Direct Instruction and Its Extension with a Community of Inquiry: A Comparison of Mental Workload, Performance and Efficiency

Giuliano Orru and Luca Longo
School of Computer Science, Technological University Dublin, Ireland

Keywords: Direct Instruction, Community of Inquiry, Efficiency, Mental Workload, Cognitive Load Theory, Instructional Design.

Abstract: This paper investigates the efficiency of two instructional design conditions: a traditional design based on the direct instruction approach to learning and its extension with a collaborative activity based upon the community of inquiry approach to learning. This activity was built upon a set of textual trigger questions to elicit cognitive abilities and support knowledge formation. A total of 115 students participated in the experiments and a number of third-level computer science classes where divided in two groups. A control group of learners received the former instructional design while an experimental group also received the latter design. Subsequently, learners of each group individually answered a multiple-choice questionnaire, from which a performance measure was extracted for the evaluation of the acquired factual, conceptual and procedural knowledge. Two measures of mental workload were acquired through self-reporting questionnaires: one unidimensional and one multidimensional. These, in conjunction with the performance measure, contributed to the definition of a measure of efficiency. Evidence showed the positive impact of the added collaborative activity on efficiency.

1 INTRODUCTION

Cognitive Load Theory (CLT), relevant in educational psychology, is based on the assumption that the layout of explicit and direct instructions affects working memory resources influencing the achievement of knowledge in novice learners. Kirschner and colleagues (2006) pointed out that experiments, based on unguided collaborative methodologies, generally ignore the human mental architecture. As a consequence, these types of methodologies cannot lead to instructional designs aligned to the way humans learn, so they are believed to have little chance of success (Kirschner, Sweller and Clark, 2006). Under the assumptions of CLT, learning is not possible without explicit instructions because working memory cannot receive and process information related to an underlying learning task. This study focuses on a comparison of the efficiency of a traditional direct instruction teaching method against an extension with a collaborative activity informed by the Community of Inquiry paradigm (Garrison, 2007). The assumption is that the addition of a highly guided collaborative and inquiring activity, to a more traditional direct instruction methodology, has a higher efficiency when compared to the application of the latter methodology alone. In detail, the collaborative activity based upon the Community of Inquiry is designed as a collaborative task based on explicit social instructions and trigger cognitive questions (Orru et al., 2018).

The research question investigated is: *to what extent can a guided community of inquiry activity, based upon cognitive trigger questions, when added to a direct instruction teaching method, impact and improve its efficiency*?

The remainder of this paper is structured as follows. Section 2 informs the reader on the assumptions behind Cognitive Load Theory, its working memory effect and the Community of Inquiry paradigm that inspired the design of the collaborative inquiry activity. Section 3 describes the design of an empirical experiment and the methods employed. Section 4 present and critically discuss the results while section 5 summarise the paper highlighting future work.

