Exploring Deviation in Inquiry Learning: Degrees of Freedom or Source of Problems?

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Abstract: The European Go-Lab project aims to promote Inquiry-based Learning (IBL) with online laboratories. To support teachers and students, the project provides an IBL model (a sequence of inquiry phases) as well as the technological infrastructure to implement it: the Graasp platform and the Golabz repository. Using these technologies, teachers create Inquiry Learning Spaces (ILSs) where they adapt the proposed IBL model to their needs, and enrich the phases with online resources, apps or labs to build open educational resources that will be distributed to the students. The aim of this paper is to reflect on the deviations from suggested standard models of learning phases that we found in practice. For that purpose, we analyzed the 102 most frequently used ILSs with respect to the perspectives taken by teachers and students. The results show deviations of the authored spaces from the pedagogical model of inquiry learning as well as deviations in the actual learning process models from the teachers' specifications. Additionally, the analysis points out practices for the learning design, particularly the inclusion of resources and apps into the spaces.

Keywords: Inquiry-Based Learning (IBL), Learning Analytics, Learning Process Models

1. Introduction

Blending web-based resources in the form of online laboratories with classroom activities is a promising approach to increase the accessibility of authentic exploration and learning in science, technology, engineering, and mathematics (STEM). In this vein, the Go-Lab European project[1] aims at promoting inquiry-based learning using online labs through its web portal (de Jong, Sotiriou, & Gillet, 2014).

Go-Lab provides teachers with an inquiry model to structure their classroom activities according to a set of phases (Pedaste, et al., 2015). This sequence can be customized and modified by teachers. Additionally, resources, apps and labs can be integrated in these phases. From the theoretical point of view, the resulting pedagogical structure enriched by apps, labs and online resources constitutes the *teacher model*. In practice, the teacher model is represented by an Inquiry Learning Space (ILS) in the project platforms. Then, the students are expected to go through the different phases and their content, either sequentially or moving back and forth between them. T

The purpose of this paper is to analyze how teachers and students adapt and follow the Inquiry Based Learning (IBL) model proposed in the project. To achieve that aim, we carried out a study over the 102 ILSs most frequently used. We defined a processing chain and applied the analytical model to different, heterogeneous data sources available in Go-Lab. We utilized a general architecture to integrate, filter and analyze contextual, activity-, and artefact-related data to generate higher abstractions such as the learning process models. Furthermore, we applied different metrics to determine deviations ("out-of-order" behaviors) on both perspectives of students and teachers. From the data analyses, this paper draws trends for teachers as well as for researchers and pedagogical instructors in the field of inquiry learning.

The rest of this paper is structured as follows: Section 2 introduces the background in terms of learning process models and the Go-Lab project; Section 3 describes the data sources and the analyses

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[1] Go-Lab project: http://www.go-lab-project.eu

process; the results obtained are presented in Section 4 and discussed in Section 5; finally, Section 6 ends with the main conclusions and the future work.

2. Background

Although process modeling has its origin in the field of business processes, it has been also applied to learning contexts. For instance, learning design models and structures the learning process similarly to business processes (Bergenthum, Desel, Harrer, & Mauser, 2012; Miao & Hoppe, 2011). Particularly for constructivist learning approaches, the role of learning design and the specification of learning flows have been discussed (Lejeune, et al., 2009; Harrer, Malzahn, & Hoppe, 2007).

Modeling learning process as a basis of learning design can be applied to different learning approaches including Inquiry-based Learning (IBL). IBL can be a successful pedagogical approach, provided that effective support is offered to the students at various levels (de Jong, Linn, & Zacharia, 2013): first, activities are structured in successive phases; second, in each phase scaffolding tools supporting the activities are provided; and third, relevant cues are given to the students when necessary.

Inquiry-based learning activities are usually structured learning activities that implement an inquiry cycle model (Kuhlthau, Maniotes, & Caspari, 2007; Pedaste, et al., 2015). Environments such as WISE (Slotta & Linn, 2009), SCY-Lab (de Jong, et al., 2010), or JuxtaLearn (Haya, Daems, Malzahn, Castellanos, & Hoppe, 2015) have an explicit and rarely flexible IBL models. Despite following a well-known predefined model may be helpful -especially to support novice teachers or students- the use of a rigid model constrains the teachers' chances to customize it to their learning contexts, and some students may have difficulties to adapt it themselves (Dillenbourg, 2002).

