interconnected rather than isolated. For instance, perceived self-efficacy combines elements of both metacognition and motivation, and the three concepts are inextricably bound together. The notion of self-efficacy is also related to metacognition, and in particular to metacognitive control. Self-efficacy, however, varies depending on the task. Moreover, our perceived self-efficacy also draws on our epistemic cognition in important ways. An accurate perceived self-efficacy requires an accurate evidence based judgement about our knowledge and understanding. We need to know our ability to succeed in a specific situation and to accomplish tasks both alone and with others for our perceived self-efficacy to be accurate. To make judgements from the evidence about our knowledge and understanding, we need to recognise what good evidence is and we need to know how to make judgements. These facilities all relate to our epistemic cognition.

Learning from the Learning Sciences

We have laid out some of the discussion with regards to the breadth of features that we need to be concerned with when trying to conceptualise a broad conceptualisation of intelligence. This chapter is not an exhaustive introduction to these concepts; however, it should be clear by now that human intelligence and learning are much broader than purely cognitive considerations. We now turn our attention to a pedagogical approach that we feel exemplifies how we can develop learners' intelligence, including and beyond their cognitive abilities: Collaborative Problem Solving (CPS). In particular, CPS as a generic skill to collaboratively solve open-ended design problems that emerge during practice-based learning activities. Such activities are an essential part of STEM education and have long been argued to help foster the skills we require of young people across subject domains (Funke, Fischer & Holt, 2018).

CPS brings together individual problem solving and the social collaborative process of more than one learner working together. For the purposes of this chapter, we define CPS as *the process of a number of persons working together as equals to solve a problem:* a definition that is informed by the OECD (2015), who define CPS competency as: "the capacity of an individual to effectively engage in a process whereby two or more agents attempt to solve a problem by sharing the understanding and effort required to come to a solution and pooling their knowledge, skills and efforts to reach that solution." It should be noted that the OECD approach to CPS was developed for individual assessment purposes and it therefore only considers CPS from an individual capacity perspective. Yet, it doesn't take different perspectives of groups and communities into account in the design and investigation of CPS processes (Dillenbourg & Jermann, 2007). By keeping the definition broad, our intention is to be able to accommodate constructs that relate to group perspectives such as equality or mutuality of contributions in the process. OECD's approach also doesn't take CPS as a tuition approach (Cukurova et al., 2016), yet it is widely used in educational settings as a pedagogical approach to improve student skills.

Collaborative learning approaches broadly, and CPS more specifically, can produce positive effects on *pupil achievement*, as measured according a wide range of metrics across different studies, *including standardized attainment tasks* (Johnson, & Johnson, 2002). It has also been shown to promote *positive attitudes to schooling* and to improve the *social climate* within classrooms (Kyndt et al., 2013). The OECD identify 3 dimensions for CPS: context, task and process. These 3 dimensions help us to unpack the concept of CPS:

1. *Context* can also be described as the *circumstances* of the problem being solved collaboratively. Context consists of the resources that are available to learners to support their collaborative learning activity (Luckin, 2010). The context of the problem relates to a wide range of elements including the content focus of the task, how it relates to other aspects of the curriculum area, and the resources associated with doing the task (see Cukurova, Luckin, & Baines, 2018 for an overview).
2. *Task*, which for CPS can be thought of as a set of features that represent a gap or crossroads where the way forward to solve the problem is to an extent unknown and must be *generated* and/or *co-constructed* by <u>two</u> or more participants. CPS might be as much about identifying a possible solution as about enacting the solution. An important element for ensuring collaboration takes place is to ensure that the task encourages members to

be mutually interdependent. This can be achieved through the task design or via other means, such as rewards and/or group roles.

3. The *process* of CPS, which requires the combination or the inter-relation of social and cognitive processes. Ideally interaction and joint problem solving will centre on a number of parallel cognitive activities, such as understanding the problem situation, clarifying sub goals and reflecting on assumptions.

In a similar manner to the features of human intelligence discussed in the initial sections of this chapter, CPS is a multidimensional construct and it requires a multilevel understanding of CPS as a complex generic skill set. This common framing permits us to use the study of CPS as a window through which to study aspects of human intelligence beyond cognition. Evaluation of the CPS process itself rather, than its particular outcomes, requires approaches that the current standardized testing strategies and psychometrics cannot provide. It is argued by Blikstein and Worsley (2014) that this problem is common to the process evaluations of all kinds of constructive approaches, such as problem-based learning, project-based learning, or experiential learning, in which the ultimate purpose is to improve complex developmental processes rather than content acquisition. It could potentially be argued that most of such constructivist pedagogies consider human intelligence beyond cognition, in a way that is similar to the position taken in this chapter. However, interpretations of such dynamic processes is problematic. One particular problem is the collection of short interval times series of high quality data on these processes (Molenaar, 2004), which require the application of novel measurement approaches to such idiographic processes (Hofman et al., 2018). We argue here that taking a multimodal approach can have the potential to provide such data to investigate multidimensional aspects of human intelligence involved in constructivist pedagogies (see fig.1 for the connection between intelligence, CPS, and MMLA). We address the need for a multimodal approach to evaluation to evaluate and support complex human intelligence features in CPS processes. In this way, we aim to exemplify the approach that is needed in learning sciences research more generally.

