An Online Learning Collaboratory to Address Multidisciplinary Learning Challenges at Scale

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Abstract. "Ensuring inclusive and quality education for all to promote lifelong learning" is among the United Nations' global time-critical sustainable development challenges. Massive open online courses and other online learning systems can potentially address this challenge by fostering high-quality online learning at scale. However, online learning introduces complex challenges that involve multiple disciplines, varied learning contexts, and diverse learner backgrounds. There are plenty of research initiatives that try to address this problem, but they are fragmented efforts that could benefit from a community effort. We propose an online learning collaboratory framework to leverage and connect ongoing research efforts. In this paper, we propose four objectives for the online learning collaboratory and discuss existing work aligned with such objectives, which are: evaluation and refinement of instructional designs, interdisciplinary communication through design patterns, design pattern implementation, and bridging communities of practice. The collaboratory should bridge different communities through design patterns and connect data-driven practices and tools to address multidisciplinary learning challenges at scale.

Keywords: collaboratory, instructional design, evidence-based design research, design patterns, online learning systems

1 Introduction

The world faces time-critical challenges ranging from climate change to global decision-making [1]. Inclusive quality lifelong education is one of the primary opportunities to equip current and future generations to tackle such global challenges, which makes it a global challenge itself. Learning challenges on such urgent topics need to be addressed quickly and at scale. Massive open online courses (MOOCs) and other online learning systems have the potential to scale learning. However, collective knowledge and experience from different stakeholders are needed to understand what makes learning work in such contexts. Plenty research initiatives seek to improve learning, but many such efforts are varied and fragmented. The research enterprise needed for such challenges span a research-practice continuum ranging from discovery to impacts—basic research, applied research, implementation & dissemination research, policy research, and impact research [2]. Furthermore, different types of researchers are needed. For example, educational psychologists may research the human learning process, cognitive scientists may research the mental processes related to learning, computer scientists may research scalable online learning systems, data scientists may extract insights from big educational data, teachers may seek to enact effective pedagogy in their classrooms, and so forth. Learning Science research is difficult because of all the necessary skill sets.

A new approach is necessary to address multidisciplinary learning challenges at scale through the achievement of four main objectives: first, facilitate the evaluation and refinement of instructional designs; second, enable interdisciplinary communication through design patterns; third support design pattern implementation across different learning contexts; and fourth, bridge relevant communities into a focused impactful learning-centric community.

Such an approach can be supported by a collaboratory, which William Wulf [3][4] defined as "a center without walls, in which the nation's researchers can perform their research without regard to physical location—interacting with colleagues, accessing instrumentation, sharing data and computational resources, [and] accessing information in digital libraries." Collaboratory is a blending of the word "collaboration" and "laboratory" which emphasizes the importance of collaboration among different stakeholders to generate knowledge. Collaboratories have been successful in various domains such as education, oceanography, physics, molecular biology, atmospheric science, and so forth [5][6][7].

Educational collaboratories have been established to provide rich learning environments for students, develop educational resources, and facilitate the development of effective pedagogy. For example, the Learning through Collaborative Visualization (CoVis) project involved several universities (Northwestern University, University of Illinois Urbana-Champaign), companies (Bellcore, Ameritech, Apple, Sun Microsystems, Spyglass), and high schools that developed and utilized networking technologies to enable high school students to work in collaboration with remote students, teachers, and scientists on project-based inquiry science learning [8]. CoVis adoption was considerably high among its members with thousands of students, hundreds of teachers, and dozens of researchers working toward finding ways to improve science education in the classroom. Preliminary research that compared working face-to-face and working remotely on a scientific collaboratory (i.e., physical and biological science) indicated that collaboratories could serve as effective learning environments [9]. However, several factors, such as students' learning styles, need to be considered in the design of such systems to ensure effective learning.

The University of Iowa Nursing Collaboratory (UINC) was created to foster collaboration between the university's College of Nursing and Department of Nursing to generate, disseminate, and apply knowledge for improving nursing practice and patient outcomes [10]. The initiatives of the collaboratory involved work that cut across four domains—education, research, practice, and informatics—and were conducted by various stakeholders including nursing faculty, nursing staff, and nursing students. The collaboratory has had much success by starting several initiatives that enabled faculty to expand their knowledge, enriched student learning experiences, and improved practice with the application of research findings.

The Mid-Columbia STEM Education Collaboratory was conceptualized through discussions led by Pacific Northwest National Laboratory (PNNL) with schools, community-based learning providers, and local business and industry with the goal of addressing local STEM education needs [5]. As of 2017, the collaboratory expanded to 17 members from high schools, colleges, research laboratories, libraries, and educational support organizations that work together in promoting STEM education, investigating new or expanded STEM education activities or programs, funding and supporting testbed projects, and disseminating best practices for teaching and learning STEM. The collaboratory has been largely successful. It has produced publicly available resources and tools for STEM education, sponsored 50 STEM learning opportunities in 2016, supported local teachers who have introduced new STEM concepts and used new teaching strategies in their classrooms, initiated design challenges and makerspace activities across several districts, and so forth.

The success of collaboratories in different domains, education, in particular, lead us to believe that a collaboratory may successfully address multidisciplinary learning challenges at scale. Our proposed framework focuses on online learning environments that accommodate large student populations such as MOOCs and online learning systems. It will utilize research, online learning systems, and tools that have already been created to facilitate collaboration among stakeholders. Evaluation is a key component of the framework that will be used refine existing learning systems and guide future research directions. Research conducted by the collaboratory not only benefits the communities of practice involved but also improves the state of online learning systems at scale.

2 Addressing Multidisciplinary Learning Challenges

A lot of groundwork on educational research has already been laid, but we have yet to design strategies that will enable different communities of practice to mutually benefit from each other. The following subsections describe prior work on four objectives that work toward addressing multidisciplinary learning challenges at scale. First, the data-driven evaluation of instructional designs helps researchers discover effective pedagogical strategies and the contexts in which they are effective. This approach will lead to the refinement of existing designs and provide better insight into building future designs. Second, design patterns can encapsulate insights from diverse educational research and serve as boundary objects that facilitate discussion among different communities of practice to enable effective collaboration. Third, design patterns can facilitate the implementation of different pedagogical designs across different learning contexts that practitioners can deploy in various learning situations. Finally, connecting data-driven practices and tools conducted by different communities of practice leads to the completion of the loop from theory to evaluation and theory refinement. Each subsection describes existing work that has already been done that aligns with the objectives mentioned earlier. Section 3 describes our vision of how to align on such objectives through an online learning collaboratory.

2.1 Evaluation and Refinement of Instructional Designs

Evidence-Based Design (EBD) practice rigorously links credible evidence validated by research and design decisions [11]. Evidence-based design research can inform future design decisions according to evaluations of instructional designs [12]. Effective instructional designs need to be promoted, and less effective ones need to be improved to better support student learning. A randomized controlled trial (RCT) is one way to evaluate the effectiveness of an instructional design by randomly exposing students to different designs and comparing their performance according to an outcome measure (e.g., answer correctness). One condition in a problem-solving activity, for example, may provide students with corrective feedback while another may provide explanatory feedback. Several studies promote explanatory feedback because experiments indicate they lead to higher student performance compared to corrective feedback and no feedback [13] RCTs seem simple, but they are often difficult to organize and scale because it requires research on several populations and learning contexts.