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2 RELATED WORK

2.1 The Cognitive Load Theory

Cognitive Load Theory (CLT) provides instructional techniques aimed at optimising the learning phase. These are aligned with the limitations of the human cognitive architecture (Atkinson and Shiffrin, 1971) (Baddeley, 1998) (Miller, 1956). An instructional technique that considers the limitations of working memory aims at reducing the cognitive load of learners which is the cognitive cost required to carry out a learning task. Reducing cognitive load means increasing working memory spare capacity, thus making more resources available. In turn this facilitates learning that consists in transferring knowledge from working memory to long-term memory (Sweller, Van Merrienboer and Paas, 1998). Instructional designs should not overcome the working memory limits, otherwise transfer of knowledge is hampered and learning affected. Explicit instructional techniques are the necessary premises for informing working memory on how to process information and consequently building schemata of knowledge. The research conducted in the last 3 decades by Sweller and his colleagues brought to the definition of three types of load: intrinsic, extraneous and germane loads (Sweller, van Merriënboer and Paas, 2019). In a nutshell, intrinsic load depends on the number of items a learning task consists of (its difficulty), while extraneous load depends on the characteristic of the instructional material, of the instructional design and on the prior knowledge of learners. Germane load is the cognitive load on working memory elicited from an instructional design and the learning task difficulty. It depends upon the resources of working memory allocated to deal with the intrinsic load. In order to optimise these working memory resources, research on CLT has generated a number of approaches to inform instructional design. One of this is the Collective Working Memory effect whereby sharing the load of processing complex material among several learners and their working memories lead to more effective processing and learning. The level of complexity of the task remains constant but the working resources expand their limits because of collaboration (Sweller, Ayres and Kalyuga, 2011). It is assumed that collaborative learning foster understanding just for high load imposed by the task when individual learners do not have sufficient processing capacity to process the information (Paas and Sweller, 2012). Results in empirical studies comparing collaborative learning with individual learning are mixed. Positive effects are found in highly structured and highly scripted learning environments where learners knew what they had to do, how to do it, with whom and what they had to communicate about (Dillenbourg, 2002) (Fischer et al., 2002) (Kollar, Fischer and Hesse, 2006) (Kirschner, Paas and Kirschner, 2009). In these environments, student working collaboratively become more actively engaged in the learning process and retain the information for a longer period of time (Morgan, Whorton and Gunsalus, 2000). The main negative effect is the cognitive cost of information transfer: the transactive interaction could generate high cognitive load hampering the learning phase instead of facilitating it. This depends upon the complexity of the task, and in tasks with high level of complexity, the cognitive cost of transfer is compensated by the advantage of using several working memories resources. In contrast, in tasks with low level of complexity, the individual working memory resources are supposed to be enough and the transfer costs of communication might hamper the learning phase. It is hard to find unequivocal empirical support for the premise that learning is best achieved interactively rather than individually but the assumption of the Collective Working Memory effect is clear: joining human mental resources in a collaborative task correspond to expanding the human mental load capacity (Sweller, Ayres and Kalyuga, 2011).

2.2 The Community of Inquiry

John Dewey reconceptualised the dualistic metaphysic of Plato who split the reality in two: ideal on one side and material on the other. In this context, Dewey suggests to rethink the semantic distinction between '*Technique*' as practice and '*Knowledge*' as pure theory. Practice, in fact, is not foundationalist in its epistemology anymore. In other words, it does not require a first principle as its theoretical foundation. *Technique*, in the philosophy of Dewey, means an active procedure aimed at developing new skills starting from the redefinition of the old ones (Dewey, 1925). Therefore, the configuration of epistemic theoretical knowledge is a specific case of technical production and *Knowledge* as a theory is the result of *Technique* as practice. Both are deeply interconnected and they share the resolution of practical problems as starting point for expanding knowledge (Dewey, 1925). The research conducted by Dewey inspired the work of Garrison (2007) who further develop the Community of Inquiry. This may be defined as a teaching and learning technique. It is an instructional technique thought for a group of learners who, through the use of dialogue, examine the conceptual boundary of a problematic concept, processing all its components in order to solve it. Garrison provides a clear exemplification of the cognitive structure of a community of inquiry. Firstly, exploring a problem means exchanging information on its constituent parts. Secondly, this information needs to be integrated by connecting related ideas. Thirdly, the problem has to be solved by a resolution phase ending up with new ideas (Garrison, 2007). The core ability in solving a problem consists in connecting the right tool to reach a specific aim. According to Lipman (2003), who extended the Community of Inquiry with a philosophical model of reasoning, the meaning of inquiry should be connected with the meaning of community. In this context, individual and the community can only exist in relation to one another along a continuous process of adaptation that ends up with their reciprocal, critical and creative improvement (Lipman, 2003).