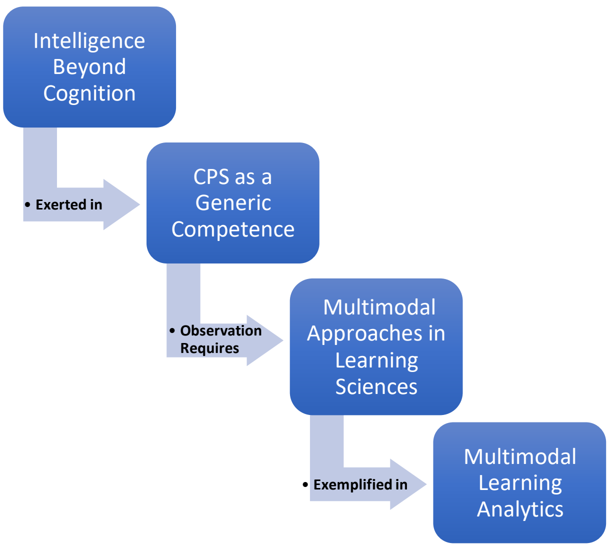

Figure 1: Connection between Intelligence, CPS, and MMLA

Multimodal Learning Analytics as an Opportunity to Move Beyond Cognition in CPS processes

As we discussed earlier, human intelligence is not limited to cognitive processes. CPS exemplifies the complex and dynamic non-routine situations in which learners frequently operate. Learning is also not constrained to a specific physical space (e.g. the classroom) or a digital environment (e.g. an institutional learning management system or a specific digital learning tool). It happens *in situ*, where the learner is (Sharples, & Roschelle, 2010). And it happens as a continuous process. The inherently blended nature of learning settings and the process-based nature of CPS, make it essential to move beyond measurements that rely solely on a single data source (e.g. grades, questionnaires, or essays) or that focus only on the interactions that occur between learners and a specific system without considering the context of such interactions.

Multimodal learning analytics (MMLA), is an approach that aims to address some of these issues. It leverages the increasingly widespread availability of sensors and high-frequency data collection technologies to provide insights into learning processes that happen across multiple settings, between a range of people, devices and resources (both physical and digital), which are often hard to model and orchestrate (Scherer, Worsley & Morency, 2012; Worsley et al., 2015; Prieto et al., 2016; Ochoa et al. 2017, Spikol et al., 2018). Some MMLA researchers embrace the complexity of learning as an activity, and attempt to identify the best modalities to track in order to capture the learning processes and to investigate the analytics for feedback (Cukurova, Milán, Luckin, & Mavrikis, 2018). By contrast, other researchers favour a bottom-up approach where the focus is on the existing data available to combine it with machine learning and AI techniques to offer a number of solutions to ubiquitous learning (Di Mitri et al., 2018).

Both the approaches discussed here have distinguishing features, but they are driven by different epistemological values, and they are both valuable to the advancement of the field (Cukurova, 2018). In addition, both approaches share the common aim of deploying learning analytics innovations, that can be used across diverse authentic learning environments to interpret and support some of the learning processes beyond cognition. They aim to capture more of the complex human intelligence involved in dynamic processes such as CPS. MMLA researchers can now perform text, speech, handwriting, sketch, gesture, affective, neurophysical, or eye gaze analyses (Donnelly et al. 2016; Prieto et al., 2016). Based on such analyses MMLA can yield novel opportunities that can generate distinctive information about what happens when students are engaged in dynamic processes such as CPS (Cukurova *et al.*, 2017, Spikol *et al.*, 2018). This information can subsequently be used to automate the support and continuous evaluation of student learning (Martinez-Maldonado, Kay, Yacef, & Schwendimann, 2012).

In the remaining sections of this chapter, we present two empirical case studies, each of which presents a different approach to the collection and analysis of data about learners involved in CPS process. The research goals of both of the empirical studies reported through these two case studies is to capture and understand more about the human learning processes, beyond cognition, that are involved in CPS . Our aim is to devise appropriate support for learners and teachers based on this analysis. In particular, our aim is to understand what data might constitute evidence about learners' progress, and how we can collect, and analyse this evidence, with a view to future automation or semi-automation of the process to produce useful feedback to students and/or teachers.

It is important to note that these case studies are not necessarily MMLA studies as they do not get into the potential automated analyses of the types of data collected. However, they present the pre-requisite stage for any theoretically grounded MMLA approach. The first case study considers the thorny problem of learning context and its relationships to CPS performance, the second case study provides a much more fine-grained analysis of observable learner actions in an attempt to identify which of these actions might be both amenable to automation and informative about learner progress.

CASE STUDY 1: The Education Hackathon

CASE STUDY 1: Methodology

Our methodology reflects the 3 dimensions of CPS discussed earlier: Context, Task and Process. We therefore discuss each of these CPS dimensions in turn:

Context

We use the Ecology of Resources (EoR) model and framework. The EoR can be used to analyse data from teaching and learning interactions and to design scaffolding interventions (Luckin, 2010). The EoR is based upon a particular definition of the term context in which learners are conceptualized as being exposed to "a single context that is their lived experience of the world a 'phenomenological gestalt' (Manovich, 2006)". Context is a reflection of the interactions that learners have experienced with multiple people, artefacts and environments. These interactions create partial descriptions of the world that act as the hooks for interactions in which action and meaning are built, in this sense, meaning is distributed amongst these interactions and interactors (Luckin, 2010)

The EoR model perceives the world as being composed of resources that are available to a learner for interaction and learning. These resources can be considered as falling into 1 of 4 categories: 1) *knowledge and skills:* these resources are the subject of learning; 2) *Tools*: the books, pens and paper, technology with which a learner can interact; 3) *People:* who know more about the knowledge or skill to be learnt than the learner does, and 4)

Environment: the location and surrounding with which the learner interacts, for example, a school classroom, a virtual world, or a place of work. The analysis of contextualized learning through CPS, requires the identification, analysis and interpretation of the relationships between the different types of resource with which learners interact. The EoR model has an associated design and analysis framework that offers a structured process for analysis and/or design that is iterative and has three phases, each of which has several steps:

Phase 1: Create an EoR Model by identifying the resource components of the EoR of the learners being studied

Phase 2: Identify the relationships within and between the resources identified in Phase 1.

Phase 3: Develop the Scaffolds and Adjustments to support learning.

For the purposes of the data analysis at the heart of this chapter, only phases 1 and 2 are needed. A full account of the framework can be found in Luckin (2010).

Task

A CPS task can be thought of as a set of features that represent a crossroads where the way forward to solve the problem is not fully known and must be generated and/or co-constructed by two or more participants. The task at the heart of the empirical study reported here was part of a larger engagement conducted over a four-month period. Students were initially engaged in a workshop where they were introduced to the idea of a 'Smart City' and asked to work in pairs and to think about and discuss the sorts of problems that technology might be used to address in such an environment. Secondly, students were tasked to identify ideas that they would like to design and build as part of a smart city. A facilitator helped students to work together with these ideas and to refine the pool of ideas down to 3 potential projects that students would like to complete: (1) a glove that controlled home devices, (2) a mobile robot to help the blind with navigation and (3) a coin reward system that gave credit to students who collected coins on school premises. The students were then set the problem of building a prototype for each of these ideas during a 2 day education hack. Students worked in three teams, with adult facilitators.