Technological advancements make it easier to collect data, analyze data, and conduct RCTs to inform design improvements that work toward achieving the first objective. Fig. 1 illustrates a commonly used methodology for conducting experiments on online learning systems to inform design decisions. First, RCTs are configured in an online learning system so that participants are randomly assigned to one of two or more conditions implementing a particular instructional design. Data from learners assigned to each condition is then collected and preprocessed for analysis. Statistical tests are used to compare predetermined outcome measures from each condition. Finally, significant differences in outcome measures are used to inform future design decisions.

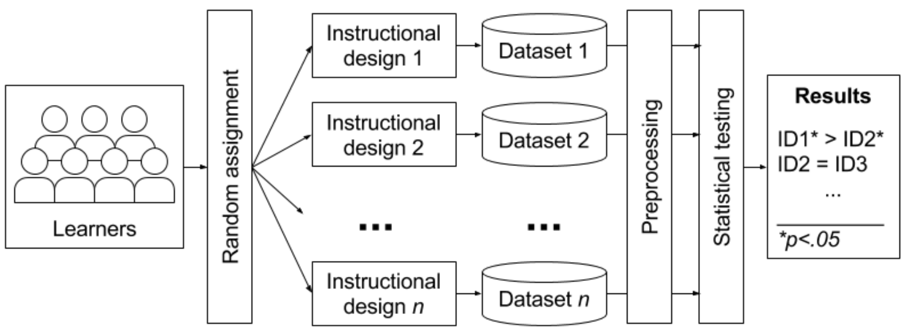

Fig. 1. A commonly used methodology to conduct randomized controlled trials.

Most online learning systems already collect learning data ranging from summative (e.g., exam scores) to formative assessments (e.g., reflection on an assigned reading), but specialized learning systems go a step further by collecting low-level data that enable deeper insights on student learning. For example, the ASSISTments online tutoring system provides tools for authoring content, collecting data, evaluating student performance, and conducting RCTs [14]. Its authoring tool allows teachers and designers to construct problem sets where they might apply different instructional designs such as practice until mastery, explanatory feedback on incorrect answers, hints on demand, and so forth. Teachers can assign problem sets to their students whose answers are automatically checked by the system. Teachers can view reports of their students' performance that informs their instruction such as focusing on confusing topics in the next lecture. Researchers, or teachers themselves, can also use the authoring tool to conduct RCTs that compare different instructional designs. Students answering a problem set that is part of an RCT are randomly assigned to a particular instructional design. The results of each group's performance can be analyzed using ASSISTMents' Assessment of Learning Infrastructure (ALI) [15] to evaluate a design's effectiveness and inform future design decisions. Low-level data such as time-on-task, number of answer attempts, number of hint requests, answers, and other data are also made available for further processing.

Cognitive Tutor Authoring Tools (CTAT) is another system that facilitates the authoring of learning content, collects data, and integrates with systems like Tutorshop and Data shop to set up experiments and analyze data [16]. CTAT simplifies the process of building intelligent tutors through the use of example-tracing tutors. These tutors are built using graphical drag-and-drop and programming-by-demonstration interfaces, which do not require programming unless advanced functionalities are required [17]. Example-tracing tutors compare student problem-solving behavior with user-provided expert problem-solving behavior to check for correctness and generate feedback. The authoring process includes an annotation step where feedback and other instructional designs can be embedded by teachers or content experts into the tutor's interface. CTAT can integrate with Tutorshop, a web-based content management system that facilitates the deployment of CTAT tutors for classroom use, provide access to student progress, and support experimentation. CTAT automatically collects log data that can be input into Datashop [18], which provides several data analysis functionalities and can be used to compare the effectiveness of different instructional designs.

There has also been some effort toward "closing the loop" from design to refinement through evaluation. Cen et al. [19], for example, used Learning Factors Analysis (LFA) to evaluate problem-solving activities in the Geometry Cognitive Tutor. They investigated different instructional designs such as the sequence of topics, the combination of concepts used in a problem, and the amount of practice on particular concepts. Their findings led to modifications in the instructional design that split some problems to provide more practice on challenging skills, retain problems that helped students master challenging skills, and merged some problems that involved skills that students easily mastered. A recent study showed that changes made to the instructional designs based on insights from LFA led to significant improvements in learning gains [20].

AXIS is a system that implements the MOOClets framework introduced by Williams et al. [21][22] that dynamically selects and utilizes the best-performing instructional designs to facilitate learning. In [22], researchers used reinforcement learning to dynamically select among various explanatory feedback to help students learn a particular Math skill. The algorithm automatically learned a policy that, over time, prioritized the utilization of explanations linked to better learning. This system is unique because it not only evaluates the effectiveness of instructional designs but also dynamically selects and utilizes the most effective one.

Most of the online learning systems mentioned earlier were designed for learning Math, but systems built for other domains may also be used and evaluated. Examples of such tutoring systems are Ecolab that supports learning Ecology [23], Andes that supports learning Physics [24], and Guru that supports learning Biology [25]. Recently systems have also been developed to support learning in ill-defined domains such as intercultural competence [26], ethics [27], and even moving a robotic arm deployed on the International Space Station [28].

The evidence-based approach requires an existing system so that so it can be applied, evaluated, and refined. Obviously, there is no online learning system for every domain. Existing research can be interpreted to mean that learning systems are possible even for complex, ill-defined domains but it is a matter of building such systems.

2.2 Interdisciplinary Communication through Design Patterns

Design patterns have been considered to serve as boundary objects to facilitate interdisciplinary discussions [29]. They have been used to facilitate discussions among people with different backgrounds, disciplines, and levels of prior knowledge in various domains such as education [30], design [31], and software development [32]. Design patterns were first introduced by Christopher Alexander [33] who described them as high-quality solutions to recurring problems in particular contexts, which can encapsulate knowledge from different stakeholders. An example of a pedagogical design pattern is the *Own Words* design pattern that suggests self-explanation as an effective strategy (solution) to assess students' understanding of a particular topic (recurring problem) discussed in lectures (context) [34]. Design patterns offer a concrete contextualized problem and solution that is abstract enough for different stakeholders to discuss, without going into details that are specific to a community. This perspective of design patterns also aligns with Star and Griesemer's [35] description of a boundary object that facilitates communication between disparate communities. Fig. 2 illustrates such a relationship wherein different stakeholders communicate through design patterns that abstract their domain-specific knowledge.

Consider a scenario where educational researchers, educators, and system developers use the *Own Words* design pattern to discuss an implementation of the self-explanation theory in the context of a MOOC lecture. System developers can use their technical knowledge to implement components, such as video players, to embed lectures in a MOOC according to the design pattern. They can also design forms to display instruction and collect feedback after lecture videos are shown to students. Educational researchers may not necessarily understand the technical aspects of the system's implementation, but they can use their knowledge to accomplish the design pattern's solution such as use self-explanation theories to design the instructions given to students, organize the questions displayed by the system, select the type of feedback to provide, construct the feedback content shown to students, and so forth.

Educators can refine the design pattern's solution based on their teaching experience. For example, when teachers are unable to provide timely feedback on students' self-explanations due to their schedule, students may disengage from an activity. It may be more effective to ask students to select the correct explanation from a list of possible options instead of writing an essay to allow the system to provide immediate automated feedback (i.e., explain why a particular option is correct or incorrect). Educators can conduct and schedule less frequent elaborate evaluations when they have time to perform the task. Many aspects influence the effectiveness of the instructional design, but refining it according to stakeholders' expertise will likely lead to improvements.