2.3 Instructional Efficiency and the Likelihood Model

Efficiency of instructional designs in education is a measurable concept. A high efficiency occurs when learning outcomes, such as test results, are produced at the lowest level of financial, cognitive or temporal resources (Johnes, Portela and Thanassoulis, 2017) . One of the measures of efficiency developed within Education is based upon a likelihood model (Hoffman and Schraw, 2010). Efficiency here is the ratio of work output to work input. Output can be identified with learning, whereas input with work, time or effort. These two variables can be replaced respectively with a raw score of performance of a learner or a learning outcome denoted as *P*, and a raw score for time, effort or cognitive load denoted as *R*:

$$E=P/R$$

R can be gathered with any self-report scale of effort or cognitive resources employed or an objective measure of time (Hoffman and Schraw, 2010). An estimation of the rate of change of performance is calculated by dividing *P* by *R* and the result represents the individual efficiency based on individual scores (Hoffman and Schraw, 2010). Previously, Kalyuga and Sweller (2005) employed the same formula extended with a *reference value*: the critical level under or above which the efficiency can be considered negative or positive (Kalyuga and Sweller, 2005). As shown in figure 1, the authors suggest to divide the maximum performance score and the maximum effort exerted by learners in order to establish whether a learner is competent or not.

$$\mathrm{Ecr} = \mathrm{Pmax} \,/\, \mathrm{Rmax}$$

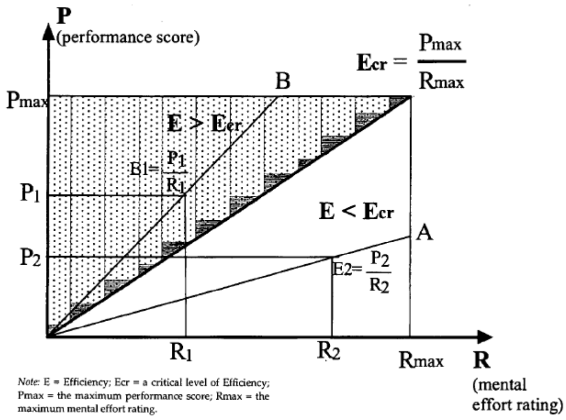

Figure 1: Critical level of efficiency (Kalyuga and Sweller, 2005).

A given learning task is considered efficient if E is greater than Ecr, relatively inefficient if E is less than or equal to the critical level Ecr. The ratio of the critical level is based on the assumption that an instructional design is not efficient if a learner invests maximum mental effort in a task, without reaching the maximum level of performance (Kalyuga and Sweller, 2005). Instead, an instructional design is efficient if a learner reaches the maximum level of task performance with less than the maximum level of mental effort. Intermediate values are supposed to be evaluated in relation to the critical level (Kalyuga and Sweller, 2005). This measure of efficiency has been adopted in this research and measures of performance, effort and mental workload have been selected as its inputs, as described below.

2.4 The Bloom's Taxonomy and Multiple Choice Questionnaires

One way of designing instructional material is through the consideration of the educational objectives conceived in the Bloom's Taxonomy (Bloom, 1956). In educational research, this has been modified in different ways and one of the most accepted revision is proposed by Anderson et al. (2001). In connection to the layout of multiple choice questions (MCQ), this adapted taxonomy assumes great importance because it explains how a test performance can be linked to lower or higher cognitive process depending on the way it is designed (Scully, 2017). In other words, the capacity of a test performance to evaluate 'higher or lower cognitive process' may depend on the degree of alignment to the Bloom's Taxonomy. This revised version has been adopted in this research to design a MCQ performance test.

2.5 Measures of Mental Workload

Mental workload can be intuitively thought as the mental cost of performing a task (Longo, 2014) (Longo, 2015). A number of measures have been employed in Education, both unidimensional and multidimensional (Longo, 2018). The modified Rating Scale of Mental Effort (RSME) (Zijlstra and Doorn, 1985) is a unidimensional mental workload assessment procedure that is built upon the notion of effort exerted by a human over a task. A subjective rating is required by an individual through an indication on a continuous line, within the interval 0 to 150 with ticks each 10 units (Zijlstra, 1993). Example of labels are 'absolutely no effort', 'considerable effort' and 'extreme effort'. The overall mental workload of an individual coincides to the experienced exerted effort indicated on the line. The Nasa Task Load Index (NASA-TLX) is a mental workload measurement technique, that consists of six sub-scales. These represent independent clusters of variables: mental, physical, and temporal demands, frustration, effort, and performance (Hart and Staveland, 1988). In general, the NASA-TLX has been used to predict critical levels of mental workload that can significantly influence the execution of an underlying task. Although widely employed in Ergonomics, this has been rarely adopted in Education. A few studies have confirmed its validity and sensitivity when applied to educational context. (Gerjets, Scheiter and Catrambone, 2006) (Gerjets, Scheiter and Catrambone, 2004) (Kester et al., 2006).

