Constructing Interpretative Views of Learners' Interaction Behavior in an Open Learner Model

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Abstract—In this paper, we discuss how externalizing learners' interaction behavior may support learners' explorations in an adaptive educational hypermedia environment that provides activity-oriented content. In particular, we propose a model for producing interpretative views of learners' interaction behavior and we further apply this model to INSPIRE*us* for visualizing specific indicators. In the proposed approach, we collect raw data from learners' interaction at various grains, model the state of interaction using a set of indicators that combine temporal, navigational and performance data with semantic data of content and available tools, and visualize this information alongside with comparative information coming from the instructor or peers. In this way, we provide users (learners, tutors, peers) with a mirror of learners' behavior and a point of reference such as the instructor's proposal or peers' behavior, in order to enable monitoring and reflection. An empirical study with students is also described investigating how they interpret the visualizations of their interaction data provided by INSPIRE*us*, the metacognitive skills they cultivate, and the personal data of peers they value for selecting collaborators. Preliminary results provide evidence about the understandability and expressiveness of the indicators of effort, progress, working style, and the visualizations used.

Index Terms—Adaptive hypermedia, interaction analysis, open learner modeling, visualization

1 Introduction

Tracking and analyzing learners' experience during their interaction within a learning environment is a challenging target for the area of technology enhanced learning. Various types of learning environments keep track of learners' interaction behavior [1] such as adaptive learning environments [2], collaborative learning environments [3], [4], course management systems [5], [6], [7], intelligent tutoring systems [8], [17]. Interaction data are usually used for various purposes in order for the environment to maintain the current state of learners and accordingly adapt its output or open it to the various stakeholders of a virtual class as evidence for learners' work and performance [1], [9], [18], [48]. In the last cases, specific aspects or results of learners' interaction behavior are usually externalized focusing on learners' knowledge state/level, navigation or aspects of social interaction. Learners' observable behavior is rarely exploited to reflect learners' cognitive activity and cultivate metacognitive skills such as reflection, planning, and self-monitoring. An open issue remains how interaction data could be used as evidence for the learning process. How could we extend the learner model with representations of personal interaction data that reflect the processes that the learner follows in order to attain specific outcomes or cultivate skills? This could be based on a theoretical model that augments interaction data with learning design characteristics of content and available tools giving meaning to learners' actions and linking them with specific outcomes. The Open Learner Modeling area investigates critical issues to this end such as contents and user control over the learner model, as well as in which ways and by whom such a model could be used in order to promote individual and social learning [10], [11], [12], [35], [47], [56]. Thus, a challenging target for both the areas of Open Learner Modeling and Interaction Analysis is the production of meaningful externalizations of learners' interaction behavior allowing different stakeholders such as learners, peers, instructors to 'explore' the learning process from their own perspective [14], [15], [56].

The task of collecting data in a web-based adaptive learning environment that correctly and accurately represents learners' interaction with the system and storing them in a well-defined and expandable database format is not as straightforward as it might seem at first, for various technical and non-technical reasons [1], [9]. Moreover, interpreting and visualizing learners' interaction raw data in meaningful and useful ways is another area of research, with great potential regarding the impact these methods can have on understanding learning processes and behavior patterns [20], [6], [4], [33]. Especially in a hypermedia learning environment, a main issue is that learners make explicit decisions repeatedly during interaction that usually results in complex interaction protocols. These protocols refer to the series of events, which occur during hypermedia usage, with corresponding time stamps [16]. However, collecting learners' actions is the first step for re-constructing a view of learners' activity able to promote learners' reflection on their explorations. Then, heterogeneous data included in interaction protocols must be carefully chosen and handled in order to yield meaningful information and build a thorough view of learners' activity. To this end, contextual data about the content, available tools and learning design issues of the learning environment is necessary. Finally, this information may be used or analyzed with different purposes depending on the context and the

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end user. For learners, it may be useful to compare their state with an 'ideal' model proposed by the instructor or an 'actual' model of interaction coming from individual peers or their group in order to detect possible mismatches that can promote reflection on their learning process. For tutors, it may be useful to have access to learners' interaction behavior in order to get insight into the learner's state and be able to intervene accordingly. For an adaptive system the whole procedure may result in a set of recommendations or corrective actions which could support learners in reaching the desired state.

It is important that interpretative views of learners' interaction produced by system designers and their expressive power of learners' cognitive processes be evaluated by the learners themselves [49], [50]. Learners' personal views on their interaction patterns or those of their peers will prove what these patterns actually reveal. Opening the learner model is the first step to this end. Then, learners should be prompt to offer their own interpretations, additional or corrective information, leading to a more precise adaptive interaction [11], [46]. In this context, it is worthwhile to further investigate (a) how learners' interaction behavior could be tracked, interpreted and visualized to provide a comprehensive view of their cognitive activity, meaningful for different types of users or uses depending on the type of learning environment or the task, and then (b) how users interpret visualizations of their learning experience.

In this paper we propose an approach to constructing interpretative views of learners' interaction behavior in a hypermedia learning environment. The way learners use and mainly interpret these visualizations is investigated. The paper is structured as follows. The literature review section presents the scope of using interaction data from three different types of learning environments. In the next section, an approach to modeling and visualizing interaction data is proposed. In Section 4, the application of the approach in the adaptive educational hypermedia system INSPIRE*us* is analyzed. Section 5 presents an empirical study investigating how students interpret views of their interaction data. The paper ends with discussion of the study results and future plans.

2 Literature Review

Different types of learning environments that keep track of interaction data, such as course management systems, computer supported collaborative learning systems, intelligent and adaptive learning environments, usually process them in order to diagnose learners' characteristics and accordingly adapt the interaction, or provide evidence of their individual/social characteristics. In some cases, they interpret interaction data providing visualizations of actual learners' interaction behavior aiming to prompt them to reflect on their actions or tutors to monitor this behavior. In this section, we discuss representative paradigms of systems and tools that exploit interaction data in multiple ways focusing on learners' interaction with the content or on social interaction.

In the area of course management systems, visualisation techniques have been adopted to analyze learners' interaction behaviour aiming to support learners and/or instructors in monitoring the learning process and gaining an understanding of their learners [5], [6], [7], [13], [19], [20]. For example, CourseVis [6] use web log data from online course management systems to visualize interaction in discussions, quiz performance and page access. By using such tools, teachers could get a view of students' work more quickly. Moodog [19] is a Moodle plugin that extends the Moodle log facility by visualizing data from the activity logs to allow students to compare their progress to others and teachers to get insight into the student interactions with the online course. It provides aggregated and meaningful statistical reports, showing the number of unique users, view counts and popularity of resources. SAM (Student Activity Meter) [13] is a tool that captures the interactions of users with resources and tools and provides simple metrics, statistics and visualizations of learners' activities, using similar to Moodog metrics but not committed to one learning platform. GISMO—Graphical Interactive Student Monitoring System—[20] provides graphical representations of data collected from real courses reflecting student attendance, access to resources, overview of discussions, and results on assignments and quizzes, i.e. information interesting to instructors.