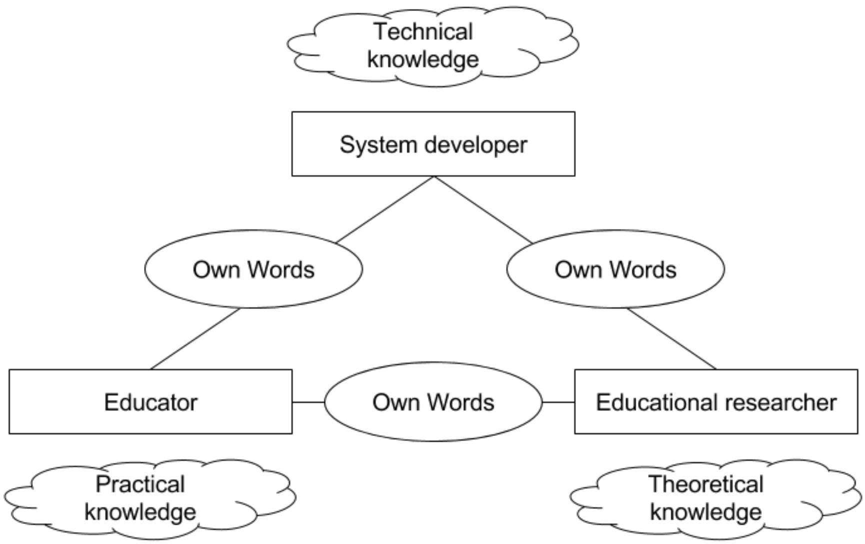

Fig. 2. Communication among stakeholders with different backgrounds facilitated by the *Own Words* design pattern.

Several design pattern languages and collections have already been developed to address problems in online learning environments. For example, the e-Len project developed 42 e-learning design patterns, which were categorized into four special interest groups namely: SIG 1: Learning resources and learning management systems (LMS); SIG 2: Lifelong learning, SIG 3: Collaborative learning; and SIG 4: Adaptive learning [36]. The TELL project [37] that involved collaboration among several European universities and institutions produced 90 design patterns for network supported collaborative learning. Avgeriou et al. [38] presented 20 LMS design patterns that addressed various problems in LMSs such as managing the course, its resources, and student collaboration, to name a few. Another example is the 32 MOOC design patterns developed by Warburton and Mor [39] that addressed various aspects of MOOC design including participation, community, structure, learning, and orientation. Finally, Mor, Mellar, Warburton, and Winters [40] compiled 29 design patterns for teaching and learning with technology, which covered learner-centered designs, learning communities, social media and learner interaction in social spaces, and assessment and feedback. There are many other pedagogical design pattern languages primarily developed for learning environments outside of online learning systems. The pedagogical design pattern language of Bergin et al. [34], for example, consists of over 300 design patterns that address various problems in classroom settings. Inventado and Scupelli [41] have started to investigate the adaptation of design patterns to address similar problems in learning environments outside of a patterns' intended context.

There are three limitations to how design patterns are written. First, design patterns have a practical approach that appeals to practitioners. Pattern authors often prefer shorter patterns to reduce the burden on the reader. Unfortunately, brevity comes at the expense of detail and exhaustiveness. Second, design patterns sometimes read as if self-contained pearls of wisdom. For example, often they usually lack the academic rigor with citations for every claim made. Third, the validity and effectiveness of design patterns may seem suspect. For example, design patterns are described as known high quality to solutions but how such claims are supported is often lacking. We point these obvious limitations to design patterns, to say that it is possible to write succinct, well argued, and evaluated design patterns. Notable exceptions include Inventado and Scupelli's work on pedagogical design patterns where these three limitations are addressed directly (e.g., [42], [43]).

2.3 Design Pattern Implementation

Evidence-based educational research has led to the development of learning design principles that can support instructors to guide their instructional designs. For example, Pashler et al. [44] shared seven recommendations to help teachers organize instruction and study materials to facilitate student learning. Graesser and his colleagues [45][46] introduced 25 cognitive principles of learning to guide educational practice using results from psychological research. Finally, Clark and Mayer [12] presented 14 research-based principles to design, develop, and deliver instruction on e-learning systems. Unfortunately, design principles and guidelines often failed to translate into successful changes for teaching practice or student learning [47][48]. Applying design principles is difficult because it requires practitioners to make many design decisions to implement it in a particular context. Furthermore, multiple design principles may be at odds with each other. For example, a principle may need adaptation to address a different context (e.g., adapting the multimedia principle to mobile devices); to consider students' individual differences (e.g., self-explanation activities for low-knowledge vs. high-knowledge learners); and to resolve conflicts with other principles (e.g., desirable difficulty vs. managing cognitive load). Such difficulties have resulted in varying quality of outcomes such as the high efficacy of Cognitive Tutor Algebra developed by Carnegie Learning [49][50][51], but reliably worse results in Cognitive Tutor Geometry that was developed by the same team [52]. Design patterns are viewed as contextualized principles that facilitate the implementation of different theories and design principles [41].

People with diverse prior experiences in design patterns and varied objectives may apply patterns differently. Fig. 3 illustrates a commonly used process for implementing design patterns (e.g., [53][54]). An experienced design pattern practitioner designing instruction or addressing a learning issue first identifies the problem or potential problem in that particular context. The practitioner uses the identified problem and context to select an appropriate design pattern from memory. The practitioner then applies the solution described in the selected design pattern to design instruction or to address the learning issue. When practitioners are unable to identify design patterns that match the problem and context, they may consult other practitioners or decide to apply their solution. If the same situation is frequently observed and a particular solution consistently resolves the problem, then the practitioner may encapsulate this experience into a new design pattern. Practitioners who are not pattern writers may enlist the help of design pattern authors to express the design pattern.

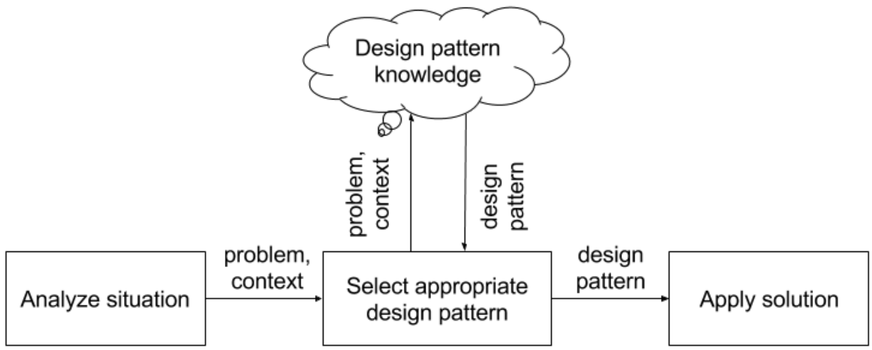

Fig. 3. Experienced design pattern practitioner's process for applying patterns.

Expert design pattern practitioners often share their knowledge of patterns with their peers and guide novice design pattern practitioners to promote the use of design patterns. It may be difficult to locate appropriate design patterns because there are many patterns available, and they are hosted in various pattern repositories and published in several publications [55]. Aside from research and literature review, design pattern practitioners learn about relevant design patterns from design pattern conferences or conversations with peers who also use design patterns. Some design pattern authors and practitioners conduct workshops or tutorials that teach about using design patterns to guide novice design pattern practitioners, get feedback on the effectiveness of their design patterns, and publicize their design patterns. For example, Iba and his colleagues have conducted several workshops to introduce their pattern language called Learning Patterns, and encourage participants to apply it in their learning [56]. In a preliminary study, we investigated the use of design patterns to help Math pre-service teachers construct feedback for their potential students. The pre-service teachers attended a lecture where we presented different design patterns and demonstrated how they could be applied to construct feedback. Participants were given a series of assignments wherein they constructed feedback using design patterns that would help students who submitted an incorrect answer to a particular Math problem. Qualitative analysis of data collected from pre-service teachers showed that they constructed better feedback with the help of design patterns compared to feedback constructed before the introduction of design patterns.

