Evolving the 4C/ID model through learning analytics approaches: Teaching and learning system design framework for supporting learners' complex problem-solving

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Abstract

In recent years, there has been a surge in studies focusing on learning analytics (LA) aimed to collecting and analyzing learning trace data from various digital learning platforms. However, there is a need for these platforms to be designed from the ground up by LA experts, ensuring that data collection and analysis procedures align with the objectives and activities of teaching and learning as informed by established instructional theories. As a result, we developed a novel framework that integrates the 4C/ID model with LA approaches to enhance learners' complex problem-solving abilities within online and blended learning environments. In developing this framework, we focused on the four core components of the original 4C/ID model along with the P-A-S cycle to determine optimal timing and methods for data collection and analysis. Our aim is to propose a framework that not only revisits and reinterprets the 4C/ID model but also fosters the development of a LA system embedded within digital learning platforms and closely tied to educational goals and learning activities. The findings of this study can serve as a valuable resource for designing and constructing adaptive teaching and learning systems, ultimately supporting learners in effectively cultivating their problem-solving skills.

CCS Concepts

• **Applied computing** → Education; Computer-assisted instruction.

Keywords

4C/ID model, Learning analytics, Complex problem-solving, Adaptive learning system design, Data-informed decision-making

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1 Introduction

A growing number of studies in the field of LA have been conducted to gather and analyze learning trace data from a variety of digital learning environments such as 'edX', 'Khan Academy', and other MOOC-based platforms, with the goal of deriving insightful findings to better understand learning events on these platforms [3, 30]. However, a significant gap exists between the design of learning platforms and the enhancement of teaching and learning using the results from the LA processes. Designing and constructing learning platforms involves substantial effort in determining the types of data to be collected and the methods for collecting them. Since digital learning platforms operate on the foundation of integrated architectures that combine data collection with corresponding feedback loops to enhance teaching and learning, it is essential for instructional designers and LA experts to rely on a well-established and validated instructional theory as a bridge connecting the teaching and learning process with LA approaches. Such an approach not only facilitates the theoretical grounding of LA applications but also broadens the scope for interpreting and applying LA results in a meaningful and effective manner to support learning processes. Therefore, it is crucial for instructional designers and experts in the field of LA to design from the bottom level, which includes designing data collection and analysis procedures that align with the goals and activities of teaching and learning from a theory-driven LA perspective [15].

The 4C/ID (four-component instructional design) model has the potential to serve as a solid foundation for designing LA architectures. The 4C/ID model was designed to structure teaching and learning for complex problem-solving, with the aim of supporting learners' intricate cognitive processes and facilitating the transfer of those skills to real-life situations [4, 25, 26]. The most significant characteristic of this model is its emphasis on enabling learners to solve complex, real-world problems by completing tasks in a sequential manner guided by the model, while receiving timely support when necessary. This means that the expected behaviors to be achieved by learners are clearly defined, and the scaffolding to promote those behaviors is meticulously structured. LA allows educators to determine which data to collect and analyze based on the defined learning behaviors and outcomes, and automates the process of providing timely and appropriate support and scaffolding needed for problem-solving tailored to individual learners [26].

This study aims to propose an augmented version of the 4C/ID model that integrates LA approaches, offering guidance for supporting learners' complex problem-solving and designing LA systems within digital learning platforms. Through LA approaches, not only