In the area of computer supported collaborative learning (CSCL), several studies have explored the issue of analyzing learners' interaction in a social context to assess group/individual performance and collaboration dynamics more objectively [21], [3], [4], [23]. Several systems that externalize these data to learners in multiple ways in order to promote learning and enhance participation and collaborative skills such as Participation Tool [22], DIAS [24], team.sPace [15], [25], COMTELLA [26], CoolModes [27], i-bee [28], ACT [29] have also been reported. For example, the Participation Tool visualizes students' contribution to their group's online communication aiming to promote group awareness. Each student is represented by a sphere and group members' spheres are grouped together. i-Bee uses the analogy of flowers and bees to visualize relationships between users and keywords in online discussions. It represents several discussion indicators, such as keyword usage frequency and recent user activity, through the distance between flowers and bees, their status such as flying or sleeping bee, blossomed or closed flower, and their orientation. Although the context and the study objectives of collaborative learning systems are quite different compared to intelligent and adaptive learning environments, research studies in this area could be used as valuable resources for modeling and visualizing learners' interaction. Useful approaches that have been proposed on how interaction behavior might be used to support interaction and collaboration, are the following [30]: (a) reflecting learners' actions by collecting raw data and displaying it to the collaborators, (b) monitoring the state of interaction by aggregating the interaction data into a set of high-level indicators or by comparing the current state of interaction to a model of ideal interaction enabling learners to self-diagnose the interaction, (c) analyzing the state of collaboration using a model of interaction, and offer advice.

Learners' interaction data are usually processed by adaptive learning environments in order to built the knowledge state or navigation paths of learners and accordingly provide guidance in the form of graphical annotations, or communicate it to learners through appropriate visualizations included in an open learner or group or social model such as ELM-ART [31], KnowledgeTree [32], ViSMod [33], Flexi-OLM [34], MyProject [54], JavaGuide [55], Progressor [35]. For example, ELM-ART and KnowledgeTree maintain data about learners' interaction with the system and externalize information, in a text-based form, about the learning resources and various tools that they worked with, such as time of access, learning activity, activity ID, visited pages, learning time, results. ViSMod is an interactive visualization tool for the representation of Bayesian learner models. ViSMod uses various visualization techniques such as color, size proximity link thickness, and animation, in order to represent the overall belief of a student knowing a particular concept taking into account the student's opinion, the instructor's opinion, and the influence of social aspects of learning on each concept. Flexi-OLM also provides multiple representations of learners' knowledge based on Felder and Silverman's style categorization. Learners' understanding of each topic and misconceptions on specific topics are illustrated through appropriate coloring of nodes. An interesting direction on the crossroads of adaptive learning environments and social learning is the adaptive social navigation support as implemented by Progressor. Progressor allows learners to share their navigation and progress data through a tabular interface that accommodates a sizable collection of content augmented with appropriate graphical annotations. In the line of sharing personal data among peers, the UMPTEEN approach [56] investigates students' views about opening their learner model more widely as well as how they use their own and peer models.

In the above studies, aspects of learners' interaction behavior with the content are externalized in a text-based or graphical form illustrating their knowledge state and/or navigation at individual or social level allowing learners to reflect on their own data and on specific occasions compare them with those of their peers. In this paper, we build on the above studies in order to further exploit learners' observable behavior and construct interpretative views of their cognitive activity as it unfolds. To this end, a qualitative description of the interaction that could provide meaning to specific learner's actions with the educational content and system functions is proposed.

3 Proposing a Modelling Approach for Learners' Interaction Behaviour

Adaptive Educational Hypermedia Systems (AEHSs) usually track learners' interaction and content usage in order to dynamically adapt the content presentation, topic sequencing, navigation or collaboration support. Interaction data may also be carefully handled in order to yield meaningful views of learners' strategies. In this process, key issues are the selection of the appropriate data, their interpretation, and the way this info is conveyed to the learner. The task of interpretation demands the construction of a model of the interaction, which is instantiated to represent the current state of interaction, and possibly the desired state [3], [30]. In [36], several purposes for user modeling are considered in I-Help, such as user modeling for locating appropriate resources, for facilitating interpersonal and inter-agent communication, for involving users in learning about themselves and other users through reflection, validation, assessment and diagnosis. In our case, the current purpose of the interaction modeling approach is to support learners' reflection and help them learn about themselves and other peers. It is then up to the learner to further elaborate on the visualization and decide what action (if any) to take.

Our proposal for designing interpretative views of learners' interaction behavior in an AEHS combines and expands ideas coming from the areas of hypermedia learning [16], open learner modeling [11], [10], [47], and interaction analysis [3], [30], [37]. The learning analytics process as described in [37] is represented as an iterative cycle carried out in three steps: data collection and pre-processing, analytics and action, and post-processing. Post-processing relates to the continuous improvement of the analytics, which is out of the scope of this paper. Following the first two steps, we initially collect appropriate data from learners' interaction with the content and system tools/modules at various levels of granularity (Phase 1: Data collection and Data pre-processing). Then, we transform data into suitable format producing several indicators of learners' cognitive and social activity (Phase 2: Analytics and Action).

The process of modeling learners' interaction has the double aim of providing a mirror of the learner's actions augmented in some cases with the desired state of interaction. Another possibility, not examined in this paper, is the system-generated recommendations whenever a perturbation arises for example among the actual and desired state of interaction or in cases of failure. In more detail, the process of modeling learners' interaction is deployed at the following phases:

Phase 1—Data collection and pre-processing. The data collection phase involves observing and recording the interaction. Important decisions when analyzing data coming from interaction with a hypermedia environment are the selection of appropriate *type of data*, as well as the definition of the appropriate *observation grain*, i.e. the precision of the events considered as units in the analysis [16].

Regarding the *type of data*, it concerns (a) data collected from learners' interaction with the content and system tools at various grains, as well as (b) variables reflecting the learning design of the environment, putting learners' interaction in context. Following [1], specific data that are available for mining in the educational area have intrinsic semantic information, relationships with other data, and multiple levels of meaningful hierarchy such as the domain model. Furthermore, it is also necessary to take into account the pedagogical aspects of the learner and the system, making interaction data valuable for extending the learner model.

In particular, *data* coming from learners' interaction are navigational and temporal data such as visits on various types of resources, sequence of resources, time spent on resources, actions performed with available tools, as well as performance data such as type of assessment, attempts on various types of self-assessment questions, performance, and progress. However, concerning temporal data, long time intervals or too short ones should be eliminated in an attempt to deal with the problem of time when working with digital learning environments where it is difficult to identify what the learners actually do. *Variables* related to the learning design of the environment such as pedagogical characteristics of the content and the available tools are considered as context variables that affect learners' behavior in a particular environment with specific affordances.

The *observation grain* relates to the events that are selected to be analyzed, ranging from global activity patterns (coarse grain) to specific aspects of the interaction (intermediate or fine grain) [16]. This relates to the principle of 'overview, zoom and filter, details on demand' proposed by Shneiderman [52] since the various grains can be considered as overview and zoom levels. Specifically, at the *coarse grain*, the activity is considered as a whole, providing the overview that reflects global features of learners' work. Large sequences of actions are taken as data units, whilst events that may have occurred within each sequence are not considered. For instance, the total time taken to perform a task may be considered as an indicator of task difficulty. The sequence of units visited during a session of hypermedia navigation can also be divided into coarse segments, i.e. areas of application like a set of particular pages as opposed to each individual page. At the fine grain level, each event recorded during the interaction will be considered, whilst at the intermediate level only some significant events are considered, both constituting different zoom levels [52]. At the *intermediate level*, critical events of interest may be selected within the interaction protocol making appropriate computations such as total time spent on specific resources or frequency of visits of particular tools. This level is useful when testing specific hypotheses about the cognitive processes at work during interaction. For instance, moves from one particular node to another can be considered, regardless of what happens in each node. An important feature of the intermediate grain is that it allows the researcher to summarize information as a set of numerical parameters like the number of times learners accessed the learner model or a node with particular characteristics.