Process

As discussed earlier in the chapter, the process of CPS combines social and cognitive skills, abilities, and knowledge. These are instantiated for the purposes of this case study in the relationships between the resources with the EoR analysis. However, the identification of a relationship, for example a social relationship between 2 learners is insufficient in and of itself. We therefore use the work of Chi et al. (1989, 2009, 2011) to categorize the processes of CPS identified through the EoR framework. Chi (2009) provides a framework with four types of student engagement in learning: *Passive* engagement: students appear to be paying attention; *Active* engagement: students are doing something with instructional materials; *Constructive* engagement: students generate some information beyond what was presented to them, and *Interactive* engagement: students engage through dialog. The significant contribution of this framework is that it defines cognitive engagement in terms of observable activities displayed by students during learning. By doing so, it moves beyond cognition towards social and interaction space. Chi *et al.* (2011) argue that students are more likely to reflect a certain level of engagement as a function of the overt activities they display. We combined the context concepts of the EoR framework with the process concepts of Chi et al. to produce the analysis framework illustrated in Table 1, which we used to code the interaction data collected in the study we report here.

Table 1- The EoR-Chi Framework for Analysis

Code No.	Code Name	Definition
0	Non-available	The resource exists within the learner's context, but is not in the learner's service.
1	Available	The resource is in the context of the learner, yet the learner is not engaged with it.
2	Passive	The resource is in the context and the learner pays attention to it.
3	Active	The learner pays attention to the resource, and physically interacts with the resource.
4	Constructive	The learner pays attention to the resource, physically interacts with the resource, and generates knowledge for themselves.
5	Interactive	The learner pays attention to the resource, physically interacts with the resource, and generates knowledge for themselves and helps others generate knowledge.

CASE STUDY 1: Participants

The participatory design-based study was conducted with 18 secondary school students aged 14-15 years. The students had little experience of computer science, but had done some programming in python. None of the students had previous experience with the technology or activity used for this study.

CASE STUDY 1: Data Collection and Analysis

A range of data sources were collected during the hack event, these included: Over 10 hours of video (2 sources for each group of learners, one video of the group and one video of the laptop screen where programming activity took place), observer notes, audio recordings, artefacts, interviews, presentations and photos. In this chapter, we focus on the video data and in particular upon the interactions of individual learners within their CPS group. Two researchers coded the video of each group according to the EoR framework and the EoR-Chi framework to identify the resources available and in use by the learners. The coding was completed from the perspective of each individual learner in each of the groups. The relationships between the resources and between the learner and the resources was identified and recorded as changes over time. Resource use was recorded at 30 second intervals. The two researchers discussed all disagreements and reached a consensus.

CASE STUDY 1: Results

Phase 1 of the EoR analysis identified the resources that were used by the learners as they developed their prototypes. This analysis illustrates that whilst all learners had a very similar range of resources available to them, their use of these resources was distinctly different both within and across groups. In total, across all student groups the most popular resource was the adult helpers. This was in preference to peers, which is perhaps a little surprising given the collaborative nature of the activity. The second most popular resource was paper, used to plan and communicate between group members. This is also somewhat surprising given the technical nature of the task. However, the emphasis on design in the task may account for the heavy paper use.

In a comparison of the total resources used by all groups of learners over the same 1-hour period of the hack event, there were clear differences between the groups. For example, the group developing the glove prototype made greater use of the adult resources available and of the technology. They also interacted with the prototype. By comparison, the coin sorter group used each other and made heavy use of paper and instructions. They used the prototype components, but had no prototype to interact with at this time.

Phase 2 of the EoR analysis identifies the relationships between the different resources in a learner's ecology. We focus on individual learners as our unit of analysis for this phase of the analysis. This focus enables us to explore the relationships between resources at a finer level of detail.

Similarly, in a comparison between two learners from the coin sorter project group, we identified that the chronology of resources used by each learner over an hour period in the middle of the first day of the Hack event were quite different. As an overview, Learner 2 (L2) interacted with learners L3, L4 and L5 as individuals more often than L1, and throughout the analysis period. L1's interactions with other learners were limited to working together with all other learners as a group and with the laptop. L2 also makes use of the non-people resources much more widely than L1 and interacts with a particular resource for longer periods of time than L1.

Looking more closely at this data illustrates the resources that were actively in use by each learner at the same time, indicating a relationship between these resources with respect to that learner. These periods of active engagement are marked differently between L1 and L2 who were working as part of the same group: L1 starts their active engagement with multiple resources 15 minutes into the session and engages actively with multiple resources for a total of 30% of the session. By contrast, L2 started actively interacting with multiple resources, much earlier in the fifth minute, and interacted in this way for 50% of the session. The individual differences between learners was reflected across all 3 groups. Table 2 illustrates the amount of time during which all learners were actively interacting with more than one type of resource and the time at which this activity started.

Name of Group	Mean average time a learner was active with more than one resource	Mean average start for being active with more than one resource
The Glove group	33 minutes (range 31:32)	Minute 2 (range 0:5).
Robot Group	26 minutes (range 26:26)	Minute 8 (range 0:16)

Coin Group	16 minutes (range 0:30)	Minute 9 (range 2:15)

Table 2 Activity with more than one resource across the groups

A closer investigation of the resources that L1 and L2 actively worked with demonstrates more clearly an interesting aspect of their resource use. The problem-solving activity required of learners during this study was a practical design and construction task, and required learners to interact with the tools provided to them, such as the Arduino technology, pens and paper. Figure 2 illustrates that L2 interacts with more resources and in more combinations than L1. In addition to which, there are 19 occasions (covering almost 32% of the session time) when L2 synchronously evidences social interactions with fellow learners and physical interactions with the design and construction tools. By comparison, L1 combines peer social interaction with design and construction tool interaction on only 9 occasions, which is 15% of the session and less than half the time spent by L2 on synchronous social and physical interactivity. The upward pointing arrows along the bottom of Figure 2 indicates the times when this social and physical tool activity took place.