2.6 Summary of Literature

Explicit instructional design is an inherent assumption of Cognitive Load Theory. According to this, information and instructions have to be made explicit to learners to enhance learning (Kirschner, Sweller and Clark, 2006). This is in contrast to the features of the Community of Inquiry approach that, instead, do not focus only on explicit instructions to construct information, but on the learning connection between cognitive abilities and knowledge construction. The achievement of factual, conceptual and procedural knowledge, in connection to the cognitive load experienced by learners, is supposed to be the shared learning outcome under evaluation in the current experiment. Kirshner and colleagues (Kirschner et al., 2006) affirmed that unguided inquiring methodologies are set to fail because of their lack of direct instructions. Joanassen (2009), in a reply to Kirchner et al. (2006), stated that, in the field of educational psychology, a comparison between the effectiveness of constructivist inquiry methods and direct instruction methods does not exist (Jonassen, 2009). This is because the two approaches come from different theories and assumptions, employing different research methods. Moreover, they do not have any shared learning outcome to be compared. We argue that both the approaches have own advantages and disadvantages for learning. This research study tries to fill this gap and it aims at joining the direct instruction approach to learning with the collaborative inquiry approach, taking maximum advantage from them.

3 DESIGN AND METHODOLOGY

A primary research experiment has been designed following the approach by Sweller et al. (2010) and taking into consideration the cognitive load effects. Two instructional design conditions were designed: one merely following the direct instruction approach to learning (A), and one that extends this with a collaborative activity inspired by the community of inquiry approach to learning (B). In detail, the former involved a theoretical explanation of an underlying topic, whereby an instructor presented information through direct instructions. The latter involved the extension of the former with a guided collaborative activity based upon cognitive trigger questions. These questions, aligned to the Bloom's Taxonomy, are supposed to develop cognitive skills in *conceptualising and reasoning*, that stimulate knowledge construction in working memory (Popov, van Leeuwen and Buis, 2017).

An experiment has been conducted in third-level classes at the Technological University Dublin and at the University of Dublin, Trinity College involving a total of 115 students. Details as below:

- Semantic Web [S.W]: 42 students;
- Advanced Database [A.D]: 26 students;
- Research Methods [R.M]: 26 students;
- Amazon Cloud Watch Autoscaling [AWS]: 21 students.

Each class was divided into two groups: the control group received design condition A while the experimental group received A followed by B. Each student voluntarily took part in the experiment after being provided with a study information sheet and signed a consent form approved by the Ethics Committee of the Technological University Dublin.

The participation was based on a criterion of voluntary acceptance. Consequently, it can be deducted that who accepted to participate in the experiment had a reasonable level of motivation, contrary to a number of students who denied to participate. At the beginning of each class, lecturers asked whether there was someone familiar with the topic, but no evidence of prior knowledge was observed. The Rating Scale Mental Effort (RSME) and the Nasa Task Load index (NASA-TLX) questionnaire were provided to students in each group after the delivery of the two design conditions. After these, students received a multiple-choice questionnaire. The collaborative activity B was made textually explicit and distributed to each student in the experimental group which in turn, was sub-divided into smaller groups of 3 or 5 students. Table 1 list the instructions for executing the collaborative activity.

Table 1: Instructions for the collaborative activity.