Lastly, at the *fine grain* level, all the observable actions are taken into account. At this level the complete sequence of events included in raw interaction protocols is analyzed. In this case, the researcher focuses on meaningful patterns, in order to achieve a global understanding of learners' activity.

Phase 2—Analytics and action. Analytics and action phase includes analysis and visualization of information as well as actions on that information focusing, in our case, on monitoring and reflection [37]. The approach adopted at this phase is mainly inspired by the collaboration management cycle as described in [30]. At this phase we aggregate the interaction data into a set of high-level indicators. These indicators combine one or more types of interaction data with learning design variables aiming to put learners' actions in context. Important design decisions at this phase are the type of indicators (such as cognitive, social), their contents (data and observation grain) and scope, the focus of the visualization, the mode of use (static, adaptable) and intended users.

Interaction analysis indicators, in our case, describe aspects of learners' interaction related to the domain model or the process or the quality of the learning activity (task related process) [3] reflecting the current state of interaction. The indicators proposed at this phase are *cognitive* and *social purpose indicators*. The *cognitive purpose indicators* reflect cognitive engagement that concerns the actions of the individuals in the learning environment referring to the process or the product of their activities [3]. In particular, these indicators reflect the mode or quality of learners' individual activity with content of a particular pedagogical profile related to specific outcomes, the type of messages that they exchange with peers, as well as their individual activity with various types of tools, supportive aids (notes, interaction data), and learner control opportunities provided by the system (open learner model, adaptive controls). Learners' interaction with the particular indicators is expected to cultivate metacognitive skills such as self- and task- knowledge, strategic knowledge and knowledge of plans and goals [39], [40]. To this end, they should be designed to assist learners in recognising their preferences / strengths / weaknesses and evaluating themselves (self-knowledge), understanding the demands of tasks and what they require (task-knowledge), setting and maintaining goals and recording what they intend to do through their learning (knowledge of plans & goals), but also assessing the usefulness of their strategies for achieving specific outcomes (strategic knowledge). The *social purpose indicators* reflect various aspects of social behavior in the learning environment that refer to communication, cooperation or collaboration of individuals as members of groups or communities [3]. They may reflect the level of forum participation, the use of sharing opportunities of their learner model and/or notes and/or forum discussions.

Regarding the *contents* of indicators, these may be simply one type of data or combinations of various types of data such as navigational and temporal data along with learning design variables. A critical issue here is the definition of the appropriate observation grain which can be linked with different purposes and metacognitive activities. The *scope* of the indicators may vary from an overview of learners' work or a more detailed observation of their work on particular tasks to a deeper view of the way learners use the resources for achieving specific outcomes. *Visualisations* of the above data may focus on a learner's interaction or on comparative information coming from tutors or peers to support monitoring and reflection. For example, it may represent the navigational path of a learner or augment the navigational path with temporal data reflecting time spent on various steps, or combine a learner's temporal (time spent on resources), navigational (number of visits) and performance data with a 'desired' state of interaction coming from peers or the tutor. Such a 'desired' state may be the pedagogical duration proposed by the tutor [45], [53] or the mean time spent on specific resources by selected peers. Visualisations may be static allowing learners to inspect the indicators or adaptable allowing learners to intervene and select options such as the observation grain or features of the 'desired' state e.g. choice with whom to compare.

The system can further analyze the above data taking into account the learners' current state, their individual characteristics and the contextual variables influencing their actions, in order to advise the learner how to proceed or propose appropriate peers. This analysis of learners' actions is based on their interaction with the resources and tools in the current context at multiple observation grains. For example, information about the type of educational resources that the learner selects, combined with learners' progress and/or learning style, provides an indication of their preferences for educational resources. Thus, in case of low performance the system may recommend another route in the content based on the desired interaction model or on a 'real' interaction model coming from peers with specific characteristics like those having high performance and similar style.

The main idea behind such an interaction modeling approach is to (*i*) enable mirroring of learners' interaction and cultivate metacognition, (*ii*) support the provision of meaningful recommendations to learners, (*iii*) guide system adaptive behavior in case of an agreement between the learner and the system, (iv) provide tools for tutors to evaluate students' work and the content.

4 The Case of INSPIRE*us*

INSPIRE [41] is an adaptive educational hypermedia environment that allows learners to freely explore the content offering them individual advice. INSPIRE provides adaptive support based on learners' individual characteristics by: (a) structuring the content around specific outcomes augmented with visual cues that inform learners about the content that they are ready to study based on their knowledge level (adaptive navigation technique), (b) providing individualized versions of the educational material pages with alternative sequencing of the modules involved based on instructional strategies that suit learners' learning style preferences as proposed by Honey and Mumford (adaptive presentation technique).

INSPIRE*us* is the latest version of INSPIRE, extended with collaborative functionalities and a flexible authoring process that allows users to reflect their pedagogical perspective on content development. In INSPIRE*us* users comprise an online community, having one or more roles with different rights, such as learners, tutors, authors, reviewers. Learners can enroll in specific virtual classes, attend online lessons at their pace, personalize the interaction, view interaction data, participate in groups, communicate and share their notes and/or discussions and/or model with their group or class. When students communicate through a forum, they can characterize the messages they exchange as well as their peers' posts as a way to better communicate their ideas. The characterizations are taken from a list based on the interaction analysis model of [42], which examines the social construction of knowledge in computer conferencing.

A main challenge for the new version of INSPIRE*us* is the visualization of interaction analysis in a meaningful way for learners and tutors. In this paper we elaborate on the new type of support provided by INSPIRE*us* through modeling the learners' interaction and visualizing this information in a meaningful way. By opening this info to learners we extend the opportunities of interaction with the learner model aiming to cultivate metacognition [12], [38], [39], [40].

4.1 Modeling the Content

INSPIRE*us* provides learners with structured *content*, as in the previous version, which is comprised of units, such as scenarios, concepts and educational material modules that can be reused by learners of different profiles. The notion of *educational scenarios* is used to underline a learner-centred content design approach. In particular, each scenario is associated with a conceptual structure that includes all the necessary domain concepts and their relationships—outcomes, prerequisites, related concepts- providing learners with an overview of how all the relevant information fits together. This structure is provided in a hypermedia form to enable the learners to freely navigate and to use the content in accomplishing the role(s) they undertake in the context of the scenario. In this new version, the educational material pages of each concept may consist of a variety of content modules according to the learning design adopted.

The design of scenarios is activity-oriented aiming to encourage learners to use tools, generate and test hypothesis in real contexts, solve open problems, explore alternative perspectives, work individually or in groups. To this end, different types of content modules such as examples, exercises, triggering or assessment questions, theoretical tips, activities, can be combined in educational material pages of various categories according to the learning design prototype proposed by the system or created by the content author. Authors are encouraged to develop content of high interactivity incorporating simulations located on the Internet, video, communication tools, and Web 2.0 tools. For example, in Fig. 1 the educational material page 'Decimal—Binary Numbering Systems' of the concept 'Computer memory organisation' (scenario 'How is data represented inside the computer?') that promotes conceptualisation and application of the particular numbering systems appears at the Content Area. The particular page consists of several modules, most appearing as links and only one being fully opened, i.e. links to an activity, an example, theoretical issues, and an exercise, and the module fully appearing is a theoretical presentation about decimal binary, octal and hexadecimal number systems which provides the necessary information through a video and prompts students to watch it and then share ideas in the forum.