Go-Lab is an ongoing European project aiming at promoting IBL with online laboratories (labs) for STEM education at school (de Jong, et al., 2014). The Go-Lab online learning environment is a single entry point to access online laboratories and to create Inquiry Learning Space (ILS). ILSs are rich open educational resources that can be collaboratively created in the Graasp[2] social media platform, shared in the Golabz[3] open repository, and exploited by the students either as standalone resources or embedded in open social or educational platforms (Rodríguez-Triana, et al., 2014).

ILSs are pedagogically structured in order to enforce IBL. Although the literature identifies different sequences or naming of phases to structure the inquiry learning process, the main idea is always to encourage the students to develop their own questioning, figure out their own responses by making proper hypotheses and designing proper experiments, and reflect on the observations. Within Go-Lab we take into consideration the following phases: *Orientation, Conceptualization, Investigation, Conclusion, and Discussion* (Pedaste, et al., 2015).

Graasp provides teachers with a recommended process model and a collection of supporting tools that can be adapted according to the needs of the learning scenario. Still, during the learning activity, a student might or might not follow this structure. The sequence of phases followed by the student corresponds to a model that represents the learning process. The degrees of freedom given to teachers and students in the design and enactment of ILS make Go-Lab an interesting example for applying analytic methods of process discovery. One of the tasks in this field is to extract process models and find deviations from this model in concrete process instances (Van Der Aalst, 2011). These deviations might be used as indicators to enforce process awareness and reflection on part of the learners, which is seen as beneficiary in inquiry learning (Garrison, 2003) besides process-oriented guidance mechanisms (Zacharia, et al., 2015). The following sections present our study around the teacher and student models in Go-Lab.

3. Data Analysis and Pre-Processing

This section describes the different data sources and analysis procedures used to obtain the results presented in Section 4. An overview of the data collection and processing is provided in Figure 1. The architecture of Go-Lab consists of a flexible backend with services for the collection and aggregation of

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[2] Graasp platform: http://graasp.eu (last visit May 2015)
[3] Golabz repository: http://www.golabz.eu/ (last visit May 2015)

action logs for the capturing of learners' traces (Hecking, et al., 2014). Aggregations of the data are available through an abstraction API for further processing. The embedment of such analysis workflows composed of micro-services with visual results displayed as OpenSocial gadgets for learners, teachers and researchers/analysts in the context of Go-Lab has been described in (Manske, et al., 2014). For our analysis, we use this architecture for the collection and processing of data, as well as the embedment of analytics apps for the proposed prototypes (cf. sec. 6).
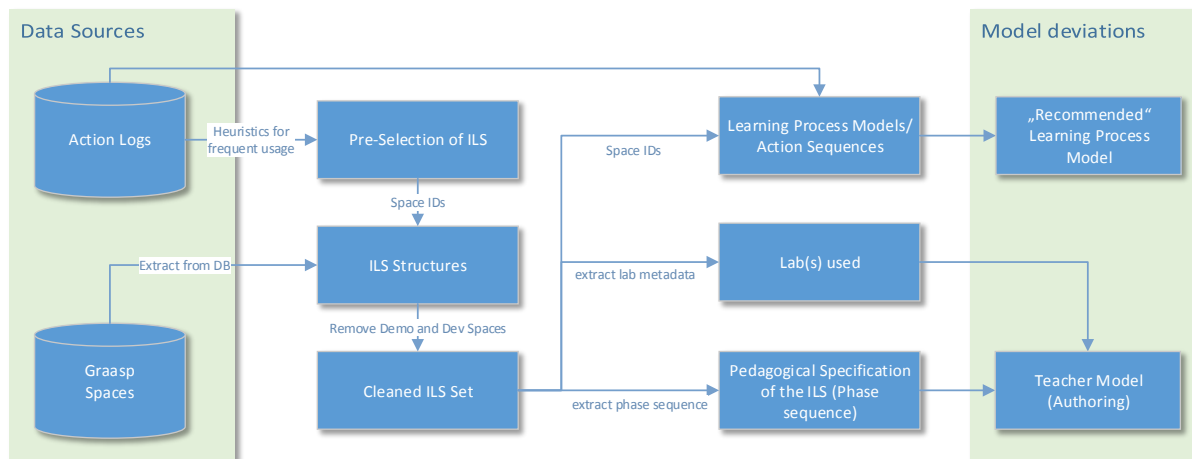
Figure 1. Overview of the data processing and analysis chain based on various data sources.