SECTION 1*: Take part in a group dialog considering the following democratic habits: free-risk expression***,** *encouragement, collaboration and gentle manners.*
SECTION 2: Focus on the questions below and follow these instructions:

- Exchange information related to the underlying topic
- Connect ideas in relation to this information
- FIRST find an agreement about each answer collaboratively, THEN write the answer by each group member individually

Followed by trigger questions…

The first section explains the social nature of the inquiry technique while the second section outlines the cognitive process involved in answering the trigger questions. Examples of the questions are showed in tables 2 and 3, and are adapted from the work of Satiro (2006). They are aimed at developing cognitive skills of conceptualisation by comparing and contrasting, defining, classifying, and reasoning by relating cause and effect, tools and aims, parts and whole and by establishing criteria (Sátiro, 2006).

Table 2: Examples of trigger questions employed during the collaborative activity in the 'Semantic Web' class.

- What does a Triple define? (*Conceptualising)*
- How a Triple is composed of? (*Reasoning)*

Table 3: Examples of trigger questions employed during the collaborative activity in the 'Advanced Database' class.

- What is a Data-warehouse? (*Conceptualising)*
- How is a date dimension defined in a dimensional model? (*Reasoning)*

With a measure of performance (the multiple-choice score, percentage) and a mental workload score (RSME or NASA-TLX), a measure of efficiency was calculated using the likelihood models described in section 2.3 (Hoffman and Shraw, (2010). Figure 2 summarise the layout of the experiment. The research hypothesis is that the efficiency of the design condition B is higher than the efficiency of the design condition A. Formally: Efficiency B > Efficiency A.

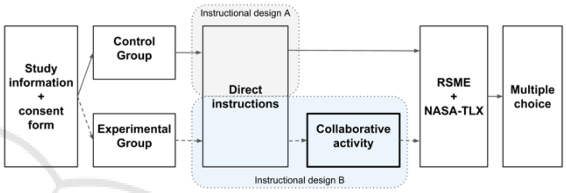

Figure 2: Layout of the experiment.

4 RESULTS AND DISCUSSION

Table 4 and 5 respectively list the descriptive statistics of the Rating Scale Mental Effort and the Nasa-Task Load indexes associated to each group.

Table 4: Means and standard deviations of the Rating Scale Mental Effort responses.

Topic	RSME mean (STD) Control Group	RSME mean (STD) Experimental Group
A.D.	36.00 (12.83)	47.91 (13.72)
A.W.S.	56.00 (25.64)	68.57 (32.07)
R.M.	47.08 (8.38)	67.85 (23.67)
S.W.	61.92 (29.19)	66.31 (32.08)

Table 5: Means and standard deviations of the Nasa Task Load indexes.

Topic	NASA mean (STD) Control Group	NASA mean (STD) Experimental Group
A.D.	43.61 (15.39)	47.80 (9.91)
A.W.S.	50.00 (8.19)	54.45 (16.12)
R.M.	49.38 (9.37)	49.85 (8.96)
S.W.	47.74 (10.98)	50.62 (9.43)

As noticeable from tables 4 and 5, the experimental group experienced, on average more effort (RSME) and more cognitive load (NASA-

TLX) than the control group. Intuitively this can be attributed to the extra mental cost required by the collaborative activity. Table 6 shows the performance scores of the two groups. Also in this case, the collaborative activity increased the level of performance of the learners belonging to the experimental group.

Table 6: Mean and standard deviation of MCQ.

Topic	MCQ mean (STD) Control Group	MCQ mean (STD) Experimental Group
A.D.	42.92 (21.26)	54.91 (14.27)
A.W.S.	61.33 (15.52)	66.42 (13.36)
R.M.	68.41 (15.72)	69.57 (18.88)
S.W.	34.42 (18.10)	47.12 (18.77)

Despite of this consistent increment across topics, the results of a non-parametric analysis of variance (depicted in table 7) shows how the scores associated the control and experimental groups are, most of the times, not statistically significantly different. Given the dynamics of third-level classes and the heterogeneity of students having different characteristics such as prior knowledge and learning strategy, this was not a surprising outcome.