Authors are allowed to select or create learning design prototypes reflecting their own pedagogical perspective. They can propose specific categories of educational material pages that comprise appropriate modules and focus on specific learning outcomes according to the learning theory they adopt. They can also propose an adaptation algorithm linked with learners' individual characteristics.

Learning design prototypes already incorporated in the system have been inspired by the inquiry based learning and the 'New Learning' model. These prototypes propose the development of various types of educational material pages that promote specific outcomes or knowledge processes. For instance, the inquiry based learning model is organized in four phases [43]. Each phase or their combinations have inspired the design of specific categories of educational material pages. The theory of 'New Learning' introduces eight 'knowledge processes' (i.e. forms of action inspiring various types of activities), each one representing a different way of making knowledge [44]: (i) Experiencing the known and the new, (ii) Conceptualizing by naming or with theory, (iii) Analyzing functionally or critically, (iv) Applying appropriately or creatively. Learning design prototypes that are based on 'New Learning' consist of

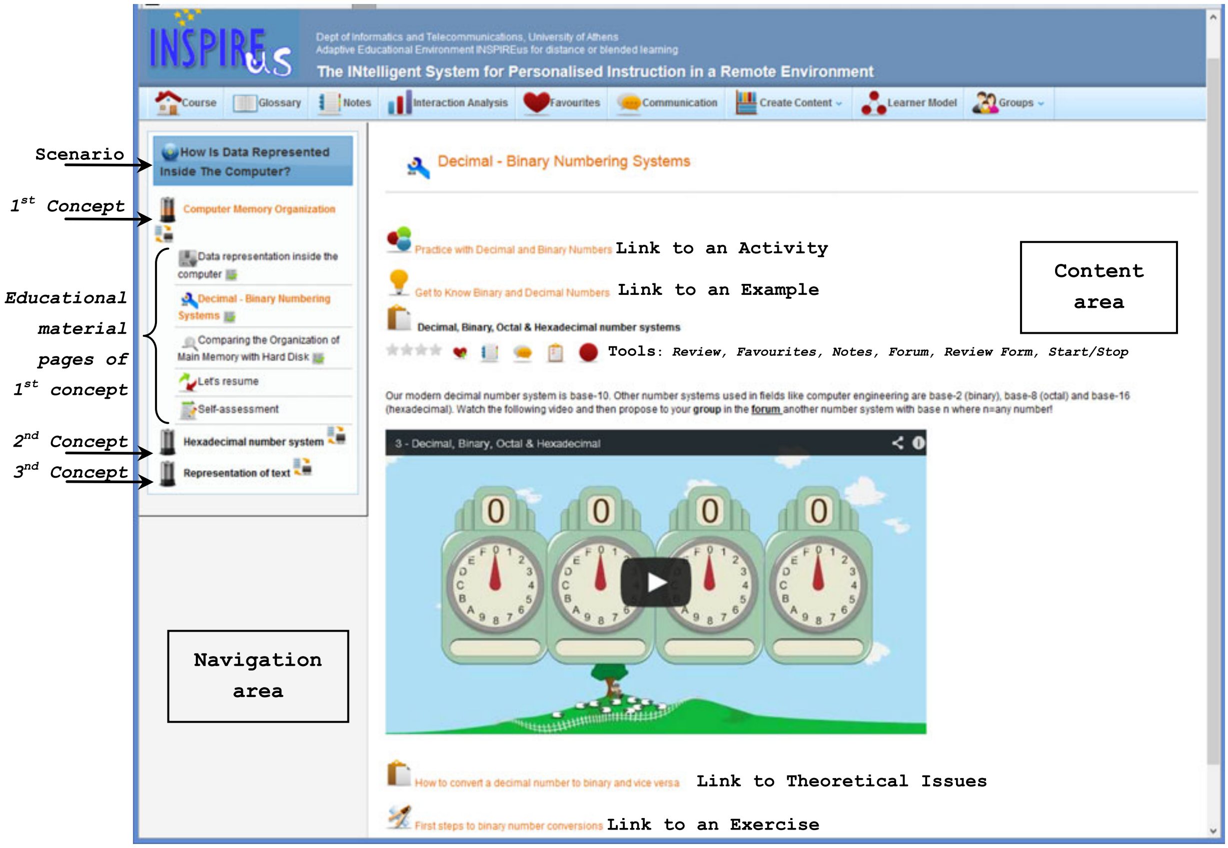

Fig. 1. The educational material page ‘Decimal—Binary Numbering Systems’ appears at the ‘Content area’ of INSPIRE*us* consisting of multiple types of modules: links to an Activity and Example, Theoretical issues that embed a video (this module appears open as it is currently being selected by the user), link to theoretical issues and an exercise. Each open module has its own toolbar (‘Tools’) with the ‘Start/Stop’ button allowing learners to declare ‘idle’ time.

specific categories of educational material pages that stimulate a particular knowledge process or combinations of processes.

4.2 Producing Interpretative Views of Learners’ Interaction Behavior

INSPIRE*us* gathers data from learners’ interaction and visualizes them augmented with contextual information, in order to support learners in gathering evidence and evaluating the efficacy of their moves. Key issues in this process are the selection of the appropriate data (learners’ actions and contextual information) and the production of interpretative views along with a meaningful way of conveying them to the learner. To this end, the approach described in Section 3 has been adopted.

Data collection and pre-processing. A combination of fine, intermediate and coarse observation grain data has been considered in INSPIRE*us*, to construct meaningful views of learners’ interaction with the system. These data range from global activity patterns at scenario and concept level (*coarse grain*), and specific aspects of the interaction with resources of particular type (*intermediate grain*), to all the observable actions where the analysis focuses on meaningful patterns at content page level (*fine grain*). In particular, *navigational data* such as number of hits, frequency of visits reflecting resources (content and tools) usage, *temporal data* such as time spent on various types of resources—cases of very short and long intervals in learners’ work are eliminated—and *performance data* such as type of assessment, attempts on assessment questions, performance on various types of questions, are recorded and calculated at scenario, concept and page level.

Aiming to set the data recorded from learners’ interaction behaviour (navigational, temporal, performance data) in context, specific variables reflecting the learning design of the environment are also considered. These variables are used to augment the data visualisation. Currently as such variables are considered:

- pedagogical characteristics of the *content* such as the pedagogical duration, type, learning outcomes in terms of knowledge process/level of performance/phase of inquiry according to the learning design prototype adopted,
- type of available *tools* providing learners with (a) controls over the learning and adaptation process such as the open learner model, adaptation controls, (b) social opportunities such as forums, sharing notes and learner models, (c) reflection opportunities like note keeping tool, interaction analysis data.