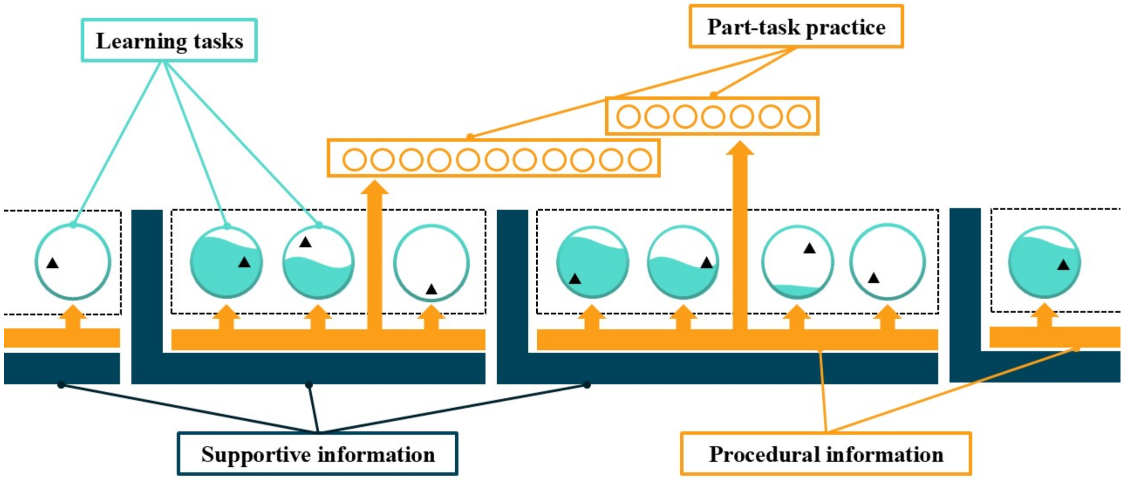

Figure 1: Structure and the core four components of the 4C/ID model

can instructional designers and educators be supported in their decision-making processes during the design and implementation of instruction, but the initial problem-solving instructional model can also be adjusted based on the analysis of data collected in online learning environments [33, 34]. In other words, this approach offers a blueprint for structuring the design model of a LA system that effectively supports learners' real-world problem-solving processes.

2 4C/ID MODEL AND LEARNING ANALYTICS

2.1 Structure and core features of the 4C/ID model

As societal changes occur at a rapid pace, the complexity of problems that every person faces has been increasing. Accordingly, there is an increasing focus on the design and implementation of instructions that effectively achieves this goal. One of the prominent models that facilitates this goal is the 4C/ID model, which incorporates elements from information processing theory and cognitive load theory [26, 27]. The 4C/ID model is founded on the instructional environments designed to teach the complex cognitive skills required for solving real-world problems should consider four essential components: (1) learning task (LT), (2) supportive information (SI), (3) procedural information (PI), and (4) part-task practice (PP) [24] (see Figure 1).

First of all, learning tasks (LT) refer to tasks or problems closely related to real-life situations. It is important to sequentially arrange learning tasks with increasing levels of complexity and decreasing scaffoldings to help students acquire the necessary knowledge and skills independently [26]. The strategies for handling task complexity can be primarily categorized into four methods:

(1) **Increasing the intrinsic complexity of a task by adding sub-elements to its structure**: For instance, in a media literacy class, teachers can make learning tasks more complexed by adding the number of elements which learners need to find, which means that the number of parameters learners need to consider gradually increases [7]; (2) **Increasing the number of learner activities:** This refers to the classes starting with a lecture-based format and gradually incorporating more interactive activities that require learner participation, such as small-group discussions, role-plays, and case simulations [17, 20]; (3) **Increasing the complexity of the knowledge and skills required to handle overall tasks**: This is related to the "emphasis manipulation" strategy proposed in the original 4C/ID model [26], where the focus shifts between different aspects of the underlying knowledge or skills within the same task rather than modifying complexity of the task itself [5, 18, 32]. For instance, in a study aiming to enhance teachers' individualized instructional skills, instead of changing the structure of the classes each time, researchers adjusted the emphasis on different individualized teaching skills within similar class scenarios [5]; (4) **Adjusting the time allocated for task performance**: For example, in surgical training, complexity can be modulated by imposing time constraints on various scenarios to help learners acquire specific surgical skills [23].

In adjusting the complexity of the learning tasks, 'cognitive task analysis' is mainly conducted by content experts, such as instructional designers or teachers. This process involves breaking down the knowledge and skills to be acquired in each task and sequentially organizing the corresponding tasks [1, 2, 8, 10, 13]. That is, learners are compelled to follow a pre-determined sequence of tasks designed for problem-solving instruction based on the 4C/ID model.

Secondly, supportive information (SI) refers to the information that helps learners deal with the non-recurrent aspects of the learning tasks, facilitating the integration of new information with the learners' pre-established schemas. Supportive information can be categorized into three main types: general information, modeling example, and cognitive feedback [26]. General information and modeling examples are provided before task execution, in the form of reading materials, textbooks, web links, case studies, and video lectures presenting theoretical knowledge [6, 8, 20, 29]. On the other hand, cognitive feedback mainly includes instructors' feedback after observing learners' performances, as well as information of peer learners' performance [22]. Among them, information of peer performance allows learners to compare their own task performance with their peers and to facilitating deeper reflection on their work [19]. Therefore, cognitive feedback can be more effectively delivered through reflection prompts, allowing instructors to present feedback in a more accessible manner [4, 6, 29]. Such materials should be available to learners before executing each task, enabling them to utilize these resources throughout the completion of their tasks.