3.1 Data Sources

The data sources contain *Graasp Spaces* and *Action Logs*. Graasp Spaces contain information about the authored learning spaces, particularly which apps, resources and labs are used in which phases. In our statistics we count labs as a special type of app – in most cases there is exactly one lab per ILS: the learning design for Go-Lab starts usually with a certain experiment that is usually aligned to a single lab. The difference between resources and apps is quite important: while apps and labs are given by Go-Lab, the resources are added or created by teachers, which represents a different degree of customizations on part of the teachers. Action logs capture the traces or learners in the system and contain contextualized information, for example, the identifier of an ILS the learner is in, or the artefact she is working on.

3.2 Dataset and Preprocessing

Taking into account the 2826 existing ILSs in *Graasp*, we ranked them according to the user activity registered, i.e., based on the amount of *Action Logs*[4]. To determine which learning spaces have been used frequently, we defined a threshold based on typical values for classroom size and a minimum amount of action logs per user if at least every space is visited and an app has been used. The product leads to a threshold of 500 actions and 10 users per space as a minimal requirement to be included in the filtered set of learning spaces, which indicates a minimum of activity to be useful for further processing. Examples of actions are logging into space, starting an app, changing a learning phase or tool-specific activities, such as adding a concept to a concept map. Afterwards, we removed from the list those ILSs that represented demo or test spaces, obtaining what we have called *Cleaned ILS set*, made up by 102 ILSs.

3.3 Data Processing and Analytics

For the analysis, we propose generic metrics that describe the ILSs in terms of the amount of user activity, the type of learning phases and the used tools. As an indication of the amount of activity

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[4] Values obtained in May 2015.

volume that takes place in an ILS, we employ the *number of logged user actions per ILS*. Thus, a high number of logs indicates a high volume of user activity and therefore a more active ILS. The *number* and the *sequence of phases* were used to describe and characterize the ILSs. The Go-Lab platform provides five typical inquiry phases (orientation, conceptualization, investigation, conclusion and discussion) but the teacher may introduce new phases or remove existing ones according to the planning of the activity. We coded the inquiry phases based on the typical inquiry model and created additional categories for non-standard phases. Besides, Graasp provides ILSs with "Vault" subspaces. The vault subspace facilitates and promotes the interaction among the students and the teacher in the ILS by exchanging learner-generated content. Through the vault, the students are able to contribute by adding their own material. The *existence of a vault* was used as a binary variable to describe the structure of the ILS, along with the number and sequence of inquiry phases. Furthermore, the teachers have the option of integrating online resources, apps and labs with an ILS to promote and facilitate specific objectives. The *number of resources, apps and labs* is used as metrics for the description of the ILSs.

Based on the aforementioned metrics, we provide a descriptive analysis of the dataset. Moreover, we clustered the ILSs of the dataset using the metrics as clustering variables following a k-means approach. The results of the descriptive analysis are presented in the following section. Finally, by analyzing the tools and resources added to the different phases, we expect to infer a collection of design trends and lessons learnt. The Go-Lab approach induces a specific, recommended inquiry model for which we can investigate, whether teachers adapt or customize their spaces. The combined study of the teacher and the learning process model may provide insights on deviations of students' practice. From the runtime-perspective, the deviations from the actual learning processes or sequences of phases can be measured to determine "out-of-order"-behavior relative to the pedagogical specification of the teacher.

4. Results

The cleaned dataset of the study consisted of 102 ILSs built by teachers on the Go-Lab platform. The teachers were able to plan the activities in various phases as well as to choose and distribute tools and resources in the ILS. The activity volume of the ILSs ranged from 500 to 16426 logs (on average 2672 logs per space). Most of the ILSs were planned over five phases (Orientation, Conceptualization, Investigation, Conclusion and Discussion) following the recommended IBL model. However, there were cases where the teachers deviated or enriched the original model, either using less (three phases minimum) or more phases (eight phases maximum) for the activity plan, e.g. by creating additional phases such as "Data interpretation", which is a sub-phase of the investigation in the Go-Lab inquiry model. There were also some cases where teachers split the original phases either because they were too long or to give more emphasis on certain processes. For example, a lecture about Electronic Circuits was planned as a three-phase activity (Orientation, Conceptualization, and Investigation). On the other hand, a teacher organized a lecture on Foucault's proof of Earth Rotation as a five-phase activity (Orientation, Conceptualization, Investigation, Conclusion and Discussion) that was further divided into sub-phases. Therefore, the teacher introduced the additional phases of *exploration*, *experimentation* and *data interpretation* as sub-phases of the investigation phase. In the end, this resulted in an eight-step chain: orientation, conceptualization, investigation, exploration, experimentation, data interpretation, conclusion, and discussion. Overall, 3.92% of the ILSs were planned with less than 5 phases and 35.29% involved more than 5 inquiry phases. The majority of the ILSs (60.78%) used the inquiry model recommended by the platform.