The two types of variables are considered valuable for tracking learners’ behaviour and building the individual and desired model of interaction. At a next phase, *learners’ characteristics* such as learning style, knowledge level (as this is defined by the learning design prototype) and social

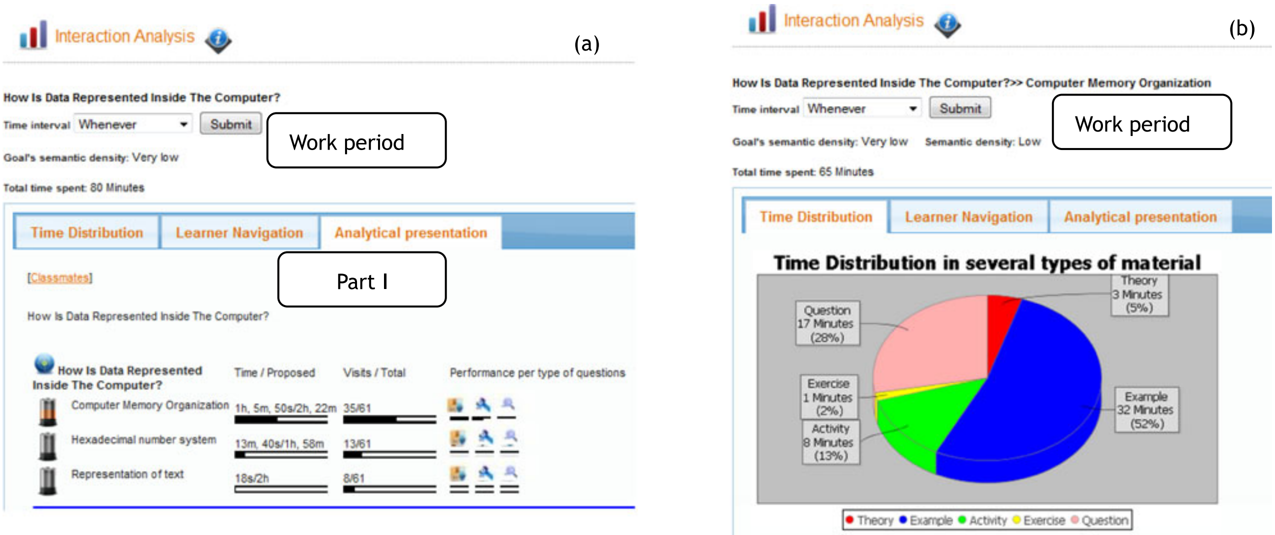

Fig. 2. *Indicator of learners' effort* mirrors learners' *engagement:* (a) illustrates *learners' effort* at scenario level for a particular work period ('Work period') at coarse grain providing temporal, navigational, and performance data (Part I) about the three concepts of the scenario "How is data represented inside the computer?", (b) illustrates how the learner has distributed his/her time on the concept 'Computer and memory organisation' among modules of various types.

interaction data can be used to assess the interaction effectiveness and to guide system recommendations.

Analytics and action. A set of cognitive and social purpose indicators has been created. In this paper, we focus on indicators that reflect cognitive engagement by representing data that concern (a) learners' interaction with the content and system affordances such as opportunities for learner control and (b) individual contributions in social knowledge construction at various observation grains. Currently, the *indicators* computed and visualized are:

a) *indicator of learners' effort* that reflects the learners' engagement with the particular scenario. This is visualized through the 'analytical presentation' of Fig. 2a that illustrates navigational and temporal interaction data at coarse grain (scenario level) along with performance data based on the learning design prototype adopted for the particular scenario. This visualisation provides an overview of learners' activity with the domain concepts of the scenario 'How is data represented inside the computer?'. In particular, information illustrated on the top of Fig. 2a (see 'Work period') represents the total period of interaction with the content of the scenario (work period is selected by the learner from a list where s/he can select a particular period, or the total period working with the scenario named 'Whenever'). Then, in Part I of Fig. 2a, learners' activity with the content of the domain concepts (i.e. 'Computer memory organisation', 'Hexadecimal number system', 'Representation of text') is depicted. For each concept, we provide: (a) the time spent by the learner along with the pedagogical duration of the resource (see 'Time/Proposed' column), (b) learners' visits along with total number of hits on the content (see 'Visits/Total' column), (c) level of performance on various types of questions (see 'Performance per type of questions' column) where each type of questions corresponds to a page category of the scenario aiming to provide progress data according to the learning design prototype of the content. Another visualization that reflects the particular indicator at intermediate grain is the pie chart (see Fig. 2b). It presents how learners' time is distributed across modules of various types at two segments, concept or a single page. The particular visualization is adaptable to the location from which the learner accesses it, depending on whether the learner is on the first page of a concept or any other page of a concept. In the first case, total data about the learner's interaction with all the content of the concept are visualized.

b) *indicator of learners' progress* that reflects the mode or quality of learners' individual activity at intermediate grain with content of particular pedagogical 'profile' reflecting also the learning outcomes that students have to attain. To this end, navigational and temporal interaction data on resources of specific type like the various page categories (introductory pages, pages covering specific types of outcomes based on the learning design prototype, self-assessment pages, recall pages) and the various types of material (activities, examples, exercises, questions, theory) at scenario or concept level are illustrated along with performance data. For instance, information illustrated on Fig. 3 reflects learners' activity with various types of content at concept level. In particular, in Part I interaction data with each of the pages of the concept 'Computer Memory Organisation' are illustrated. Then in Part II, interaction data are added up for each category of educational material pages (Recall, Assessment, Category A, Category B, Category C) illustrating (a) the time spent along with the pedagogical duration of all the resources of each particular category (see Fig. 3—Part II 'Time/Proposed' column) and (b) visits along with total number of learners' visits on the content of

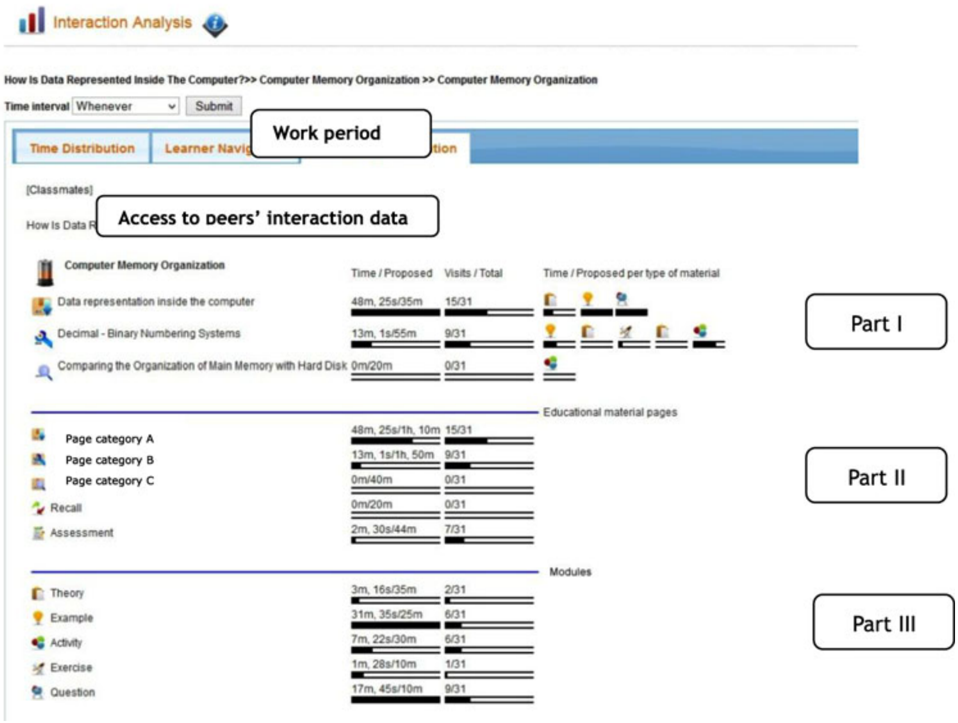

Fig. 3: *Indicator of learners' progress* mirrors learners' work with particular types of content at intermediate grain for a particular work period (see 'Work period') depicting their activity with various categories of content pages (Part II) and particular types of modules (Part III) for the 'Computer Memory Organisation' concept.