Table 7: P-values of the non-parametric analysis of variance of the performance scores (MCQ), the perceived effort scores (RSME) and the workload scores (NASA-TLX).

Topic	MCQ	RSME	NASA
A.D.	0.2250	0.1164	0.3695
A.W.S.	0.3718	0.3115	0.3709
R.M.	0.9806	**0.0103**	0.6272
S.W.	**0.0369**	0.8319	0.1718

In order to test the hypothesis, an efficiency score for each participant was computed according to the likelihood models described in section 2.3 (Hoffman and Schraw, 2010). Table 8 lists the efficiency scores across groups and topics. Under the assumptions of the likelihood model, the evidence of the positive impact of the collaborative inquiry activity (design condition B) is limited to the 'Semantic Web' class where there is a significant difference in the efficiency of design conditions when the RSME is used. The control group is on average below the critical level, while the experimental group above it. In detail, as depicted in figure 3 and 4, the distribution of the efficiency scores, with the RSME measure, reveals that 54% of the students in the control group experienced an efficiency below the critical level whereas 46% above it. Contrarily, in the experimental group, a higher 66.6% of students experienced an efficiency above the critical level and 33,3% below it.

Table 8: Mean of efficiency computed with the RSME (+ is positive, - is negative). Critical Level 100/150=0.666.

Topic	Mean efficiency (with RSME) Control group	Mean efficiency (with RSME) Experimental Group
A.D.	1.304 > 0.666 (+)	1.239 > 0.666 (+)
A.W.S.	1.440 > 0.666 (+)	1.336 > 0.666 (+)
R.M.	1.505 > 0.666 (+)	1.152 > 0.666 (+)
S.W.	0.656 < 0.666 (-)	0.922 > 0.666 (+)

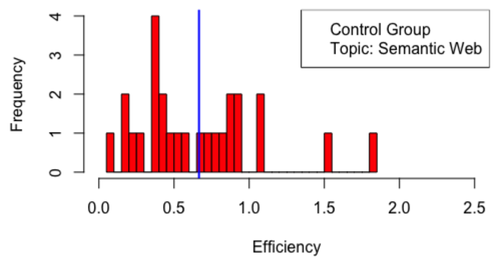

Figure 3: Distribution of the efficiency scores of learners in the control group for the topic 'Semantic Web'.

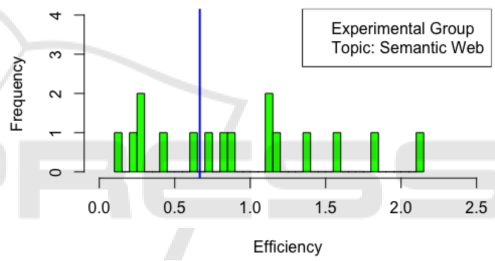

Figure 4: Distribution of the efficiency scores of learners in the experimental group for the topic 'Semantic Web'.

A similar analysis was conducted by using the NASA-TLX as a measure of mental workload for the likelihood model (Table 9) where a more coherent picture emerges. In fact, the efficiency scores are on average always higher in the experimental group.

Table 9: Mean of Efficiency computed with the NASA-TLX (+ is positive, - is negative). Critical Level 100/100=1.

Topic	Mean efficiency (with NASA) Control group	Mean efficiency (with NASA) Experimental Group
A.D.	1.153 > 1 (+)	1.244 > 1 (+)
A.W.S.	1.241 > 1 (+)	1.340 > 1 (+)
R.M	1.425 > 1 (+)	1.440 > 1 (+)
S.W.	0.750 < 1 (-)	0.964 < 1 (-)

Despite of the general increment of the efficiency scores, these are not statistically significantly different across design conditions. In fact, all the p-values of Table 10 are greater than the significance level (alpha=0.05).

Table 10: P-values of the Kruskal-Wallis test on the efficiency scores (with the NASA-TLX) and the Wilcoxon test of the efficiency scores (with the RSME).