The teachers were able to choose freely the applications and resources for their lectures. On average, each ILS made use of 15 items: 6 (Mean = 5.81, σ = 2.489, N = 102) of them were applications while 9 items (Mean = 9.08, σ = 8.946, N = 102) were learning resources of various types (pictures, videos etc.). In Figure 2 we present the distribution of the number of phases, applications and resources, used over the ILSs. The 57% of the ILSs integrated more than 5 applications while the 55% of the spaces used more than 5 resources. Out of the 102 learning spaces that we studied, only 27 allowed the use of the vault. The vault allowed the permanent and visible contribution of students to the learning space but it was not widely used as means of promoting reflection or participation.
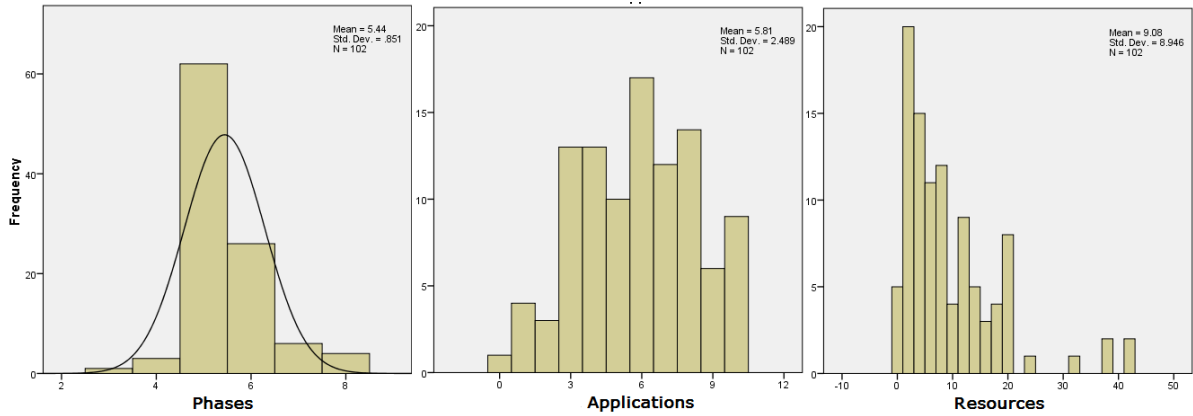
<u>Figure 2.</u> Histograms of the distribution of phases, applications and resources over the ILSs.

The descriptive statistics for the ILSs are displayed in Table 1. The analysis of the results showed there is a statistically significant, but weak, correlation between the number of applications used in an ILS and the number of logs recorded during the activity ($\rho=0.215, p<0.05$). This indicates that student activity in an ILS increases with the number of available applications. Furthermore, the number of resources correlates significantly but in a negative way with the number of phases ($\rho=-0.233, p<0.05$). This indicates that teachers tend to distribute the available resources over the various phases.

Table 1: Descriptive statistics for the ILSs of the study.

	logs	phases	items	apps	resources
Average	2761.58	5.44	14.892	5.81	9.08
Min	500	3	1	0	0
Max	16426	8	48	10	42