the particular concept (see Fig. 3—Part II 'Visits/Total' column). Moreover, in Part III, temporal and navigational data are provided for each type of *content modules* included in the educational material pages of the concept like activities, examples, exercises, theory and questions (see Fig. 3, Part III 'Time/Proposed' and 'Visits/Total' columns). The particular visualisation is adaptable allowing learners to select the working period, with whom to compare (tutors or selected peers), as well as if the visualisation will reflect their interaction behaviour at scenario or concept level based on their location when they visit interaction analysis data. So, if learners are on the first page of the scenario, then the visualisation will reflect their interaction at scenario level providing data for each concept of the scenario, and the various page categories of all the concepts of the scenario. Accordingly, if they are on the first page of a concept, like in Fig. 3, the visualisation will reflect their interaction at concept level.

c) *indicator of learners' working style* that reflects learners' strategies while working with content of particular pedagogical 'profile' related to specific outcomes at fine grain. The 'learner navigation' representation visualizes the learners' navigation path on content pages and particularly the sequence of learners' visits on various types of modules (activities, examples, exercises, questions, theory) at a fine grain by recording every visit and its duration at page level. In Fig. 4 the navigation history of two students in a particular content page that contains a question, an example and an exercise is depicted. Both students spent time on all the available resources, although Student A seems more concentrated on the question, whilst Student B seems to prepare himself before visiting and probably answering the question. Lastly, in Fig. 4, by combining information from two representations (learner navigation and time distribution—pie chart) for a particular student such as Student B, we can also have a view of how a learner distributes her time to various types of resources.

d) *indicator of learner control* that reflects learners' individual activity with specific system tools that allow learners to personalise the interaction at three coarse segments (i.e. scenario, concept, page), through the particular actions (view/update) they performed with their learner model, the note keeping tool and the various interaction data visualizations.

e) *indicator of learners' contribution in social knowledge construction* reflecting the type of messages that the learner exchanges with peers at forum level. The particular indicator focuses on individual contributions. It can be adapted to a single forum of a module selected by the learner, or to all the forums of a page, concept or scenario.

All the above indicators can be used by individual learners, groups, and tutors. Learners are allowed to share interaction data with peers (at group and/or class level) so as to compare themselves to others (see on the top of Fig. 3, Access to peers' interaction data). Such information coming from peers can also give them new ideas and encourage deeper thought about the implications of their own strategies or support them find appropriate peers when seeking for help. It may also support tutors in acquiring an image of the learners' activity, progress and needs as well as in

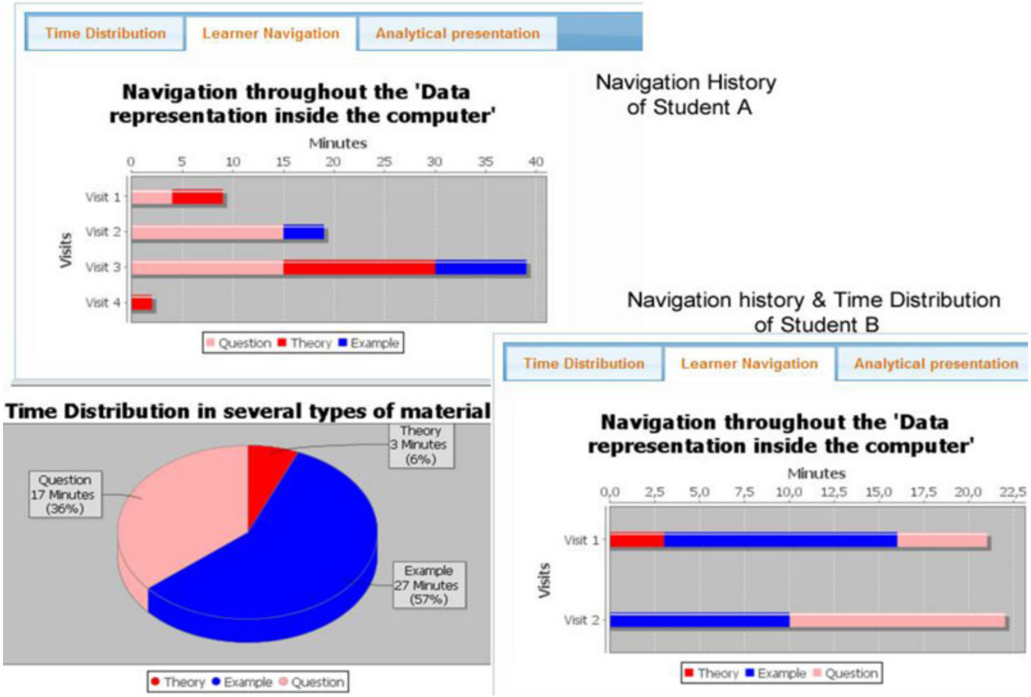

Fig. 4. *Indicator of learners' working style* mirrors learners' activity on the page "Data representation inside the computer" at fine grain providing data about the sequencing of learners' visits and their duration on particular type of modules illustrated through various colours i.e. red for theory, blue for examples, pink for questions. At this illustration the navigation history of Student A and the navigation history and time distribution (pie chart) to various types of resources of Student B appear.

evaluating the resources offered to learners with particular profiles. To this end learners' self reports would be also valuable since many visits on particular content may reflect a preference for that content but also difficulty to deal with the particular task (this is also supported by the results of the study presented in Section 5).

5 Empirical Study

The empirical study aimed at investigating how students interpret specific visualizations of their interaction behavior provided by INSPIRE*us*. This study was conducted in the context of a technology enhanced learning course, offered to graduates of a variety of disciplines that attend the one-year postgraduate certificate in education of the School of Pedagogical and Technological Education (ASPETE). One class of 50 students participated in the study. The study focused on the following research questions:

- How do students interpret visualizations of their interaction behavior?
- Which evaluation criteria do learners use for selecting collaborators based on their interaction data?

5.1 Procedure

Students had to follow a structured usage protocol in order to work with the main functionalities of INSPIRE*us*, the learning design of the environment, the educational material structure and contents, and specific indicators. Appropriate guidelines and open questions were included in a worksheet, leading students to work individually with the first concept of a scenario, visit specific indicators and try to interpret them, then perform a collaborative task, working in groups of three or two (only two groups of two were formed). The groups of students had to select between two scenarios, both of which were based on the same learning design. They had two weeks to perform the tasks asynchronously, complete and submit the worksheet. Group work was organized and scheduled mainly by the members of each group whilst group collaboration was done through the forum of INSPIRE*us* or other communication tools selected by the group like Skype or email. The first time they logged on INSPIRE*us*, they submitted the questionnaire of Honey and Mumford in order for the system to automatically identify their learning style. During the interaction, they were allowed to change it manually through the learner model. Finally, students were asked to answer an evaluation questionnaire with closed questions (see Appendix A), in order to reflect on and evaluate their learning experience.

5.2 Data Collection and Tools

The data collected were the students' worksheets, log data and questionnaires.

Worksheet. The worksheet included guidelines recommending specific content to study and indicators (called visualizations in the worksheet) to reflect on. Throughout the guidelines, open questions were introduced asking students to visit interaction analysis data and interpret the particular visualizations. The structure of the worksheet is presented in Table 1.