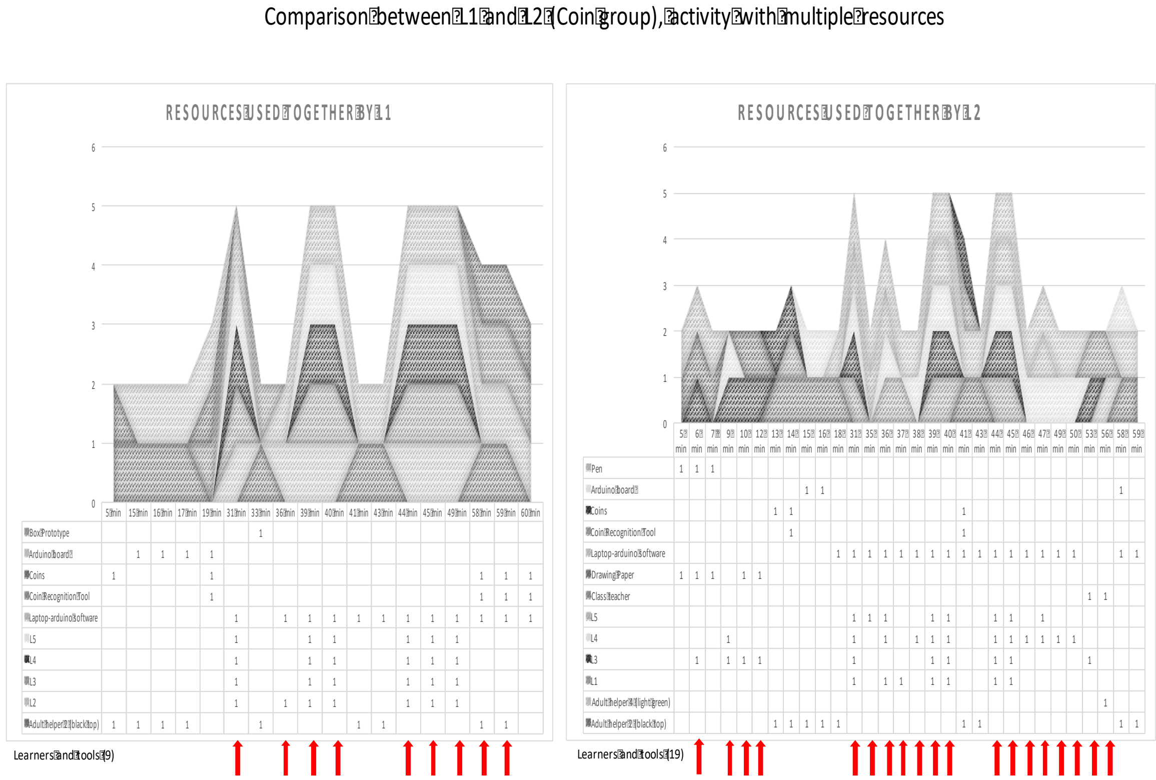

Figure 2 Resources used together with L1 and L2

The final part of this results section presents the findings from the analysis using the EoR-Chi framework, which enabled us to probe learners' activity with resources in greater depth. In particular we focus our attention on the interactions between learners and resources that are coded as EoR-Chi 4: The learner pays attention to the resource, physically interacts with the resource, and generates knowledge for themselves; and EoR-Chi 5: The learner pays attention to the resource, physically interacts with the resource, and generates knowledge for themselves and helps others generate knowledge. Initially we consider the EoR-Chi analysis for the learners whose activity is illustrated in Figure 2. We then consider findings across all learners and compare the result with the evaluations of the same sessions provided by an independent expert.

The EoR-Chi analysis for L1 and L2 reveals that there is only 1 minute, which is less than 2% of the hour-long session in which L1 interacts at EoR-Chi levels 4 or 5, both socially with other learners and physically with the tools required for the problem-solving activity. This suggests that L1 engages in little CPS activity in this particular hour-long session of the Hack Event. By contrast, L2 interacts at EoR-Chi levels 4 or 5 both socially with other learners and physically with the tools required for the problem-solving activity for 23 minutes (38%) of the session.

We present results for all learners across a later session in the Hack Event in Tables 3 and 4. The results illustrated in these tables indicate greater evidence of activity that could be considered as evidence of CPS activity.

Table 3 The % of the session that each learner spent interacting with Constructive or Interactive engagement with a resource

	Robot Group	Coin Group	Glove Group
L1	62.5	65.83	95
L2	72.5	72.5	96.67
L3	45	56.67	91.67
L4	31.67	72.5	96.67
L5	43.33	70.83	88.33
Average	51	67.67	93.67

Table 3 shows the variance across all learners in the observable evidence of CPS, which ranges from 31.67% of the session for L4 in the Robot group to 96.67% for L2 in the Glove group. It also illustrates the range of Constructive and Interactive activity across the groups and shows both the variance between groups and the high levels of activity amongst the members of the Glove project group, who were active at EoR-Chi levels 4 or 5 for 93.67% of the session.

To verify the validity of the EoR-Chi video analysis we sought independent verification. An expert research professor from another university who had not previously been involved in our study data collection or analysis provided this verification. We asked her to watch our video data of the 3 groups who took part in the Hack Event as illustrated in Tables 3 and identify the times during the learners' interactions when in her judgement there was evidence that the group was engaged in CPS process. Table 4 illustrates her judgement across all groups.

Tables 3 and 4 represent the same session of the Hack event and it I interesting to note that the coding using the EoR-Chi framework to identify signifiers of observable CPS ranks the groups in the same order as the independent expert. The EoR-Chi framework is more conservative than the independent expert, who rates activity of the learners as being consistent with CPS more frequently. The data concerning the Robot group is at particular variance between the EoR-Chi analysis and the human expert. The possible explanation for this may lie in the fact that the Robot group were unable to develop their own prototype from scratch, because the task was simply too far in advance of their skill levels. The adult helper therefore introduced a ready-made robot to the session. The coders using the EoR-Chi framework coded the students' interactions with this ready-made robot as interactions with the prototype, the independent expert didn't consider students' interactions with this ready-made robot as constructive interactions. Closer investigation of the data suggests that it is likely that this difference of opinion is responsible for almost all of the variance in the CPS evaluations between the EoR-Chi framework and the independent expert. It is however important to recognize the significance of such a disagreement, because a successful automated MMLA system for CPS would need to be able to cope with such differences in judgement about the status of a resource.