Online tools have been developed to facilitate the application of design patterns in online learning contexts. For example, Beehive is an application framework that helps instructors facilitate computer-supported collaborative learning (CSCL) activities in LMSs [57]. Instructors using the system select a design pattern that addresses the problems they wish to resolve and customize the specific tasks related to that design pattern. In implementing the *Brainstorming* design pattern [58], for example, the instructor can decide whether students collaborate through chat or video-conferencing. The system automatically generates the specific components required to implement the design pattern and presents them to participants in sequence on the LMS. Pattern Manager (PatMan) is a system that is quite similar to Beehive but focuses on the use of person-centered e-learning (PCeL) design patterns [59]. Similarly, instructors select an appropriate design pattern from a list of patterns presented by the system and configure the implementation accordingly. The system also generates the components required to implement the selected pattern that students access through the LMS. Finally, Collage is a tool that helps instructors create learning designs for CSCL environments using Collaborative Learning Flow Patterns (CLFPs) [60]. In the case of Collage, instructors specify their learning objectives, identify specific problems they wish to address, and provide the complexity of the learning experience they wish to design. CLFPs that satisfy the specifications are listed, and instructors can select the most appropriate one with the help of the pattern descriptions provided. Instructors are shown a visual representation of the selected CLFPs' components that they can further customize by incorporating relevant CLFPs, providing details about the activities associated with the CLFP, adding resources, and so forth. Learning designs created through this process can then be interpreted and executed in the instructor's LMS. Web Collage is a recent web-based extension of Collage that not only allows the configuration of learning activities but also supports assessment design [61].

Design patterns operate on different levels and granularities, but they often work in tandem so that they form a pattern language. Most of the systems previously discussed utilize pattern languages instead of individual patterns to address multiple aspects of a problem. The Pattern Language for Math problems and Learning Support in Online Learning Systems, for example, contains design patterns at varying levels of granularity. The *Image Enhanced Hint* and *Personal Video Hints* design patterns guide fine-grained design decisions on the use of textual, visual, or video feedback [42][62]. Design patterns for feedback work together with patterns for problem content such as *All Content in One Place* that avoids added cognitive load from task switching [63]. Finally, the *Just Enough Practice* design pattern works on a higher level to control the amount of practice problems (with associated feedback) that is given to students to provide them with the appropriate amount of practice for skill mastery [63].

Design patterns are context-specific, so they may not work effectively in all learning systems. The *Personalized Problems* design pattern, for example, suggests the use of problem-solving activities that are appropriate for students' skill level to help them understand concepts taught in class and avoid negative learning experiences such as frustration, boredom, and disengagement [63]. Systems like Cognitive Tutor track students' skill mastery, which allows it to select problem-solving activities that involve skills that students still need to learn [64]. Such a capability allows Cognitive Tutor to apply the *Personalized Problems* design pattern, but this may not be available in other systems. The ASSISTments online learning system tracks students' performance on the current problem-solving activity but does not specifically track skill mastery [14]. Although the design pattern may be adapted to only use prior performance, it does not ensure a high-quality solution. Inventado and Scupelli [41] have started to investigate methodologies that investigate and refine design patterns to translate or create design patterns that adapt to new learning contexts.

2.4 Bridging Communities of Practice

There is a lot of intersection in the research and the members of communities involved in the online learning domain. Communities working in the online learning domain that we have considered so far focus on four aspects: theory, implementation, application, and evaluation. Fig. 4 illustrates the complex relationship between these aspects and how one might inform the other. Many of the educational theories, learning principles, and design patterns come from the work of the cognitive science, educational psychology, and design pattern communities. However, educators and students can share valuable insights from their first-hand experience with theories in actual learning situations. Discussion among these communities helps generate ideas to refine and evaluate theories.

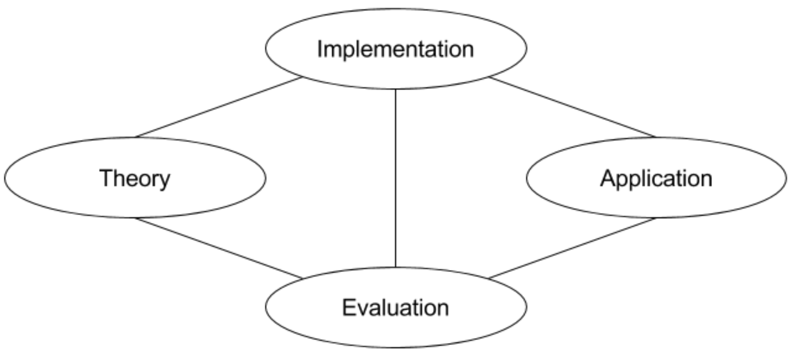

Fig. 4. The relationship between four aspects often considered by communities working in the online learning domain.

The computer science, human-computer interaction (HCI), and design communities are often responsible for the creation of online learning systems. Pedagogy experts, practitioners, and students can co-design and provide feedback on such systems to address concerns from their perspective.

Educators can take advantage of online learning systems to facilitate learning in their classes, sometimes even at scale. Deploying such systems in a real setting is tricky, and educators can learn strategies from pedagogical experts, get advice to leverage the capabilities of the system from developers, and revise the usage of such systems from experts, peers, and student feedback.

The psychometrics, educational data mining (EDM), and learning analytics and knowledge (LAK) communities utilize data collected from real learners who use online learning systems to evaluate the effectiveness of different learning activities and instructional designs. A lot of contextual information is often lost during data collection, but educators and students can help complete the picture and offer insights that may explain findings. Results from evaluation may confirm existing theories or enrich them based on cases in which they did not perform as expected. Educator and student feedback help identify issues with the system that can be addressed in the next iteration. Similarly, feedback on the use of such systems can help educators find strategies to address concerns. Research studies are often conducted to find evidence on the effectiveness of theory implementations but may be limited to the specific contexts studied. Such studies need further validation through replication in different learning environments, learner populations, domains, and so forth. Inventado et al. [65], for example, worked with developers of the ASSISTments online tutoring system, data scientists, and teachers for over a year to evaluate theories on hints and the *Hint on Demand* design pattern [66]. They replicated an experiment to evaluate the effectiveness of hints on student learning that revealed hints were effective for a particular group of students who answered a problem set within the fall semester of an academic year, but hints had no added benefits for another group of students who answered the same problem set as part of their summer work. Further work is needed to develop appropriate feedback strategies for different learning situations, but more importantly, this case shows the complexity of the learning process that requires in-depth analysis to uncover what pedagogical strategies are effective for whom and in which context. Communities that work on related theories can replicate studies to uncover the contexts where theories work well, identify the problematic contexts, and determine underlying reasons why.

Ideally, theories need to be implemented so they can be evaluated and refined. However, it takes a significant amount of time and resources to go from theory to evaluation and refinements. A notable example is the work of Koedinger and his colleagues who spent more than ten years to complete the loop in one of their studies that used LFA to significantly improve instructional designs for problems in the Geometry Cognitive Tutor [19][20]. There are still many unanswered questions awaiting inquiry. According to the calculation of Koedinger et al. [67], looking only at three particularly important factors that affect learning—instructional technique, dosage, and timing—there are already 205 trillion instructional design combinations that have yet to be fully investigated. Obviously, a community effort is required to address such large challenges.