Questionnaire. The questionnaire included open and close ended questions, and it was structured in two Sections, each one having a different focus (see Appendix A where the question appears at the first column, the number of students that answered 'Yes'/'No' at the second/third columns, percentage of positive answers at the forth column):

TABLE 1
Interaction Protocol for Evaluating Visualizations

Indicator of learners' effort. Guideline 1 (G1): Study the first page of category A of the first concept of the scenario. Question 1 (Q1): Estimate how much time you devoted to the various types of modules. G2: Visit the 'pie chart' visualization and observe which type of module you spent more and less time on. G3: Study the second page of category B of the first concept. G4: Submit the assessment test of the concept and study the summary. G5: Visit the 'pie chart' visualization and observe which type of modules you spent more and less time on.
Indicator of learners' working style. G6: Check your navigation history visualization for the first concept, observe the sequence you followed through the various types of content. Q2: Interpret the strategy you followed while studying.
Indicator of learners' progress. G7: Check the analytical presentation of the first concept and record the time that you spent along with the pedagogical duration, and the number of your visits, at (a) the various types of modules, (b) each page category related to specific knowledge processes. Q3: Write your reflections and try to interpret the way you worked. Q4: Guess your next movement based on this data.

- Part A stimulated learners to interpret aspects of their interaction behavior represented in the indicators.
- Part B aims at eliciting if students would share their interaction behavior data and how they would use their peers' data in order to select collaborators.

5.3 Data Analysis and Results

Data gathered were 44 completed worksheets, log data of these 44 students, and their evaluation questionnaires. Six out of 50 students did not manage to complete the worksheet mainly due to their own time restrictions. Based on demographic data, fifteen men and twenty-nine women participated in the study. Nine had a strong preference for the 'activist' learning style, ten for the 'theorist' style, twenty-three for the 'reflector' style, and two for the 'pragmatist' style. Based on log data, two activists changed their style during the interaction as they thought that the instructional strategy adopted for presenting the content didn't suit their preferences.

- *How do students interpret visualizations of their interaction behavior?*

Students' answers to the worksheets and questionnaires were collected and categorized. The analysis focused on the expressiveness of the interaction analysis indicators based on the students' self reports coming from their own answers to similar questions from the worksheet and the questionnaire, and combining them with real log data. We also investigated their self reports gathering evidence for the metacognitive skills cultivated. Below data analysis is presented about each of the various indicators following the structure of the interaction protocol of Table 1.

Since the *indicator of learners' effort* reflects learners' engagement with the content focusing on the time that the learner devotes to various types of resources, in the analysis process we cross-check students' perceptions about the time they spent on resources with actual log data as well as with their interpretations of the correlation of time with their way of studying. Thus, by comparing students' answers to the *first question* of the worksheet (see Table 1, Q1) to their log data reflected on the pie chart of the indicator (see Table 1, G2 and Fig. 2b), we conclude that 20.5 percent of the students had a different impression compared to the actual one depicted on the pie chart (another 20.5 percent had a small declination whilst the 59 percent just copied the pie chart). This provides evidence for the potential of the particular representation of the *indicator of learners' effort* to increase students' *self-knowledge and support self-monitoring*. The first two questions of the evaluation questionnaire provide more evidence in this direction. Both questions aim at eliciting students' interpretation of time. In Question 1 of the evaluation questionnaire appearing in Appendix A (*study time of content*), most students suppose that when they spend short/long time on studying specific content, this behavior reflects how easy/difficult the particular content is for them as well as their effort to study, whilst 25 percent of the students don't seem to be concerned about time. Especially, 59 percent of the students link long study time with hard study. In Question 2 of the evaluation questionnaire appearing in Appendix A (*study time of content of particular type*), 77 percent of the students relate again (as in Question 1) their study time to the difficulty of the tasks they work with, whilst half of the students (50 percent) suppose that the time they spend on content of specific type reflects their preferences for the particular type of content. However, 39 percent of the students seem not to be interested in the time.

Since the *indicator of learners' working style* focuses on the learners' navigation through the resources, students' own interpretations about the strategies they adopt were considered important. Students were asked to study particular content, and then to try to interpret their interaction data (see Table 1, G6 and Fig. 4). By analyzing students' reflections to the *second question* of the worksheet (see Table 1, Q2) we observe that most students interpret the sequence they follow based on their style characteristics although they weren't asked to. It is encouraging that all the students understand the visualizations. In particular, we distinguish four categories of answers: (a) descriptions of the sequence they followed without interpretations of their selections (5 students - 11.4 percent), (b) reflections on their preferred style of studying which is in accordance with the system proposal ("I need to fully understand the theory/examples and then go into action") (31 students - 70.5 percent), (c) reflections on the type of the content they worked mainly with and the knowledge processes they intended to develop (e.g. "I focused on application and analysis of concepts in order to accomplish the task") or their needs ignoring the system proposal which is based on their style characteristics (e.g. "I tried to do the activity but I needed more information so I moved on to theory") (8 students—18.2 percent). What is obvious in students' reflections is the increased *self-knowledge,* as learners seem to recognise and comment on

TABLE 2
Students' Interpretations and Plans Inspired by the Indicator of Learners' Progress

Study time vs Pedag. duration	Interpretation	Next movement
Students that spend less time than the proposed one: 18.2% (8 out of 44)	*No comments*: 1 *Doubt about data accuracy*: 4 *Strategy adopted (style)*: 3	*No comments*: 3 *Plan next steps focusing on type of material*: 5
Students that spend more time than the proposed one: 56.8% (22 out of 44)	*No comments*: 3 *Lack of familiarity with INSPIREus*: 9 *Strategy adopted (style, deep study, difficulties)*: 13	*Time restrictions*: 2 *No comments*: 3 *Focus on time improvement*: 2 *Plan next steps focusing on type of material*: 5 *More focused study*: 9
Students that spend more time in some cases and less in other: 31.8% (14 out of 44)	*No comments* 0: 1 *Lack of familiarity with INSPIREus*: 1 *Strategy adopted (style, deep study, difficulties)*: 12	*Time restrictions*: 1 *No comments*: 4 *Focus on time improvement*: 3 *Plan next steps focusing on type of material*: 4 *More focused study*: 1

their strengths/weaknesses /preferences and evaluate themselves. They also recognize the strategies they follow and interpret them based on their style characteristics, goals or needs. Their answers to Question 3 and 4 of the evaluation questionnaire appearing in Appendix A support the above findings. In Question 3 (navigation history in various types of content) students seem to relate their navigation and the time they spent on various resources to their preferred studying/learning strategy (Question 3, 63 percent) but also to the planning of their study (Question 3, 52 percent). In Question 4 (high frequency of visits on specific type of content), most students (61 percent) agree that such behavior is related to difficult content and few (27 percent) relate it to understandability/usefulness of the content.