Third, procedural information (PI) is the information that assists learners in addressing the recurrent aspects of learning tasks. Procedural information is divided into just-in-time information and corrective feedback [26]. Just-in-time information is typically provided in the form of manuals, checklists, quick reference guides, step-by-step instructions, and hints [4, 11, 13]. This information should be removed as learners move on to the next task. In face-to-face learning contexts, the provision and removal of procedural information depend on instructors or facilitators to determine the appropriate timing [22]. Conversely, in online learning environments, procedural information is often digitalized and embedded within the learning tasks or content modules. It is presented through pop-up windows that can be accessed as needed and then promptly removed [5, 10, 12]. Corrective feedback refers to feedback aimed at timely correcting errors that occur during the learners' performance. Instructors or facilitators directly correct errors immediately when observing learners [19, 20], or through Q&A boards within learning platforms [13].

Lastly, part-task practice (PP) refers to the repetitive training of elements within a learning task that need to be automated. It is important to provide learners with a lot of opportunities for part-task practice when they think they need additional practice throughout the overall learning process [20]. For example, extra sessions were held for teachers to practice their teaching [5], or learners can engage in role-plays to acquire repetitive communication skills [22]. Furthermore, in online learning environments, learners can acquire knowledge and skills that need to be automated by completing multiple-choice quizzes, with part-task practice tailored to the types of errors generated during their task execution [4].

Despite the various advantages of designing and implementing problem-solving instruction based on the 4C/ID model, some kind of challenges must be addressed. First, it is labor-intensive for instructors and instructional designers to adaptively create learning tasks suitable for individual learners while considering the complexity and their sequence of the tasks [5, 8, 23, 29]. Second, the supportive information, procedural information, and part-task practice required for executing these learning tasks must be provided and removed in a timely manner, which poses limitations for a small number of instructors and designers working with a large number of learners [17]. This challenge becomes even more pronounced in face-to-face learning situations where instructors must closely follow each learner's progress [13, 32]. Although the 4C/ID model systematically presents design principles for learning tasks and scaffolding, it provides relatively limited guidance on how to analyze learner characteristics such as cognitive load or motivation, as well as how to evaluate learner performance, thereby exacerbating these challenges [5].

Considering these points, establishing an adaptive and agile structure that allows for the collection and analysis of data related to the 4C/ID model-based instructional process can serve as a prerequisite for effectively implementing the core design principles outlined in the model. LA plays a crucial role by shortening the cycle of data collection, analysis, and feedback within the instructional process. In other words, by combining the systematic principles of task and scaffolding design presented by the 4C/ID model with LA approaches that determine what kind of data to collect and analyze from learners and the learning environment, we can derive guidelines for designing an instructional system that adaptively supports the problem-solving teaching and learning described in the 4C/ID model.

2.2 Integrating the 4C/ID model with learning analytics

In this section, we explore how each main component of the 4C/ID model integrates with LA approaches. A critical aspect of LA is determining which data to collect and when to collect it. This challenge can be addressed by applying the P-A-S cycle proposed by [28], as illustrated in Figure 2.

The P-A-S cycle emphasizes learner autonomy and agency by suggesting that in 4C/ID-based problem-solving instruction, learners should be able to select their next tasks based on their performance evaluations. The fact that the activities learners engage in for each task are defined indicates that specific observable phases of learner behaviors in the instructional process are also determined. This means that the Performance (P), Assessment (A), and Selection (S) stages serve as conceptual junctures, facilitating the observation and collection of data during the instructional process. Constructing a feedback loop that integrates the data collected and analyzed at each juncture into the overall problem-solving instructional process is crucial, as it enhances the systemic connection between LA and instructional design and implementation. Applying the P-A-S process allows for the creation of new linkages between tasks, even within the same instructional objectives, thereby generating personalized learning paths and learner profiles [28]. These learner profiles can then inform the design of the next task and the necessary scaffolding, providing tailored guidance that supports the subsequent Selection (S) phase for learners.