Table 4 The % of the session that an independent expert rated as consistent with CPS

	%
Robot Group	18
Coin Group	47
Glove Group	95

Case study 1 presents the results of our investigation of secondary school students' CPS process as part of a two-day Hack Event. A pre-requisite to the design of MMLA for CPS is the assessment of CPS learning activity. This assessment demands an analytical methodology that can identify the observable signifiers of CPS with regards to students' interactions with resources. The data underlying these observable signifiers must also be amenable to automatic capture through MMLA.

The EoR-Chi analytical framework brings together the useful concepts of *educational context* and *constructive and interactive engagement*. Our results using this framework show that both individual students and groups of students present different patterns of engagement with the human and tool resources around them during CPS task. We argue that these differences between the groups and individual students' use of resources may indicate their different degree of engagement with the CPS process. The external verification reported in this case study indicates a possible correlation between expert human assessment of CPS processes and assessment of CPS through identification of students' Constructive or Interactive engagement with the resources available to them.

The data used for the EoR framework requires identification of the resources that each learner interacts with during a learning session. This is an interesting computer vision challenge, but can potentially be overcome with currently existing software and tools (e.g. Babenko, Yang, & Belongie, 2009; Kalal, Mikolajczyk, & Matas, 2012). The addition of the extra evaluations in the creation of the EoR-Chi framework require identification of interactions that differentiate between learner activity beyond observable physical interaction to the identification of evidence of knowledge generation. To the best of our knowledge, this fine-grained differentiation of behaviours concerning knowledge generation is not amenable to automated capture yet, and it requires human intervention. Future research must be conducted to evaluate the extent to which 1) the identification of knowledge generation is essential to the assessment of CPS, and 2) the identification of knowledge generation can be achieved via observable signifiers that can be automatically captured with MMLA. Furthermore, it is clear from our results that certain constellations of resources are preferable to individual learners. Further exploration of these constellations is required to gauge the relationship between CPS processes and particular resource constellations in learning activities.

CASE STUDY 2: Practice-based activity with school aged learners

In Case Study 2, we present an empirical study through which we explored the CPS process in six groups of three students (aged 11-12 years) while they were working on a practice-based design activity. The main goal of this study was to investigate observable differences between student behaviours during CPS. These differences can be used to automate the identification and support of behaviours that lead to effective CPS processes beyond cognition. First, we describe the context of our experiment (participants, tasks and environment) and then present the results and analysis of the data collected. We finish with a discussion of these results and the presentation of some final conclusions.

The overarching research aim to identify observable behaviour differences of students' CPS processes was shaped into two research questions:

RQ1) What are the observable differences between groups, in terms of the amount of time spent in different CPS competencies?

RQ2) What are the observable differences between groups, in terms of nonverbal indexes of students' physical interactivity?

CASE STUDY 2: Participants

The participants were eighteen secondary school students in the first year of their secondary education (aged 11-12 years) from a girls-only secondary school in the UK. All students were recruited from a computer science class. We obtained written consent from both students and their parents/guardians in line with our institution's ethics procedures.

CASE STUDY 2: Learning Activity

Students were set the task of building a working prototype of an interactive toy using an Arduino-based physical computing kit, called TALKOO, that was created as part of an EU-funded project (www.pelars.eu). The TALKOO kit comprises hardware modules, a visual IDE and prototyping material (Katterfield et al., 2018). Sensor and actuator modules are pluggable and do not require soldering, and no prior knowledge of electronics is needed. The components have the ability to "talk" back to the visual IDE and to a learning analytics system. The students were also provided with craft materials (coloured paper, paper cups, wooden sticks, glitter, glue, etc.) with which to create their working prototypes in combination with the physical computing kit.

CASE STUDY 2: Sessions

The study involved two sessions that were run two days apart.

Session 1 took place in the school's IT (Information technology) lab, during school hours, and involved the entire class of 18 students. The session lasted for 1 hour and 20 minutes, during which students worked with a TALKOO kit in pairs or groups of three. The purpose of Session 1 was for students to familiarise themselves with the physical computing kit through a number of predefined activities that exemplified the function of specific components (RGB light, temperature sensor and potentiometer) and logic functions (if statement, mapping function and switch function). A researcher, who was assisted by 3 colleagues and the class teacher, ran session 1.

Session 2 took place at the university and involved 18 students from the same class as Session 1. The participants were arranged into 6 groups of three students, and each group was identified by a different colour. The students were grouped by their teachers based on her knowledge of their skills and knowledge – her aim was to create balanced groupings. The session lasted about four hours and involved:

a) A refresher session, during which students worked through predefined activities that exemplified the functions of TALKOO components and logic functions (as in Session 1) - 30 minutes
b) An open-ended activity to build an interactive toy – 2 hours
c) A brief activity to demonstrate the function of a motor – 15 minutes
d) An open-ended activity to build an artefact using a motor – 1 hour
Activities (a) and (c) were led by a researcher, who demonstrated how to connect and program the components. During activities (b) and (d) students worked independently, but each group was supported by an adult, who assisted the students with troubleshooting the TALKOO kit and debugging the visual programming.

CASE STUDY 2: Data Collection

We used a range of different data sources to answer our research questions. The first source targeted the first research question and took the form of human collected observation data. The collection of this observation data was structured by a theoretical framework developed through previous empirical work: the PELARS CPS framework (Cukurova et al., 2016). This framework was informed by the OECD's CPS assessment and encompasses three collaboration competencies (establishing and maintaining shared understanding, taking appropriate actions to solve the problem, establishing and maintaining group organisation) and six problem-solving competencies (identifying facts, representing and formulating knowledge, generating hypothesis, planning and executing, identifying knowledge and skill deficiencies, monitoring-reflecting-applying). The framework has been used to develop an observation protocol and mobile application that runs on phones, tablets and laptops. The interface to this system is illustrated in Figure 3. During the study reported here, human evaluators used this mobile tool to code student behaviours in real time while students were working on a design problem.