Topic	Kruskal-Wallis (NASA)	Wilcoxon RSME
A.D.	0.5865	0.9349
A.W.S.	0.6945	0.4191
R.M.	0.8977	0.1105
S.W.	0.1202	0.1778

The Likelihood model behaves differently when used with different measures of mental workload. In fact, on one hand, with the unidimensional Rating Scale Mental Effort, the design condition B (experimental group) on average had a lower efficiency than the design condition A (control group) across topics. On the other hand, with the multidimensional NASA Task Load Index, the efficiency of the design condition B (experimental group) was always better than the design condition A (control group) across topics. This raises the question of the completeness of the unidimensional measure of mental workload (RSME). In line with other researches in the literature of CLT, the criticism is whether 'effort' is the main indicator of cognitive load (Paas and Van Merriënboer, 1993) or others mental dimensions influence it during problem solving (De Jong, 2010). In this research, we believe that a multidimensional model of cognitive load seems to be more suitable than a unidimensional model when used in the computation of the efficiency of various instructional designs. We argue that a multidimensional model, such as the NASA-TLX, better grasps the characteristics of the learner and the features of an underlying learning task. Results shows that the average performance (MCQ) is higher in the experimental group than the control group. This can be attributed to the layout of the collaborative activity designed to boost the learning phase and enhance the learning outcomes, namely the achievement of factual, conceptual and procedural knowledge. According to the collaborative cognitive load theory (Kirschner et al., 2018), nine principles can be used to define complexity. Among these, task guidance/support, domain expertise, team size and task complexity were the principles held under control in the current experiments. In particular, three factors were observed that can be used to infer task complexity: 1) amount of content delivered; 2) time employed for its delivery; 3) level of prior knowledge of learners. In relation to 1 and 2, A.D. had 28 slides (50 mins), A.W.S. 25 slides (25 mins), R.M. 20 slides (35 mins), S.W. 55 slides (75 mins). In relation to point 3, prior knowledge can be inferred from the year the topic was delivered: S.W. first year BSc in Computer Science; AWS (third year), A.D. (fourth year), and R.M. (post-graduate). As it is possible to note, S.W. was the learning task with the higher level of complexity in terms of slides, delivery time and prior-knowledge. Results are in line with the assumption of the collaborative cognitive load theory: collaborative learning is more effective when the level of the complexity of an instructional design is high (Kirschner et al., 2018). In fact, on one hand A.D., A.W.S. and R.M. are of lower complexity to justify the utility of a collaborative activity that involves sharing of working memory resources from different learners. On the other, the higher complexity of S.W. justifies the utility of the collaborative activity and the exploitation of extra memory resources from different learners in processing information and enhance the learning outcomes.

5 CONCLUSIONS

A literature review showed a lack of studies aimed at comparing the efficiency of instructional design based on direct instruction and those based on collaborative inquiries techniques. Motivated by the statement provided by Kirshner and colleagues (2006) whereby inquiries techniques are believed to be ineffective in the absence of explicit direct instructions, an empirical experimental study has been designed. In detail, a comparison of the efficiency between a traditional instructional design, purely based upon explicit direct instructions, and its extension with a guided inquiry technique has been proposed. The likelihood model of efficiency, proposed by Kalyuga and Sweller (2005), was employed. This is based upon the ratio of performance and cognitive load. The former was quantified with a multiple-choice questionnaire (percentage) and the latter with a unidimensional measure of effort first (the Rating Scale Mental Effort) and a multidimensional measure of mental workload secondly (the NASA Task Load Index). Results demonstrated that extending the traditional direct instruction approach, with an inquiry collaborative activity, employing direct instructions, in the form of trigger questions, is potentially more efficient. This is in line with the beliefs of Popov, van Leeuwen and Buis (2017) whereby the development of cognitive abilities, through the implementation of cognitive activities (here collaboratively answering trigger questions and following direct instructions), facilitates the construction and the achievement of knowledge. Future empirical experiments are necessary to demonstrate this point held statistically.

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