When generating appropriate subsequent task candidates for learners to choose, two key factors must be considered: the hierarchy of subtasks and the procedurality of task classes. These factors are closely related to the fundamental assumptions underlying the 4C/ID model [26]. On the one hand, the hierarchy of subtasks indicates that as learners progress through the subtasks within a single task class, the complexity and the resulting cognitive load they experience gradually increase. The overall complexity and difficulty experienced by learners rises progressively depending on the

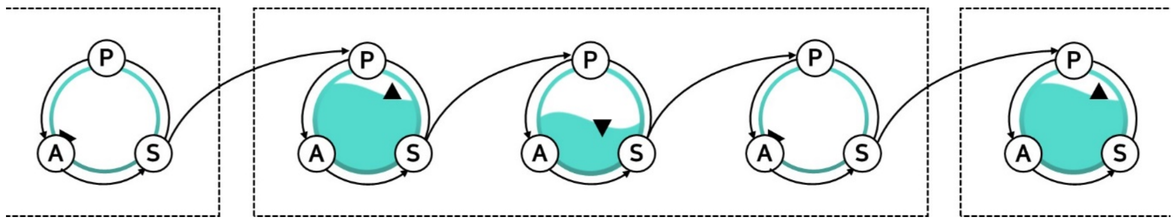

Figure 2: P-A-S cycle

intrinsic complexity of each subtask and the amount of support and guidance provided during its execution [26]. Without completing the preceding tasks, it would be difficult for learners to acquire the prerequisite knowledge or skills necessary for the subsequent tasks. In other words, there exists a hierarchical order among subtasks, akin to a prerequisite structure.

On the other hand, the procedurality of task classes means that there is a certain sequence among task classes. Although changing the order of task classes does not necessarily prevent goal achievement, there is an optimal sequence to follow in terms of efficiency [26]. Considering these two dimensions, by synthesizing data from learners' subtask performance and evaluation results, it is possible to provide appropriate recommendations considering the hierarchy of subtasks and the procedurality of task classes. In other words, the complexity of suitable subtasks for learners can be calculated, and options can be presented accordingly. Upon completing an entire task class, a personalized suggestion can be provided for the next most effective task class to perform. This tailored approach not only helps regulate the cognitive load experienced by each learner but also facilitates the effective acquisition of prerequisite knowledge or skills needed for completion of learning tasks. Ultimately, this can be achieved through the timely and appropriate provision of the three remaining components—supportive information, procedural information, and part-task practice.

In summary, by systemically integrating these insights within the structure of the 4C/ID model, it is possible to produce LA prescriptions at various levels to support learners' performance, evaluation, and selection processes throughout the problem-solving instructional process. This approach can further be effectively leveraged to assist instructional system designers in adapting and refining the instructional system design.

3 4C/ID_LA framework for complex problem-solving

3.1 4C/ID_LA framework

We have developed a LA framework based on the 4C/ID model, referred to as the 4C/ID_LA framework, as shown in Figure 3. This framework outlines how to leverage a LA approach to collect data in a structured manner and determine the appropriate timing for data collection, all with the goal of providing adaptive and personalized interventions during the process of problem-solving instruction.

The framework is represented in a two-dimensional structure, considering both hierarchy and procedurality—two key dimensions essential for adjusting personalized learning tasks. Learners engage in the problem-solving instruction process based on the 4C/ID model by sequentially completing subtasks, starting from the leftmost subtask within the frontmost task class. Each task class is depicted within a light blue rectangle, emphasizing that the LA engine continuously supports the primary components and associated activities following the 4C/ID model, with the ongoing process of data collection and monitoring. An elaboration of the core features of this model is shown in Figure 4, providing detailed information on the four main components.

First, the most notable feature of this model is that each learning task (LT) integrates the P-A-S cycle [26]. The model builds upon the core principles of the traditional P-A-S cycle to allow for the integration of LA throughout the task performance process. During the Performance (P) phase, learners complete subtasks, and the LA system collects data on their behavioral changes, achievements, and outcomes. This data is subsequently analyzed and presented to learners via an LA dashboard. Upon completing the task, learners move to the Assessment (A) phase, where they reflect on and self-evaluate their performance using the analyzed data from the Performance (P) phase. Based on the learner's performance (P) and self-assessment (A), the system then offers tailored options for selecting the next subtask (S). If the learner struggled with the previous task, a similar task with equivalent levels of support and guidance may be recommended. Conversely, if the learner performed well, tasks with reduced support and higher complexity would be suggested to progressively challenge them.