The aforementioned metrics were used in order to cluster the ILSs of the dataset using a k-means clustering approach. The number of extracted clusters was set to 3 as estimated by a plot-based method (Everitt & Hothorn). The main objective was to find related groups in the dataset and discover potential dependencies between factors that describe ILSs. The results of the cluster analysis provided one dominating cluster of learning spaces (cluster 2) and two smaller - but nonetheless distinctive - ones (clusters 1 and 3) in Figure 3. Cluster 1 consisted of 8 out of 102 spaces and cluster 3 consisted of 5 out of 102 spaces. The spaces of these two clusters integrated a vault in their structure and made use of a great number of resources and applications. In particular, Cluster 3 consisted of the learning spaces with the biggest number of resources. Cluster 2 contained 89 learning spaces. The majority of these spaces did not include a vault in their structure and the number of resources was similar to the number of the applications used. The cluster analysis does not provide any further indication with respect to the inquiry phases implemented in the learning spaces.
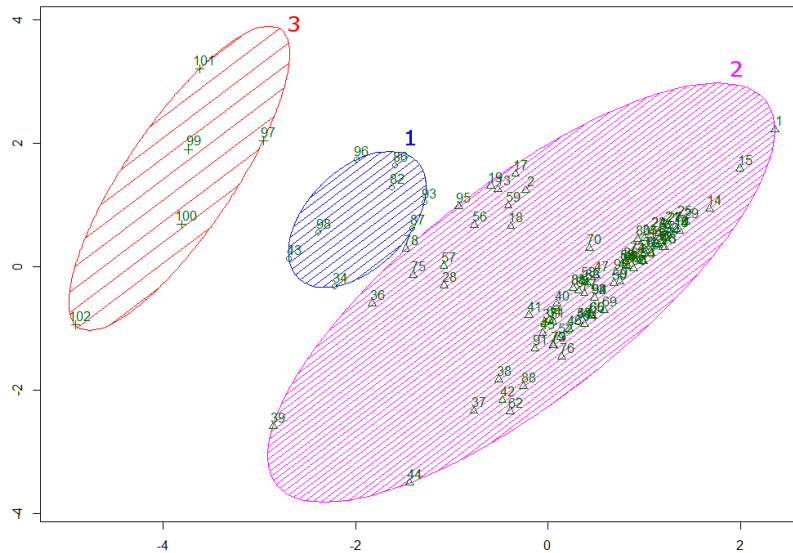
Figure 3. Results of the cluster analysis based on descriptive metrics of the learning spaces.

In order to gain insight with respect to the design of inquiry phases, we studied the use of resources and applications within the various phases. This analysis is based on the hypothesis that different inquiry phases serve different purposes. Therefore, the use of resources and applications should vary depending on the objective of the inquiry phase. In Figure 4, we present the average number of resources and applications used per inquiry phase. Overall, resources are mostly used in the Orientation and Conceptualization phases. In all other phases of the recommended IBL model (Investigation, Conclusion and Discussion) as well as in other phases (i.e. phases introduced by teachers) the applications have a higher usage. This is particularly interesting since it indicates a shift into more active learning process where the students are encouraged to participate. The teachers do not focus on distributing their own resources around the classroom but promote the active involvement of students through the use of applications.
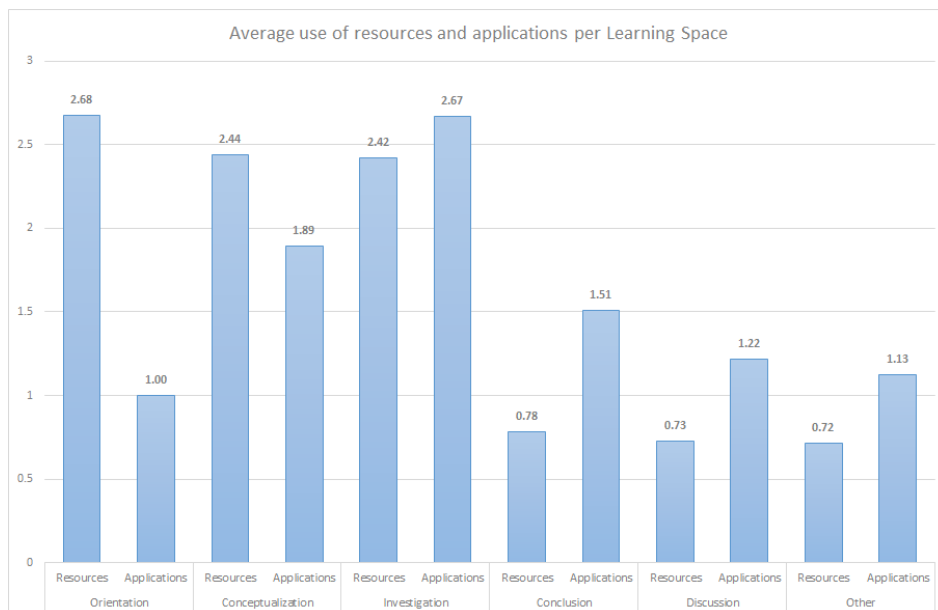
Figure 4. Results of the cluster analysis based on descriptive metrics of the learning spaces.