In addition to the human observation data, we also collected video recordings of all of the empirical sessions. This data source targets research questions 2. The data we discuss in this chapter focuses on Session 2 described in sessions section above, as the purpose of Session 1 was to familiarise students with the TALKOO kit. During activities (b) and (d), each group was observed by an adult, who used the mobile application to code the instantiates of collaboration and problem solving, as defined by the protocol in the PELARS CPS framework. In order to ensure a high kappa between different coders, all coders were trained in a daylong, hands-on workshop about the CPS competencies and the observation tool. In parallel, the groups were video recorded. We analysed the video data using two dimensions that can also be automatically collected with MMLA (Spikol et al., 2018):

a) students' hand positions, that can be used to represent their physical engagement with objects;

b) students' face directions, that might indicate their degree of involvement in the activity (depending on whether they are looking at the manipulated objects, at other students in their group, or at something outside the activity being carried out).

CASE STUDY 2: Classroom Teacher and Facilitators' Judgement of Group's CPS

The classroom teachers and facilitators involved in the practice-based activity were asked to use their expertise and experiences as teachers to judge each groups' collaborative solving competence. This was done in order to create an independent variable to categorise the differences between groups of students. They were all asked to watch the video recordings of the six group sessions and to independently rank groups as high, medium and low competence CPS groups. Then, teachers and facilitators were brought together to discuss their individual judgments. In their individual judgements of the CPS competency of the groups, there were only discrepancies for two groups. Discussion between teachers and facilitators was used to agree a final competency value for these two groups. Table 5 below shows the results of this expert evaluation of groups' CPS levels.

Table 5 Teachers' judgments of groups' CPS levels

The colour code of the group	Teachers' judgment of CPS competency level
Green	Low

Red	High
Purple	Medium
Blue	Medium
Yellow	High
Black	Low

CASE STUDY 2: Results, Identifying Observable Differences in terms of the Amount of Time Spent by student groups on Different CPS Competencies

In this section, we present the analysis and results for research question 1. As mentioned previously, human researcher observers recorded and graded the different stages of student interaction during the learning activity. This information was collected in a tablet, using a mobile observation tool designed to code the CPS competencies. As shown in Figure 3, the mobile tool interface reflects the analysis framework with the three key dimensions for collaboration represented as columns and the six key dimensions of problem-solving competency represented as rows. The human observers watched student activity and used the tool to mark the critical incidents that related to the dimensions of collaboration and problem-solving as they occurred. The tool also recorded the exact date and time each dimension was marked by the human observer.

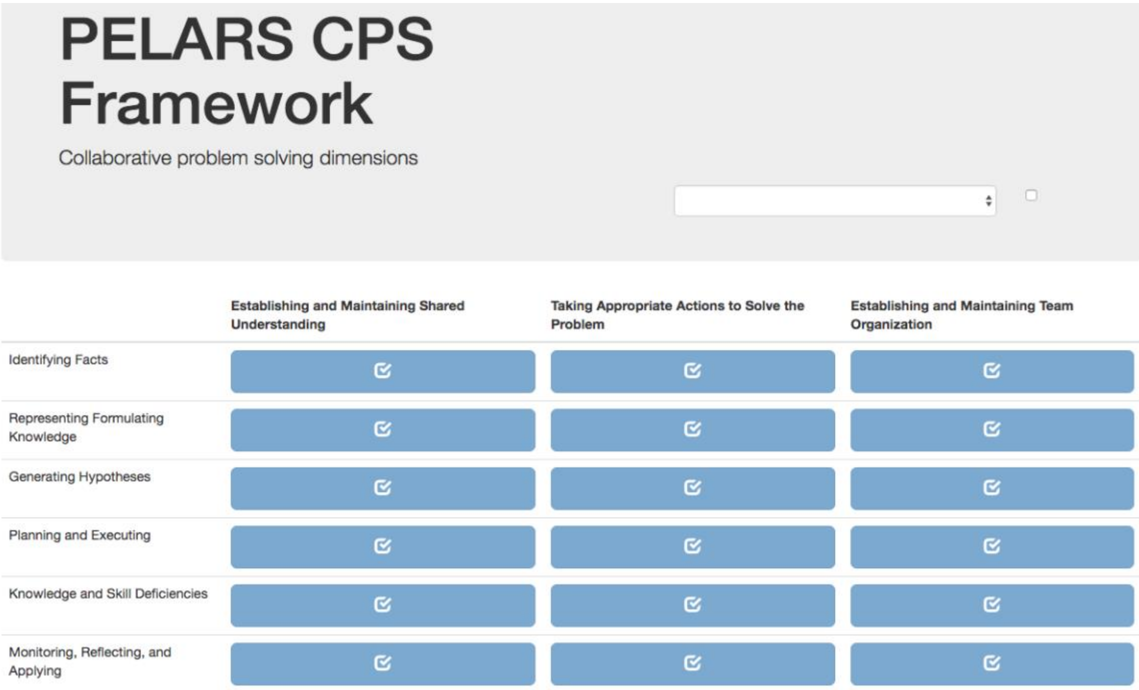

Figure 3 Screen shot of the coding tool used by observers

The data collected with this observation tool was used to compute the values of the following research variables:

1. T_{PS} (G, Ci) = Percentage of time each group G spent in each competence level Ci (relative to *problem solving* C**PS**), where G = {Red, Green, Purple, Blue,

Yellow, Black} and i=1, 2, 3, 4, 5, 6.

2. T_{CL} (G, Ci) = Percentage of time each group G spent in each competence level Ci (relative to *collaboration* **C**PS), where G = {Red, Green, Purple, Blue, Yellow, Black} and i=1,2,3.

We anticipated that the human observation data would provide valuable information about the students' CPS processes. The results of the data analysis indicate differences between the groups in terms of the amount of time each group spent on the different activities involved in collaboration and problem-solving.