Researchers developed many tools that can facilitate collaboration and bridge research and practice in the online learning domain. Figure 5 shows a subset of existing systems that support four aspects of the online learning domain. Learning theories, design principles, and design patterns were collected and hosted in various online repositories such as the Design Principles Database (DPD) [68], LearnLab's

Theory Wiki[1], the Integrated Learning Design Environment (ILDE) [69], and the Open Pattern Repository for Online Learning Systems (OPROLS) [70].

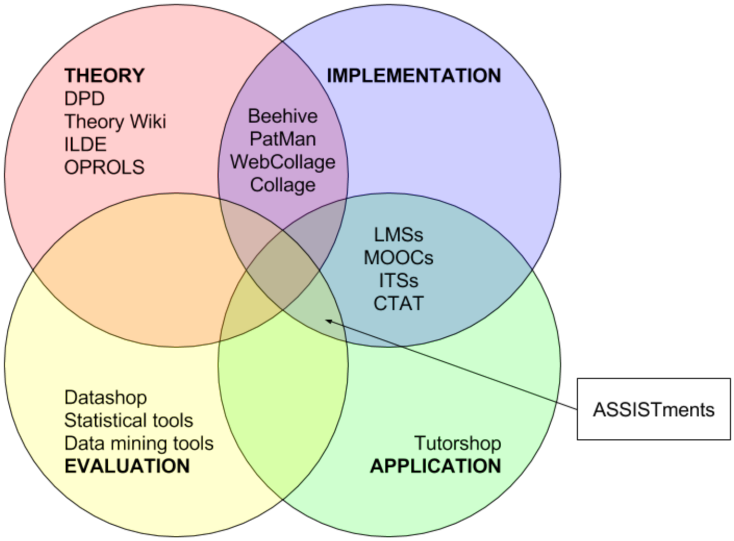

Fig. 5. Existing systems that support the four aspects of the online learning domain: DPD - Design patterns database; ILDE - Integrated Learning Design Environment; OPROLS - Open Pattern Repository for Online Learning Systems; PatMan - Pattern Manager; CTAT - Cognitive Tutor Authoring Tools; ITS - Intelligent Tutoring System; LMS - Learning Management System; MOOC - Massive Open Online Course).

Tools such as Beehive [57], PatMan [59], Collage [60], and WebCollage [61] are capable of translating design patterns into components that can be embedded into LMSs thereby bridging the theory and implementation aspects. LMSs and MOOCs are increasingly popular tools that many instructors use to create instructional content and learning activities. Such technologies are applied in real learning settings that extend traditional classrooms online and enable fully online classes that are often at scale.

Intelligent tutoring systems (ITSs) may be created programmatically or with the help of authoring tools such as CTAT [16]. Some ITSs are packaged as desktop applications while others are accessible to students online. Tutorshop is an LMS that facilitates the deployment of tutors in classrooms, which is also integrated to CTAT to easily deploy example-tracing tutors online [16]. Most online learning systems support data collection, which can be exported, processed, and then analyzed.

There are several free and commercial tools that can be used for statistical analysis and data mining (e.g., SPSS, SAS, R, Weka, RapidMiner) [71]. Datashop [18] is the largest repository of learning interaction data that also provides several data analysis functionalities. ASSISTments is an online tutoring system that supports the

[1] http://learnlab.org/research/wiki/

implementation, application, and evaluation aspects of the online learning domain by providing an authoring tool, an interface to deploy and interact with content, and analyze data collected from student interactions [14][15].

Although CTAT, Tutorshop, and Datashop are separate systems, they are closely integrated and thus, capable of supporting implementation, application, and evaluation [16]. Note that many of these tools focus on specific learning activities and platforms. Beehive and Collage, for example, focus on supporting collaborative learning activities on LMSs while ASSISTments, CTAT, Tutorshop, and Datashop focus on problem-solving activities from within their respective platforms. We were unable to identify a system supporting all four aspects of the online learning domain.

3 An Online Learning Collaboratory

An online learning collaboratory, patterned after Wulf's [3][4] description, should enable relevant communities of practice to interact, exchange information, and share computational resources without regard to the physical location to build an impactful learning-centric community. We propose an online portal that lists on-going work, which different communities of practice can collaboratively develop. Such a list may contain theories, pedagogical design patterns, implementations, experiments, and so forth. Specifically, we encourage using design patterns to facilitate interdisciplinary communication between communities of practice that may serve as a good starting point for collaboration.

Consider that the *Own Words* design pattern, introduced in Section 2.3, is an object listed in the portal. Possible communities of practice that may be interested in this pattern are cognitive scientists, educational psychologists, design pattern authors, instructional designers, system developers, instructors, educational data scientists, educators, and students. Participants can discuss the pattern and utilize project management tools and collaborative editing tools to design and maintain a project that investigates self-explanation as assessment in various learning situations, subject domains, and learning platforms.

Relevant theories, principles, and design patterns can be imported by cognitive scientists, design pattern authors, or educational psychologists into the portal from existing theory-related repositories (e.g., DPD, LearnLab's Theory Wiki, OPROLS). Designers and developers can provide insights regarding the capabilities and limitations of technology to implement such theories (e.g., system's limited capability to interpret students' essays). Educators and students have a first-hand experience in the application of such theories providing them with a practical perspective (e.g., disengagement from the lack of timely feedback). Data scientists and learning scientists can suggest methodologies and strategies for conducting experiments that can validate the application of selected theories (e.g., run RCTs to compare performance with and without self-explanation).

Designers and system developers can use existing tools or create new systems to provide a platform for implementing theories. Existing systems like Beehive, PatMan, and Web Collage help automate the process by facilitating theory implementations into LMSs, ITSs, MOOCs, and other learning environments. Researchers can ensure that theories are properly modeled in the implementation, while educators and students can share insights about its usability (e.g., lack of a save feature to address connection timeouts). Data scientists and learning scientists can identify the type of data that need to be generated by learning systems to allow evaluation (e.g., activity duration log).

Educators benefit from improved student learning provided by theory-based implementations and pedagogical strategies, but also create opportunities to collect evaluation data. Systems like ASSISTments and Tutorshop can help educators manage problem sets and tutors that they can deploy in class. Researchers can help educators select and apply pedagogical strategies supported by evidence (e.g., provide self-explanation activities after lectures). Designers and developers can support educators using learning systems and address technical challenges (e.g., creating activities in an online learning system). Students can give immediate feedback that educators can use to refine teaching strategies that utilize the learning system (e.g., difficulty accessing website). Data scientists and learning scientists can coordinate with educators to ensure that data is properly collected from the right student population (e.g., select diverse classes to represent student populations equally).

Finally, data scientists and learning scientists can configure experiments and analyze its results that enrich theories, provide feedback on system designs and implementations, and facilitate the deployment of such systems in learning settings. They can collaborate with system developers to embed various designs into learning activities and instruction, and coordinate with educators to deploy them to diverse student populations on various learning platforms (e.g., distribute students equally across conditions in experiments). Educators and students have a better understanding of the learning context so they can help data scientists interpret data correctly. Datashop, as well as statistical and data mining tools, can facilitate analyses, especially when dealing with large educational data sets.