Complementary to this, the authoring also consists of the adaptation of the inquiry cycle. The teacher might or might not change the ordered sequence of recommended phases. Therefore we take the (static) number of phases and their sequence as a parameter for each ILS. The learner might then follow this sequence or deviates from the specification. Based on this, we can observe different parameters

connected to deviations ("out-of-order-behavior"), such as *inversions* in the learning process sequence ("LPS"), or the *length of the LPS*, counted with and without repetitions. For example, an inversion is the jump from an experiment back to the conceptualization, which is against the natural ordering of the phases in a teacher's specification. If the length of the LPS without repetitions is smaller than the number of phases specified, at least one phase has been omitted by the learner. Figure 5 shows the distribution of LPS lengths across the static number of phases specified in the ILSs. Only few learners followed the recommended sequence and omitted at least one phase.
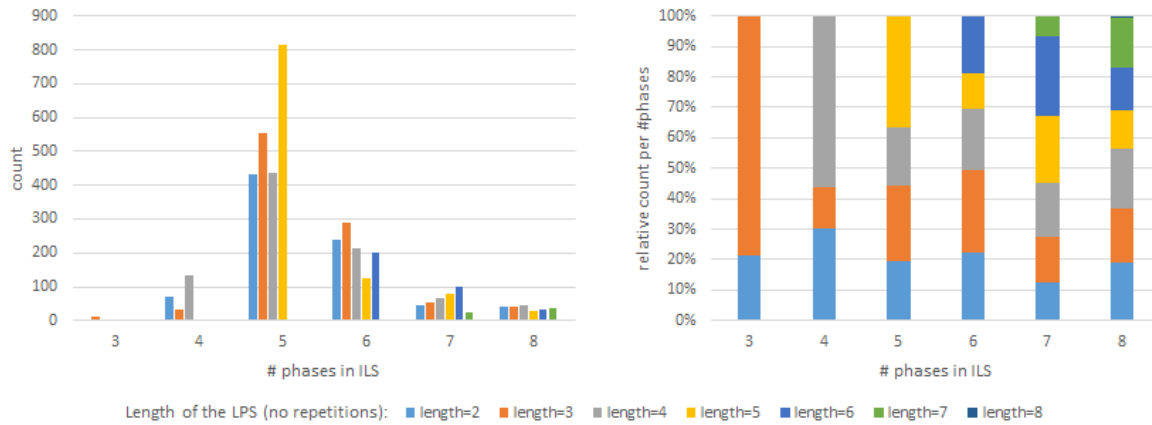

Figure 5. Absolute (left) and relative (right) number of learning process sequences (without repetitions) of a specific length (color coded) aggregated by the number of phases per ILS.

The distribution of omissions of inquiry phases on the learners' part is shown in Figure 6. The right part of this figure relates the number of visited and of omitted phases to the number of phases specified. It demonstrates a clear trend: the more phases are specified, the higher the probability of deviations – particularly omissions of phases on part of the learner. The left part of this chart shows a more detailed view about the phases that have been omitted, aggregated by the number of phases specified in the ILSs. The phase "other" is a special coding for spaces that do not directly refer to the inquiry cycle, but for additional information or monitoring. Spaces are named for example "dashboard" or "reflection" and are usually for self-reflection or monitoring. Surprisingly, the orientation phase is one of the more frequently skipped phases. This might indicate that the learners focus more on the tasks in other phases – orientation phases usually are typically very general descriptions for the students or a collection of motivational resources. Videos, for example, might have been skipped as a consequence of bad internet connectivity. Another peak is the discussion phase that has been present in spaces with more than four phases on the one hand, but then frequently skipped on the other hand. A possible reason might be that such phases could potentially be carried out to classroom activities and teachers might not really see the need for ICT support in this phase. Due to typical time or room constraints when dealing with ICT in classrooms, this might have been omitted.
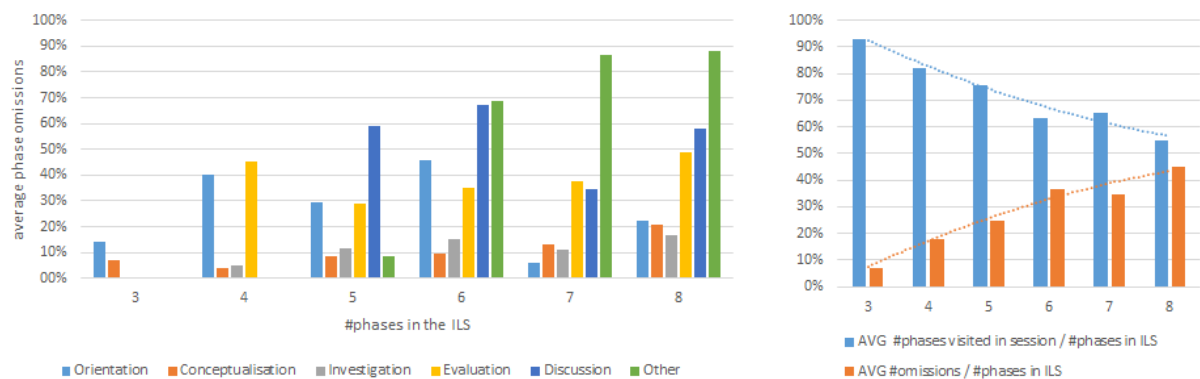
Figure 6. Distribution of average phase omissions aggregated by the number of specified phases in ILSs (left). Right: number of phases visited and omissions relative to the number of phases.