The red and yellow groups (which were identified as high competence CPS groups by their teachers) showed a more balanced segregation of different problem-solving behaviours: they spend their time fairly equally on the different dimensions. By contrast, the other groups show unbalanced segregation of time spent in different CPS competencies. It appears that green and black groups (which were identified as low competence CPS groups by their teachers) spend most of their time on identifying knowledge and skill deficiencies. They spent very little or no time on some of the important stages of problem solving, such as representing and formulating knowledge, generating hypotheses, and planning and executing. These behaviours might therefore be indicative of a less effective CPS pattern. The data from the red and yellow groups also evidences that they spent similar shares of time on different aspects of collaboration. The green and purple groups, by comparison, present a greater difference in terms of the amount of time spent on the different aspects of collaboration. It appears that groups who had been evaluated as low CPS by human experts spent very little time on establishing and maintaining team organization, compared to other groups.

CASE STUDY 2: Results, Observable Differences in Nonverbal Indexes of Student Interactivity

Video data analysis was performed by two researchers using a very simple coding scheme, which could be automated with current MMLA approaches. The coding scheme makes use of three digits, 0, 1 and 2 to represent passive, semi-active and active student states. The active code (2) was used whenever a student's hand was active with an object; the semi-active code (1) was used when a student was not physically active but their head was directed towards a peer who was active; and the passive code (0) was used if a student's hands were not physically active with any object and their head was directed somewhere other than any of the peers who were active. Students' behaviours were coded using ten-second windows. Therefore, the variable used for this research question is the activity index AC, which takes values 0,1, 2 and is defined as:

AC (S, G, t) = Activity code of student S of group G at time t, S = {1,2,3}; G = {Red, Green, Purple, Blue, Yellow, Black} and t= {10, 20, …..}.

Two coders applied this coding scheme to all groups' video data using the 10-second window, to validate the coding,. This procedure was used as a way of testing the reliability of the coding system generated. Where there was disagreement, the researchers discussed the data and agreed a revised coding accordingly. We first investigated whether the perceived degree of physical activity showed any differences. To this end, we defined new research variables

N(G, i) = Percentage of i states in group G, where i=1,2,3 and G={Red, Green, Purple, Blue, Yellow, Black}.

The results illustrate that the percentage of active states (2) was similar across all six groups and ranged from 46.4% (Black) to 66.4% (Yellow). It wasinteresting to observe that the 2 groups with the highest percentage of active codes (2) were also the 2 groups rated by human experts and having the highest CPS competency. Similarly, the 2 groups with the lowest of active codes (2) were rated by human experts as less competent in CPS. However, the results were not consistent across all groups. For example, the other group rated by our experts as having low CPS competency had the second highest percentage of active codes (2), and the other group rated as being high CPS competency has the second lowest percentage of active codes (2). This result suggests that the crude measure of the percentage of active states may not be a good indicator for differentiating the CPS processes in a group (i.e. just individual student's activity with objects may not be contributing to CPS processes overall). However, we also considered if students' passive codes (0) might be a predictor. The red and yellow groups had the lowest percentages of passive codes (0). By contrast, the green and black groups had the highest percentages of passive codes (0). This result is surprising because the most researched and tracked indicators in learning analytics research are often related to what students are doing. This case study's results suggest observing what students *are not doing* might be also informative.

We also wanted to analyse whether there were any patterns in the data that could be provide information about the degree of activity for each individual student. To this end, we defined a new research variable:

Nj(G, i) = Percentage of i states for student j in group G, where j=1,2,3; i= 1,2,3,4,5,6 and G={Red, Green, Purple, Blue, Yellow, Black}.

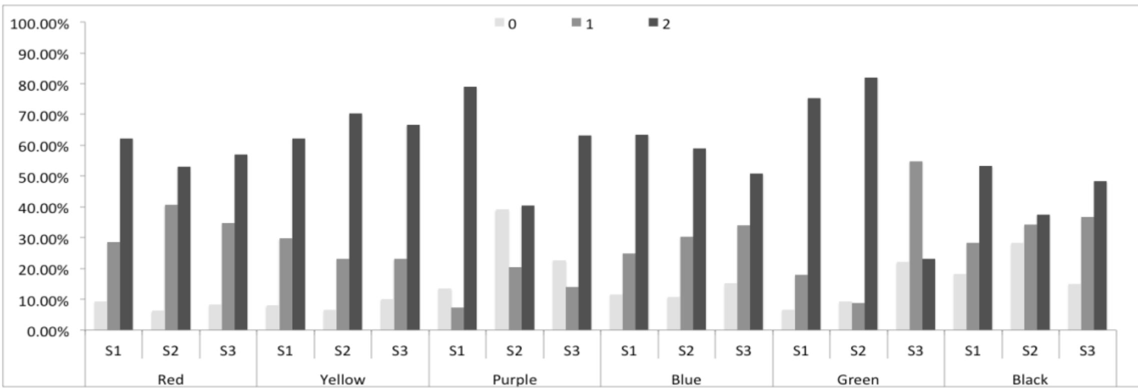

Figure 4 Percentage of individual student's number of passive 0, semi-active 1, and active code 2

Figure 4 presents the values obtained for these new variables. It illustrates that the individual students in the red and yellow groups get similar values for all the codes. The rest of the groups, by contrast, illustrate bigger differences between each student's individual contributions. In the red group, all three partners show a similar degree of involvement in the activity, ranging from 53,1% to 62,2%.

However, in the green group there is a bigger difference in the degree of involvement (from S_3 is 23.1% to S_2 is 82,1%). Clearly, in the red and yellow groups all members were contributing to the task at similarly active ways, while in the other two groups students' physical interactions were more passive and varied more.

Discussion

In this chapter, we have discussed the richly varied repertoire that is human intelligence, a repertoire that extends way beyond cognition. We have also presented several methods for identifying differences between the ways in which different groups of learners take part in CPS. We show that learning from these differences in observable behaviours can be informed by research from the learning sciences, such as the ICAP framework (Chi, 2001), Ecology of Resources (Luckin, 2010), and PELARS framework (Cukurova *et al.*, 2016). We have also illustrated methods of analysis that could potentially be automated with MMLA technologies to generate insights into the learning *proceses involved in CPS* beyond the frequently studied cognitive aspects (Spikol *et al.*, 2018).