Results from the collaboration among different communities can inform the refinement of existing theories, implementations, and applications. For example, if self-explanation sufficiently captures students' understanding of a lecture then it is evidence of the effectiveness of the *Own Words d*esign pattern and the self-explanation theory. However, if it does not, then it may warrant further experimentation, refinement of existing theories, or development of new theories. A possible reason may be that self-explanation inaccurately measures the mastery of complex tasks [72][73]. Follow-up studies may reveal the types of topics in which self-explanation is effective or less effective as an assessment. Such a finding can refine existing theories about self-explanation regarding complex tasks. It could also open new lines of research such as evaluating the *Try it Yourself* design pattern that suggests using exercises to assess students' understanding of a task described during lectures [34]. The same communities of practice can investigate this design pattern, but other participants may also join the collaboration. Results from work on this related design pattern may be connected to the *Own Words* design pattern as well as other related design patterns. This example shows the types of rich interactions that may arise from an online learning collaboratory. It also illustrates how the loop from theory to evaluation and theory refinement can be connected through the collaboration of different communities of practice. Several researchers can work together through the collaboratory that could potentially speed up research and utilize resources more efficiently.

The goal of the proposed collaboratory is to facilitate knowledge sharing and collaborative experimentation. An "open" collaboratory approach to learning makes it easier for researchers to learn from each other and share what they know works. It also serves as a platform to test new ideas. Practitioners may want to try new pedagogies that are likely to work, instead of simply using what comes to mind first. The collaboratory makes it easier for people to work on the state of the art in theory and practice instead of starting from scratch. Evaluation of theories, implementations, and applications can potentially refine existing theories that foster better learning. The collaboratory potentially makes it easier to connect existing research, tools, and stakeholders in one place.

3 Discussion

The proposed framework focused on the design, evaluation, and refinement of instructional content, but other aspects may influence student learning. For example, the quality of instruction delivered by an instructor, students' emotional state, students' motivation to complete the learning activity, students' relationships with instructors and their peers, and so forth. Information on these aspects of learning are harder to collect and interpret, but there is work in this area such as detecting students' academic emotions [74], identifying unproductive learning behavior such as gaming, wheel spinning, and mind wandering [75][76][77], and predicting students' motivation to complete a learning activity or course [78]. There are fewer design patterns that encapsulate high-quality solutions in such areas, which make it an interesting topic to investigate through the online learning collaboratory. Work in this area would involve experts in fields like Psychology, Education, Learning Science, Educational Data Mining, and so forth.

Language, cultural, and contextual differences need to be considered in the design of learning systems as well as in stakeholder collaboration. Language can be a barrier for learners to access resources. Aside from translating content, cultural contexts also need to be expressed appropriately to accommodate different perspectives. Certain designs may resonate with a particular culture and context, but may not in others. The role of culture and language in learning systems can and should be investigated through the online collaboratory. It is important to acknowledge that language and culture may limit collaboration within collaboratory. That said, there are ways to overcome language and culture barriers. For example, Wikipedia is translated in multiple languages. More importantly, the stakeholders need to be willing to collaborate with people from different backgrounds and cultures. Such challenges need to be explicitly explored further as people work in the collaboratory.

Interoperability among existing systems is another challenge in implementing the online learning collaboratory. Section 3 listed repositories, learning systems, and tools to support the collaborative process by sharing data. However, these systems were developed by different communities and follow different formats. Standards will need to be developed to facilitate information sharing, and the systems themselves will need modification to leverage such information.

The online learning collaboratory requires a community effort. We are currently working towards implementing our proposal and have started building connections with various communities such as the design pattern community, learning scientists, designers, and teachers who can also connect us with their students. We have done preliminary work in building a design pattern repository that connects existing literature with design patterns, design pattern implementations, and evaluations of its applications [70].

4 Summary and Future Work

Online learning can potentially address learning challenges at scale. However, this is a large undertaking that requires extensive collaboration among different communities of practice. There are technologies in place to facilitate work within communities, but they need to be focused on iteratively closing the loop from theory, implementation, to evaluation, and iterative refinements.

We propose the development of an online learning collaboratory focused on design patterns to facilitate collaboration between different communities of practice. The collaboratory should support virtual interaction, information exchange, and sharing of computational resources to engage in learning challenges using the expertise of a multidisciplinary community. Such a collaboratory can consolidate shared information and, potentially, streamline the research process and utilize resources more efficiently.

Although this paper has focused on only four aspects of the online learning domain—theory, implementation, application, and evaluation—the grand vision for this work is to support the entire research practice continuum ranging from discovery to impact [2]. Researchers from different communities of practice are encouraged to work together in developing this online learning collaboratory.

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References

1. Glenn, J.C., Florescu, E., The Millennium Project.: 2015-16 State of the future, The Millennium Project (2015)
2. Trochim, W. M. K., Donnelly, J. P., Arora, K.: Research methods: The essential knowledge base, Cengage Learning (2016)
3. Wulf, W. A.: The National Collaboratory--A White Paper, Appendix A in Towards a National Collaboratory, An unpublished report of a National Science Foundation invitational workshop. March (1989)
4. Wulf, W. A.: The collaboratory opportunity. Science, 261(5123), pp. 854--855 (1993)
5. Willcuts, P. H., Kennedy, C.: Collaboratory = Collaborate + Laboratory: The Mid-Columbia STEM Education Collaboratory. Connected Science Learning 1(3), (2017)

6. National Research Council.: National collaboratories: Applying information technology for scientific research, National Academies Press (1993)
7. Olson, G. M., Atkins, D. E., Clauer, R., Finholt, T. A., Jahanian, F., Killeen, T. L., Prakash, A., Weymouth, T.: The upper atmospheric research collaboratory (UARC). Interactions, 5(3), pp. 48--55 (1998)
8. Ramamurthy, M. K., Wilhelmson, R. B., Pea, R. D., Gomez, L. M., Edelson, D. C.: CoVis: A national science education collaboratory. In: 75th American Meteorological Society Meetings, (1995)
9. Sonnenwald, D. H., Li, B.: Scientific collaboratories in higher education: exploring learning style preferences and perceptions of technology. British Journal of Educational Technology, 34(4), pp. 419--431 (2003)
10. Dreher, M., Everett, L., Hartwig, S. M.: The University of Iowa Nursing Collaboratory: A partnership for creative education and practice. Journal of Professional Nursing, 17(3), pp. 114--120 (2001)
11. Ulrich, R. S., Zimring, C., Zhu, X., DuBose, J., Seo, H., Choi, Y., Joseph, A.: A review of the research literature on evidence-based healthcare design. Health environments research & design journal, 1(3), pp. 61--125 (2008)
12. Clark, R. C., Mayer, R. E.: E-learning and the science of instruction: Proven guidelines for consumers and designers of multimedia learning, John Wiley & Sons, (2016)
13. Van der Kleij, F.M., Feskens, C.W.R., Eggen, T.J.H.M.: Effects of feedback in a computer□based learning environment on students' learning outcomes: A meta□analysis. Review of Educational Research, 85(4), pp. 475--511 (2015)
14. Heffernan, N., Heffernan, C.: The ASSISTments Ecosystem: Building a Platform that Brings Scientists and Teachers Together for Minimally Invasive Research on Human Learning and Teaching, International Journal of Artificial Intelligence in Education, 24(4), pp. 470--497 (2014)
15. Ostrow, K. S., Selent, D., Wang, Y., VanInwegen, E. G., Heffernan, N. T., Williams, J. J.: The assessment of learning infrastructure (ALI): the theory, practice and scalability of automated assessment. In: Proceedings of the Sixth International Conference on learning Analytics & Knowledge, pp. 279--288. ACM (2016)
16. Aleven, V., McLaren, B. M., Sewall, J., van Velsen, M., Popescu, O., Demi, S., Ringenberg, M., Koedinger, K. R.: Example-tracing tutors: intelligent tutor development for non-programmers, International Journal of Artificial Intelligence in Education, 26(1), pp. 224--269 (2016)
17. Aleven, V., Mclaren, B. M., Sewall, J., Koedinger, K. R.: A new paradigm for intelligent tutoring systems: Example-tracing tutors, International Journal of Artificial Intelligence in Education, 19(2), pp. 105--154 (2009)
18. Koedinger, K. R., de Baker, R. S. J., Cunningham, K., Skogsholm, A., Leber, B., Stamper, J.: A data repository for the EDM community: The PSLC datashop. In: S. Ventura, C. Romero, M. Pechenizkiy, & R. S. J. D. Baker (Eds.), Handbook of educational data mining, pp. 43--55. CRC Press (2010)
19. Cen, H., Koedinger, K. R., & Junker, B.: Learning Factors Analysis: A general method for cognitive model evaluation and improvement. In: M. Ikeda, K. D. Ashley, T.-W. Chan (Eds.) Proceedings of the 8th International Conference on Intelligent Tutoring Systems, pp. 164--175. Springer-Verlag (2006)
20. Liu, R., Koedinger, K.: Closing the loop: Automated data-driven cognitive model discoveries lead to improved instruction and learning gains. Journal of Educational Data Mining, 9(1), pp. 25--41 (2017)
21. Williams, J., Li, N., Kim, J., Whitehill, J., Maldonado, S., Pechenizkiy, M., Chu, L., Heffernan, N.: The MOOClet Framework: Improving Online Education through Experimentation and Personalization of Modules. Social Science Research Network Working Paper Series (2014)