The left part of Figure 7 presents a distribution of inversions across different learning process sequence lengths. The relative proportionality shows that the pedagogical design, for instance number of phases in an ILS plays a subordinate role – in contrast to the actual learning sequence. This might indicate a lack of process awareness on the side of the students, which could play an important role in guiding students focused through the inquiry process. This diagram shows that there is likely proportionality between the length of the LPS and the average number of inversion.
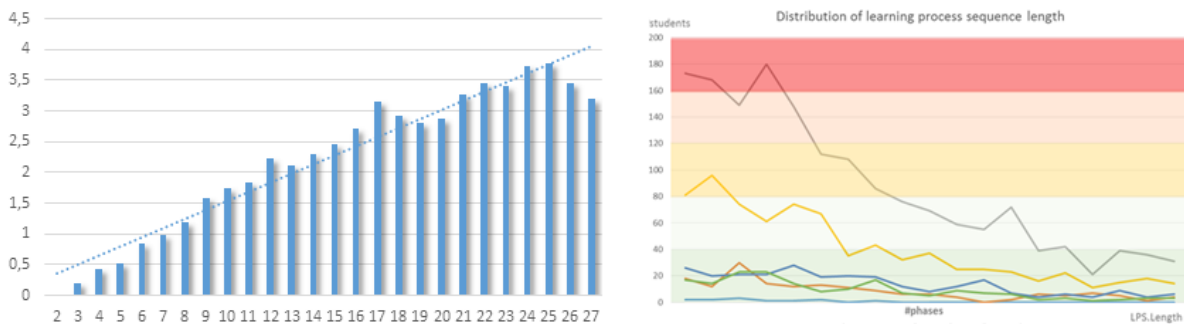
Figure 7. Left: Average number of inversions depending on the length of the LPS (domain axis). Right: Number of students depending on the LPS length aggregated by number of phases specified.

Furthermore, we compared the results obtained from the pedagogical specification of ILSs. This comparison allowed us to find deviations between the ILS model and the recommendations provided to the teachers regarding the use of the Golabz apps and labs. As a consequence, this gives some insights on deviations from the recommended inquiry model in the authoring perspective. From the runtime-perspective, the deviations from the actual learning processes or sequences of phases can be measured to determine "out-of-order"-behavior relative to the pedagogical specification of the teacher. The right part of Figure 7 shows the distribution of phase sequences lengths (i.e. the number of sequential phases) that are extracted from the actual learning process models of the students. It points out that most of the scenarios contain 5 or 6 phases and a high number of the phase sequences are longer than the recommended model. The color code per graph area indicates the number of students.

5. Discussion

The analytical results of this paper point out that (structured) IBL induces a shift to learning activities where students are encouraged to actively participating. In 39.22 % of the ILSs, teachers took advantage of the possibility of customizing the inquiry sequence to their needs. In these spaces, there is a high number of deviations of the learning sequence from the specification. Therefore, appropriated apps would be necessary in order to support teachers and students regulate and intervene in case of out-of-order behaviors during the learning process. For example, apps for monitoring the learning-process might help teachers to be aware of the student activity and to identify out-of-order behavior based on the metrics used for the work in this paper.