To assess the impact of the *indicator of learners' progress* we initially used log data to categorize students based on their behavior compared to the 'desired' one, resulting to three categories of students, those that spent on studying the resources (see Table 2, column 1): (a) less time than the proposed one (18.2 percent), (b) more than the proposed one (50 percent) and (c) more time in some cases and less in others (31.8 percent). Then, students' reflections on their studying behavior and progress towards specific outcomes of particular page categories (see Table 1, G7, Q3 and Fig. 3) were further analyzed and categorized in (a) the interpretations that appear in Table 2, column 2, and (b) the plans that appear in Table 2, column 3. The interpretations of the particular indicator are quite interesting as they focus on the strategies that the students adopted seeking the origins of their behavior. We also observed that students' interpretations of the first group differ from those of the second and third ones as well as their plans. Specially students whose behavior is 'worse' than the 'desired' one (i.e. those that spent more time than the proposed one) try to argument about this behavior usually linking it with lack of familiarity with the system (10 students in total: 9 from the second group and 1 from the third group) (see Table 2, *second column, lack of familiarity with INSPIREus*). Only students of the first group seem to doubt the accuracy of the time recorded since "time runs even if the students work out of the system" (see Table 2, *second column, Doubt about data accuracy)*. The students' reflections also included comments about the strategies they adopt while studying particular content focusing on (see Table 2, *second column, strategy adopted*): (a) preferences for particular content that sometimes were also linked to learning style preferences or to the usefulness of the content, (b) difficulties that they faced with particular content, (c) demanding tasks asking for higher order thinking skills and deep study. However, it is worth noting that students of the first group link their way of studying only with their style preferences (3 students out of 8). Moreover, these visualizations seem to help students organize their study focusing on specific type of content (see Table 2, *third column, plan next steps*). Specially those students of the second and third groups elaborate on changes to their way of studying towards the desired one and goal setting related to the improvement of the time they spent on various types of resources leading to more focused study (see Table 2, *third column, more focused study*). However, in three cases (see Table 2, *third column, time restrictions*) the particular data about time seem to have a negative impact on students' attitudes, making them focus on staying within the proposed time by restricting their explorations only to the available content.

This provides evidence for the potential of the *indicator of learners' progress* to increase the students' *strategic-knowledge* as it stimulates conscious thinking about the way they use resources and their usefulness in achieving outcomes. Moreover, students' plans about their next step provide evidence for increased *knowledge of plans and goals* referring to learners' capacity to set what they intend to do through their learning.

The above findings are corroborated through the students' answers to the six and seven questions of the evaluation questionnaire appearing in Appendix A. In Question 6 (*study time compared to time proposed by teacher)* students again (as in Table 2) relate study time that exceeds the time proposed by the tutor with (a) demanding content (82 percent), i.e. focusing on the characteristics of the content, (b) deep study of the content (79 percent), i.e. focusing on themselves and the way they study, (c) their interest in the material (52 percent), i.e. focusing on themselves and their learning preferences. Moreover, some students doubt the accuracy of the time as a point of reference but in this case they are referring to the time proposed by the tutor which they consider "may be inaccurate due to wrong estimation of the tutor"; however only 63 percent of the students answered this option. Accordingly in Question 7 of the evaluation questionnaire (*study time compared to the mean time of their group)* students, by comparing themselves to their peers, acknowledge the same origins of their behavior as when having the tutor's time as a point of reference, but in different percentages, i.e. 64 percent of the students report that spending *more time studying* the content than the mean time of their group reflects demanding content, 64 percent deep study of the content, and 45 percent of the students report that it reflects their interest in the material. It is worth noting that 48 percent of the students would like to know those peers with less time and good results.

Lastly, assessment data seem also to support students in organizing their study. In Question 5 (*assessment tests evaluating specific outcomes)*, many students state that this information helps them identify their level of performance (72 percent) and weaknesses (82 percent), increasing their self knowledge. Moreover, 81 percent of the students suppose that this information helped them to change their planning and to focus on content that supports specific outcomes.

- *Which evaluation criteria do learners use for selecting collaborators based on their interaction data?*

Most of the students (93 percent) answering Questions 9 and 10 of the evaluation questionnaire would agree to open this information at class level and all of them (100 percent) to their group. Concerning the selection of collaborators based on interaction data, various approaches are proposed in Question 8 of the evaluation questionnaire. In particular, 52 percent of the students would prefer as collaborators peers with a profile similar to their own, whilst 43 percent prefer peers with a totally different profile but great performance. However, students' performance compared to the time proposed by the teacher seems not to be considered as a criterion for selecting collaborators since only 18 percent care about this information. Finally, it is interesting that 62 percent of the students do not care about study time and performance of their peers and focus on their answers to questions, exercises and activities.

6 Discussion and Future Plans

In this paper, we propose a model for producing interpretative views of learners' interaction behavior. This model focuses on the definition of relevant indicators of learners' interaction with the content and system tools which can be further linked to specific learner characteristics, leading to useful recommendations. Challenging research goals in this process are selecting appropriate data from learners' interaction, describing the 'context' that affects learners' actions and visualizing this information in a meaningful way. The proposed modeling approach can be implemented in any adaptive and/or hypermedia educational system that has data with semantic information and multiple levels of meaningful hierarchy such as the domain model.

The empirical study performed with students working with the indicators of INSPIRE*us*, provided evidence for the expressiveness of the indicators. Preliminary results show that students want to have access to information maintained by the system for them and their peers. In particular, based on the results of the study, most students managed to interpret their interaction data following a quite directive usage scenario. This usage scenario proved to be quite useful in guiding students to use the various functionalities of the system as well as in interacting with the visualizations offered. This is in line with other studies focusing on how to support learners in interpreting the contents of their model and using them creatively [51]. Actually, while students observe the particular indicators, they engage in several metacognitive activities. It is worth noting that the indicator of learners' effort helped them acquire an overview of how they organize/distribute their studying time. This information seems to support them in evaluating their strengths/weaknesses as well as the demands of the tasks they work on increasing their self and task knowledge. Furthermore, students' reflections on the indicator of working style focus on the evaluation of their behavior towards the attainment of specific outcomes making them identify their needs in order to deal with specific tasks (focus on tasks) as well as the strategies they adopt and their preferences for particular types of tasks (focus on themselves). These data provide evidence for the impact that the particular indicator may have on their self and strategic knowledge. As a result, a useful guideline is that the visualizations should represent the content augmented with pedagogical information. In this way, learners are supported in relating their selections to the expected outcomes and evaluating the role of various types of content and their own strategies in achieving them.

Lastly, students' reflections on the indicator of progress show that they use and interpret similar interaction data in multiple ways. The comparison of their behavior to a desired one seems to play a critical role as students interpret data in different ways in cases of success or failure. On the one hand, success seems to make students concentrate on their way of working, helping them recognize the strategies they adopt, whilst in cases of failure the 'desired' state motivates them to change their plans and strategies. As a result, another useful guideline is that the 'desired' state should follow learners' movements providing a point of reference like the state of an expert-tutor or real data coming from peers who are worth following.

Furthermore, this research contributes to the investigation of students' attitudes towards viewing the learner model of others and making their models accessible to others. Most students are willing to share interaction data with peers. This information looks useful for selecting collaborators, although various approaches were observed, reflecting differences in students' preferences. Moreover, most students prefer their own behavior as a point of reference for selecting collaborators to the time proposed by the instructor. They also seem to appreciate their peers' contributions to various tasks more than time information. This is an argument for allowing and encouraging learners to share their ideas and answers. The design of social indicators will focus on this direction.

Currently, the evaluation of the learner model of INSPIRE*us* is on progress. The next step will be to evaluate the impact of the indicators in a real context involving also tutors and allowing learners to freely interact with the content. We also intend to further work on building interpretative views of learners' social interaction. We plan to involve learners in the interpretation of their interaction data in order to minimize arbitrariness in the identification of meaningful patterns [46] and link interaction behaviour with their individual characteristics. This is considered critical for the system in order to personalise tasks, tools or study advice to individuals or groups, and to encourage social interaction, providing a basis on which learners will share their experiences as well as for group formation and group development purposes.

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