22. Williams, J. J., Kim, J., Rafferty, A., Maldonado, S., Gajos, K., Lasecki, W., Heffernan, N.: AXIS: Generating Explanations at Scale with Learnersourcing and Machine Learning. In: Proceedings of the Third Annual ACM Conference on Learning at Scale, pp. 379-388. ACM (2016)
23. Luckin, R., Du Boulay, B.: Ecolab: The development and evaluation of a Vygotskian design framework. International Journal of Artificial Intelligence in Education, 10(2), pp. 198--220 (1999)
24. Vanlehn, K., Lynch, C., Schulze, K., Shapiro, J. A., Shelby, R., Taylor, L. Don, T., Weinstein, A., Wintersgill, M.: The Andes physics tutoring system: Lessons learned. International Journal of Artificial Intelligence in Education, 15(3), pp. 147--204 (2005)
25. Olney, A. M., D'Mello, S., Person, N., Cade, W., Hays, P., Williams, C., Lehman, B., Graesser, A. C. . Guru: A Computer Tutor That Models Expert Human Tutors. In ITS 2010, LNCS, vol. 7315, pp. 256--261, Springer, Heidelberg, (2010)
26. Walker, E., Ogan, A., Aleven, V., Jones, C.: Two Approaches for Providing Adaptive Support for Discussion in an Ill-Defined Domain. In: Proceedings of the Workshop on Intelligent Tutoring Systems for Ill-Defined Domains, 9th International Conference on Intelligent Tutoring Systems, pp 1--12. Springer Verlag (2008)
27. Sharipova M.: Supporting Students in the Analysis of Case Studies for Ill-Defined Domains, in ITS 2012, LNCS, vol. 7315, Springer, Heidelberg, (2012)
28. Fournier-Viger P., Nkambou R., Nguifo E.M.: Building Intelligent Tutoring Systems for Ill-Defined Domains, in Advances in Intelligent Tutoring Systems, SCI, vol. 308. Springer, Heidelberg (2010)
29. Mor, Y.: . Embedding design patterns in a methodology for a design science of e-Learning, in Investigations of E-Learning Patterns: Context, Factors, Problems and Solutions, pp. 107--134, Information Science Reference (2010)
30. Mor, Y., Warburton, S., Winters, N.: Participatory pattern workshops: a methodology for open learning design inquiry, Research in Learning Technology, 20(supp. 1), pp. 163--175 (2012)
31. Chung, E. S., Hong, J. I., Lin, J., Prabaker, M. K., Landay, J. A., Liu, A. L.: Development and evaluation of emerging design patterns for ubiquitous computing. In: Proceedings of the 5th conference on Designing interactive systems: processes, practices, methods, and techniques, pp. 233--242. ACM (2004)
32. Unger, B., Tichy, W. F.: Do design patterns improve communication? An experiment with pair design. In: Proceedings of International Workshop on Empirical Studies of Software Maintenance, pp. 1--5. (2000).
33. Alexander, C.: The timeless way of building (Vol. 1), Oxford University Press (1979)
34. Bergin, J., Sharp, H., Chandler, J., Sipos, M., Eckstein, J., Völter, M., Manns, M. L., Wallingford, E., Marquardt, K.: Pedagogical patterns: advice for educators, Joseph Bergin Software Tools (2012)
35. Star, S. L., Griesemer, J. R.: Institutional ecology, 'translations' and boundary objects: Amateurs and professionals in Berkeley's Museum of Vertebrate Zoology, 1907-39, Social studies of science, 19(3), pp. 387--420 (1989)
36. Rusman, E., Lutgens, G., Ronteltap, F.: The production of e-learning design patterns, and a research road map for e-learning (Ref num: 101421-CY-2002-1-CY-MINERVA-MMP), http://www2.tisip.no/E-LEN/documents/ELEN-Deliverables/Report_WP3_ELEN-Roadmap.pdf (2005)
37. TELL project: Design patterns for teachers and educational (system) designers, Pattern book output of WP3. December (2005).
38. Avgeriou, P., Papasalouros, A., Retalis, S., Skordalakis, M.: Towards a pattern language for learning management systems. Educational Technology & Society, 6(2), pp. 11---24 (2003)
39. Warburton, S., Mor, Y.: A set of patterns for the structured design of MOOCs. Open