Figure 8 shows the prototypes of supportive apps for process awareness of teachers and students. The teacher app provides an overview of the phase sequences of each student. The app allows the teacher to uncover deviations in the sequence of phases as well as in the time spent per phase (e.g., a short time devoted to an experimentation phase in comparison to the recommended value). The statistics show that a lot of students omitted phases in their run, which can be monitored with such an application. On the other hand, students need to be aware of their own learning processes in order to adopt inquiry models in a useful way. Therefore, cognitive scaffolds to foster process awareness and self-reflection are needed. The prototype of the student app displays an interactive learning process visualization, which provides information about the process sequence on two levels (phases and apps) as well as the time spent by the student in each phase. The visualization shows the transitions between phases and also between apps inside a phase, so that a student can evaluate the deviations of her learning process from the suggested model. For the purpose of reenactment, the visualization animates the history of transitions.
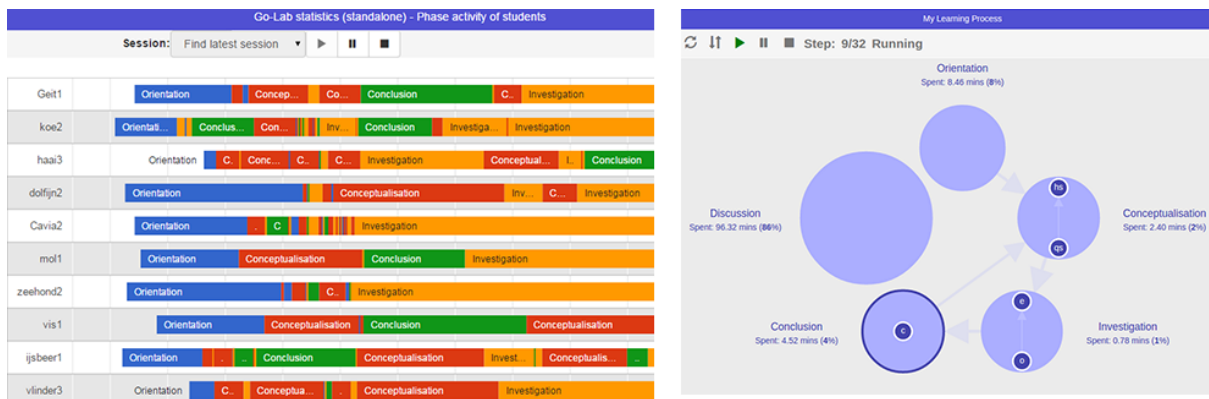
Figure 8. Prototypes of process awareness tools for teachers (left) and learners (right).

The necessary amount of instructions and guidance mechanisms in IBL lead to a discourse, pointing out the danger in going for less is better (Kirschner, Sweller, & Clark, 2006). As a consequence, both the learning design and the learning process need to be aligned, while support tools for monitoring processes can help with enforcing process awareness to improve learning and metacognitive or reflective skills.

From the analysis of the ILSs and the distribution of artefacts that were used to facilitate the IBL process over the ILSs, it was evident that the teachers consider the use of more applications while they keep the use of resources limited. Even though the average number of applications and resources added to an ILS is similar, the majority of spaces use a minimum number of resources and they tend to increase the number of applications. Furthermore, the use of resources is negatively correlated to the number of inquiry phases. This is an indication that teachers tend to design and build phases without necessarily adding new content, in the form of resources but using more applications. Maybe, this is also due to the fact that applications lead to an increase in students' activity and therefore applications are perceived as a way to support and encourage students to act and take the initiative.

6. Conclusions and Future Work

This paper analyses the activity of learners and teachers in the context of inquiry-based learning with online experimentation in Go-Lab. Our study is based on more than 100 inquiry learning spaces and combines heterogeneous data sources with various filters, metrics and indicators. The results show teacher trends in the design of their ILSs, e.g., in terms of number of phases, apps and resources per phase. The teacher models can be further evaluated taking into consideration parameters such as the functional type of apps regarding the inquiry process (e.g., apps for reflection, metacognition, etc.) and the concrete types of resources a learning space is composed of.

Additionally, the results point out that although most of the teachers adopt the recommended inquiry model, a significant number adapts it according to the needs imposed by the learning context. What is noteworthy is that, often, students do not follow the teacher model. These deviations might originate from a lack of process awareness that could be overcome through appropriate scaffolds. The detection of "out-of-order"-behavior is a complex task and possibly includes a variety of indicators. To support process awareness, we have proposed prototype applications for students and teachers. In the future work we will validate our prototypes regarding the interpretability of the rich representations of learning processes. Other metrics such as dynamic time warping could be useful to measure the costs to match an actual learning sequence into a sequence specification. Such a metric will involve different kinds of deviations (inversions, insertions, repetitions, etc.). As a continuation, first participatory design studies with teachers will show their usefulness and provide some further input on the indicators. This involves particularly a more integrated usage of the metrics and indicators in rich representations that go further than a simple mirroring of values. From the perspective of learners, this can be useful to support self-reflection and metacognition, fostering 21st century learning skills as well as helping teachers to support such competencies.

Acknowledgements

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