The richness of human intelligent behaviour can only be understood through a wide range of evidence and MMLA systems provide one way to capture and analyse such evidence. The results of the case studies presented in this chapter support the suggestion that there is a relationship between a group's CPS competence and that group's observable behaviour patterns. This relationship requires further investigation at scale with more robust evaluations. However, the initial results are encouraging for those interested in using multimodal approaches in learning sciences such as MMLA, as they can inform how we can collect, analyse, and automate the process of providing useful feedback about the CPS process to students and/or teachers .

Various approaches to the design and use of technology to interpret the behaviour patterns investigated in this chapter are possible. For instance, the first case study investigates students' interactions with their context and provides information on the relationship between these interactions and their CPS processes. Computer vision systems that can identify and track students and resources in a learning environment can provide measures of students' interactions with their surroundings and use this information to provide valuable insights into the CPS processes of students. The second case study provides a much more fine-grained analysis of observable learner actions in CPS during practice-based learning. In this case, whilst some of the features can be automatically detected, such as the students' non-verbal interactions studied here (e.g Cukurova *et al.*, 2018; *Spikol et al.*, 2018; Landolfi *et al.*, 2017; Healion *et al.*, 2017), other features require human interpretations which can be supported and augmented with MMLA support. The CPS competences of collaboration and problem-solving that we collected though research observers, for example.

The emerging field of MMLA provides examples of how data science can help researchers in the learning sciences to overcome obstacles that arise when conducting investigations into learning processes *in situ*. The richness and complexity of human intelligence can only be interpreted, evidenced, and supported with rich, multimodal data. Data produced through the use of digital technologies are large in volume, even for single learners. They are heterogeneous too, because they stem from different devices (e.g. keyboard, mouse, video camera), are of different kinds (e.g.; actions in an online problem-solving environment, answer to online quizzes, or learners gaze when studying a simulation), and/or of different time-scales (e.g. single testing instance or continuous sampling). We argue that such large-volume, heterogeneous and, more importantly, complex data can potentially help us to shed light on human intelligence in a holistic manner beyond cognition. However, so far, most research in the learning sciences considers large-volume data in the form of sampling data from thousands of learners at one point in time. Through the analysis of multimodal, large amounts of data, collected *in situ* to investigate the process of CPS with two case studies, our aim has been to exemplify a potential approach that should be taken in learning sciences research more generally.

Concluding Comments

The research reported here has been conducted with small sample sizes and an explorative approach. Any conclusions we draw about how to support students in their CPS processes should therefore be approached with caution. Our case studies indicate that students' interactions with resources in situ, both human and non-human resources, must be supported if they are to be constructive and interactive in their nature. Moreover, learners also need to be supported to avoid spending most of their time on particular aspects of problem-solving, such as the identification of knowledge and skill deficiencies. Learners must be supported to progress into the other equally-important aspects of problem solving. The results reported here, have also been found to be similar for engineering students working on design problems (Noel et al., 2018). Finally, students should be supported to achieve effective equality and synchrony in terms of their contributions to the CPS task at hand.

Perhaps more importantly than identifying these implications for supporting students' learning through CPS, the potential of multimodal approaches should be realized in the learning sciences. These approaches hold the promise for overcoming some of the major limitations of past research on learning processes and human intelligence. The ability to analyze data about learning processes at a fine-grained temporal level, allows for investigating the mechanisms of learning across sequences of learning opportunities (e.g. Gerjets et al., 2014). It also provides the potential to link evidence about learners' sequences of learning opportunities to the development of a range of elements of human intelligence (e.g. Milligan & Griffin, 2012).

It should, of course, be noted, that these techniques are still being developed and they do not come without their challenges. It is worth emphasising that understanding theories and empirical findings from the learning sciences challenges the field of learning analytics to conuct further research to advance our understanding. For instance, in order to investigate the comprehensive representations of learning processes theorized in the learning sciences (see context interactions in case study 1 and nonverbal student interactions in case study 2), it is necessary to take multiple types of data into account (Martinez-Maldonado & Hernandez-Leo, 2016). However, the collection, organisation, and analysis of such heterogeneous data poses significant research challenges.

For instance, the identification of some of the collaborative learning processes that happen in practice-based learning and that have been identified in the literature, such as, equality, mutuality, or individual accountability of student interactions (Cukurova *et al.*, 2018) requires data collection from students' body movement and face recognition. To identify individual students, and their manipulation of learning objects, for example. Data collection on these features poses significant research challenges that can only be overcome with further advances in data science research.

Similarly, the identification of the rich intra-individual variation in the complex learning process of CPS requires the study of these processes at the level of the individual (Molenaar, 2004). And, the collection of short interval time series of high quality data about CPS processes can only be achieved with further advancement in learning analytics research (Hofman *et al.*, 2018).

Thirdly, the integration of heterogeneous big data is a significant research challenge (e.g Schneider, Di Mitri, Limbu, & Drachsler, 2018). Although, data from a depth camera (average 25 frames per second) and a microphone to track specific aspects of the communication of a learner (average 44100 of volume values per second) can provide invaluable insights into learning processes; integrating and making sense of these different streams of data in order to support learning is a significant challenge for data sciences (ibid). In terms of data analysis, the processing of learners' process data from different behavioural traces do not carry much semantic information when considered individually. They are however predictive of knowledge states when big data sets are processed. They also pose significant research challenges for data sciences (see Dillenbourg, 2016 for an overview).

Lastly, the accuracy and transfer of models from one population to another remains a challenging problem in the field of data science and requires substantial additional research effort (e.g., Daxenberger *et al.*, 2018).

The challenges outlined here are significant. They do however also offer opportunities to illustrate the reciprocal nature of the relationship between learning sciences research and multimodal approaches to studying educational technologies. When human intelligence is considered as a multidimensional construct that is strongly related to most of the generic skills of constructivist pedagogies. And when human intelligence is studied accordingly, this has the potential to lead to advancements in various fields that are relevant to, but distinct from each other.

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