Learning: The Journal of Open, Distance and e-Learning, 30(3), pp. 1--15 (2015)
40. Mor, Y., Mellar, H., Warburton, S., Winters, N.: Practical design patterns for teaching and learning with technology, Sense Publishers, (2014)
41. Inventado, P. S., Scupelli, P.: Adapting Design Patterns Across Learning Environments. In: Proceedings of the 10th Travelling Conference on Pattern Languages of Programs (VikingPLoP 2017). ACM (in press)
42. Inventado, P. S., Scupelli, P.: Design patterns for helping students to learn to represent math problems in online learning systems. In: Proceedings of the 21st European Conference on Pattern Languages of Programs (EuroPLoP 2016). ACM (2016)
43. Inventado, P.S., Scupelli, P.S., Heffernan, C., Heffernan, N.: Feedback Design Patterns for Math Online Learning Systems. In: Proceedings of the European Pattern Languages of Programs. (EuroPLoP 2017). ACM (in press)
44. Pashler, H., Bain, P., Bottge, B., Graesser, A., Koedinger, K., McDaniel, M., Metcalfe, J.: Organizing Instruction and Study to Improve Student Learning (NCER 2007-2004), National Center for Education Research, Institute of Education Sciences, U.S. Department of Education (2007)
45. Graesser, A. C.: Inaugural editorial for Journal of Educational Psychology, Journal of Educational Psychology, 101(2), pp. 259--261 (2009)
46. Graesser, A. C., Halpern, D. F., Hakel, M.: 25 principles of learning. Washington, DC: Task Force on Lifelong Learning at Work and at Home. Retrieved from http://www.psyc.memphis.edu/learning/whatweknow/index.shtml
47. Donovan, M. S., Bransford, J. D., Pellegrino, J. W. (Eds.).: How People Learn: Bridging Research and Practice, National Academies Press, (1999)
48. Cai, J., Morris, A., Hwang, S., Hohensee, C., Robison, V., Hiebert, J.: Improving the Impact of Educational Research, Journal for Research in Mathematics Education, 48(1), pp. 2--6 (2017)
49. Koedinger, K. R., Anderson, J. R., Hadley, W. H., Mark, M. A.: Intelligent tutoring goes to school in the big city. In: Proceedings of the 7th World Conference on Artificial Intelligence in Education, pp. 421--428. Association for the Advancement of Computing in Education (1995)
50. Ritter, S., Kulikowich, J., Lei, P.-W., McGuire, C. L., Morgan, P.: What Evidence Matters? A randomized field trial of Cognitive Tutor Algebra I. In: Proceedings of the 2007 conference on Supporting Learning Flow through Integrative Technologies, pp. 13--20. IOS Press (2007)
51. Cabalo, J. V., Jaciw, A., Vu, M.-T.: Comparative effectiveness of Carnegie Learning's Cognitive Tutor Algebra I curriculum: A report of a randomized experiment in the Maui School District, Empirical Education, Inc. (2007)
52. Pane, J. F., McCaffrey, D. F., Slaughter, M. E., Steele, J. L., Ikemoto, G. S.: An Experiment to Evaluate the Efficacy of Cognitive Tutor Geometry, Journal of Research on Educational Effectiveness, 3(3), pp. 254--281 (2010)
53. Magnussen, E.: Pedagogical patterns – A method to capture best practices in teaching and learning. Paper presented at the 4:e ogiska inspirationskonferensen, LTH, Lund University (2006)
54. Rusman, E., Van Bruggen, J., Cörvers, R., Sloep, P., Koper, R.: From pattern to practice: Evaluation of a design pattern fostering trust in virtual teams, Computers in Human Behavior, 25(5), pp. 1010--1019 (2009)
55. Köppe, C., Inventado, P.S., Scupelli, P., and Van Heesch, U.: Towards Extending Online Pattern Repositories: Supporting the Design Pattern Lifecycle. In: Proceedings of the Pattern Languages of Programs (PLoP 2016). ACM (in press)
56. Iba, T.: Pattern Languages as Media for the Creative Society. In: Proceedings of the 4th International Conference on Collaborative Innovation Networks (COINs2013). (2013)
57. Turani, A., Calvo, R. A.: Beehive: A Software Application for Synchronous

Collaborative Learning, Campus Wide Information Systems, 23, pp. 196--209 (2006)
58. Derntl, M.: The Person-Centered e-Learning pattern repository: Design for reuse and extensibility. In: Proceedings of EDMEDIA'04 - World Conference on Educational Multimedia, Hypermedia & Telecommunications, pp. 3856--3861. (2004)
59. Derntl, M., Calvo, R. A.: E-learning frameworks: facilitating the implementation of educational design patterns, International Journal of Technology Enhanced Learning, 3(3), pp. 284--296 (2011)
60. Hernández-Leo, D., Villasclaras-Fernández, E. D., Asensio-Pérez, J. I., Dimitriadis, Y., Jorrín-Abellán, I. M., Ruiz-Requies, I., Rubia-Avi, B.: COLLAGE: A collaborative Learning Design editor based on patterns, Journal of Educational Technology and Society, 9(1), pp. 58--71 (2006).
61. Villasclaras-Fernández, E., Hernández-Leo, D., Asensio-PéRez, J. I., Dimitriadis, Y.: Web Collage: An implementation of support for assessment design in CSCL macro-scripts, Computers & Education, 67, pp. 79--97 (2013)
62. Inventado, P.S., Scupelli, P.: Patterns for Learning-Support Design in Math Online Learning Systems. In: Proceedings of the 23rd Pattern Languages of Programs (PLoP 2016). ACM (in press)
63. Inventado, P.S., Scupelli, P.: A Data-driven Methodology for Producing Online Learning System Design Patterns. In: Proceedings of the 22nd Conference on Pattern Languages of Programs (PLoP 2015). ACM (in press)
64. Ritter, S., Anderson, J. R., Koedinger, K. R., Corbett, A.: Cognitive Tutor: Applied research in mathematics education. Psychonomic bulletin & review, 14(2), pp. 249--255 (2007)
65. Inventado, P.S., Scupelli, P., Van Inwegen, E., Ostrow, K., Heffernan, N., Baker, R.S., Slater, S., Almeda, M.V., Ocumpaugh, J.: Hint Availability slows completion times in summer work. In: Proceedings of the 9th International Conference on Educational Data Mining, pp. 388--393. (2016)
66. Zimmerman, M., Herding, D., Bescherer, C.: Pattern: Hint on Demand. In Mor, Y., Mellar, H., Warburton, S., and Winters, N (Eds.) Practical design patterns for teaching and learning with technology, Sense Publishers (2014)
67. Koedinger, K. R., Booth, J. L., Klahr, D.: Instructional complexity and the science to constrain it, Science, 342(6161), pp. 935--937 (2013)
68. Kali, Y.: The Design Principles Database as a Means for Promoting Design-Based Research. In: A. E. Kelly, R. A. Lesh & J. Y. Baek (Eds.), Handbook of design research methods in education: Innovations in science, technology, engineering, mathematics learning and teaching, pp. 423--438. Routledge (2008).
69. Hernández-Leo, D., Chacón, J., Prieto, L. P., Asensio-Pérez, J. I., Derntl, M.: Towards an integrated learning design environment. In: European Conference on Technology Enhanced Learning, pp. 448--453. Springer Berlin Heidelberg (2013)
70. Inventado, P.S. and Scupelli, P: Towards an open, collaborative repository for online learning system design patterns, eLearning Papers, 2015(42), pp. 14--27 (2015)
71. Baker, R. S., Inventado, P. S.: Educational data mining and learning analytics. In: Learning analytics, pp. 61--75. Springer New York (2014)
72. Feldon, D. F.: Do psychology researchers tell it like it is? A microgenetic analysis of research strategies and self-report accuracy along a continuum of expertise. Instructional Science, 38(4), pp. 395--415 (2010)
73. Yates, K., Sullivan, M., Clark, R.: Integrated studies on the use of cognitive task analysis to capture surgical expertise for central venous catheter placement and open cricothyrotomy. The American Journal of Surgery, 203(1), pp. 76--80 (2012)
74. Ocumpaugh, J., Baker, R., Gowda, S., Heffernan, N., Heffernan, C.: Population validity for Educational Data Mining models: A case study in affect detection. British Journal of Educational Technology, 45 (3), pp. 487-501 (2014)

75. Baker, R.S.J.d., Corbett, A.T., Koedinger, K.R., Roll, I.: Generalizing Detection of Gaming the System Across a Tutoring Curriculum, in ITS 2006, LNCS, vol. 4053, pp. 402--411, Springer, Heidelberg, (2006)
76. Beck, J. E., Gong, Y.: Wheel-spinning: Students who fail to master a skill, in International Conference on Artificial Intelligence in Education, LNCS, vol. 7926, pp. 431--440, Springer, Berlin, Heidelberg (2013)
77. Bixler, R., D'Mello, S.: Toward fully automated person-independent detection of mind wandering, in International Conference on User Modeling, Adaptation, and Personalization, LNCS, vol. 8538, pp. 37--48, Springer, Cham (2014)
78. San Pedro, M.O.Z., Baker, R.S.J.d., Bowers, A.J., Heffernan, N.T.: Predicting College Enrollment from Student Interaction with an Intelligent Tutoring System in Middle School. In: Proceedings of the 6th International Conference on Educational Data Mining, pp. 177--184. (2013)