When learners complete all the subtasks in a task class based on their hierarchical nature, the customization of task classes sequentially occurs. Data collected during the learner's progression through the task class can inform the selection of the subsequent task class, allowing for personalized guidance not only within a task class but also between different task classes. This adaptability is depicted visually as if task classes are interconnected and can be adjusted based on individual learner performance, visualized as a flexible insertion of "slates."

The model integrates not only learning tasks but also the remaining three elements of the 4C/ID model. First, supportive information (SI) is presented as general learning information accessible to learners from the beginning of a task and throughout its execution. It is depicted in the model using the same "L" shape as in the original 4C/ID model. It is important that learners in an online or blended learning environment are informed about where and how to access this digitized supportive information whenever needed. In addition to general learning information, cognitive feedback, which helps learners reflect on their performance, can be delivered through an LA dashboard. This dashboard can display a variety of information, such as characteristics of each subtask,

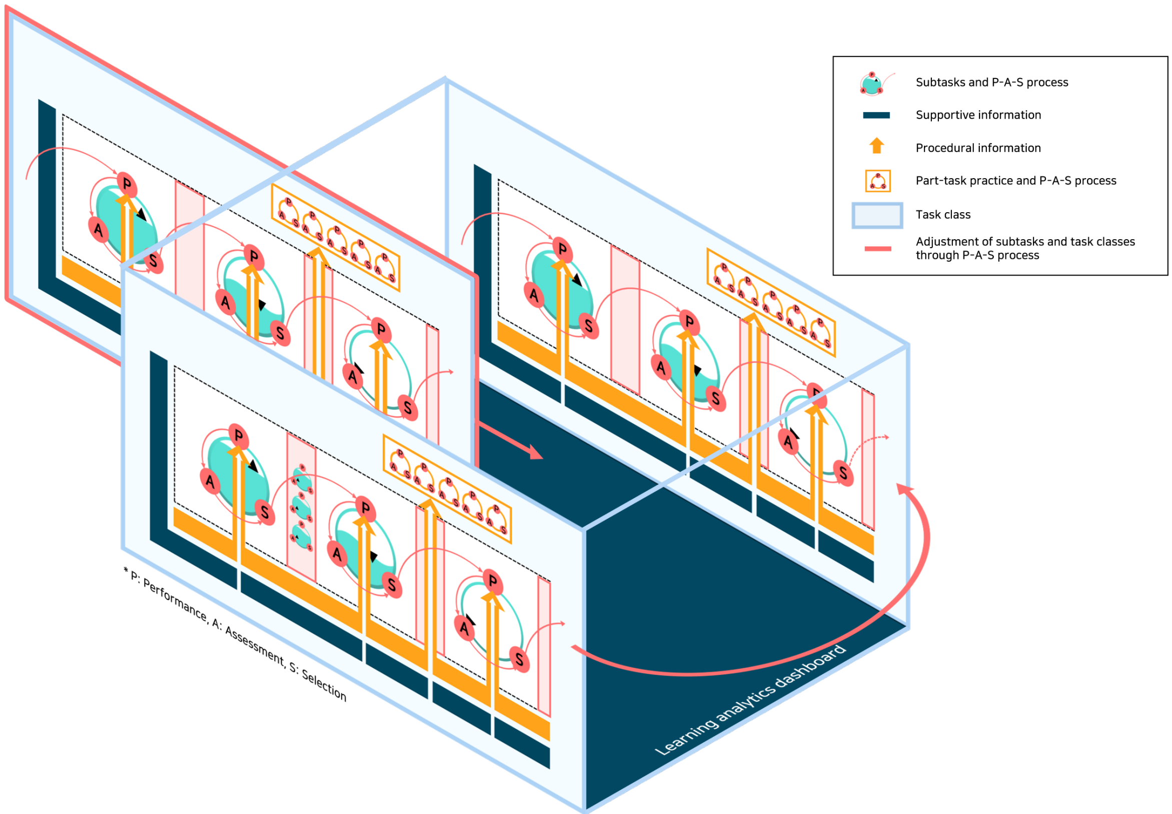

Figure 3: 4C/ID_LA framework

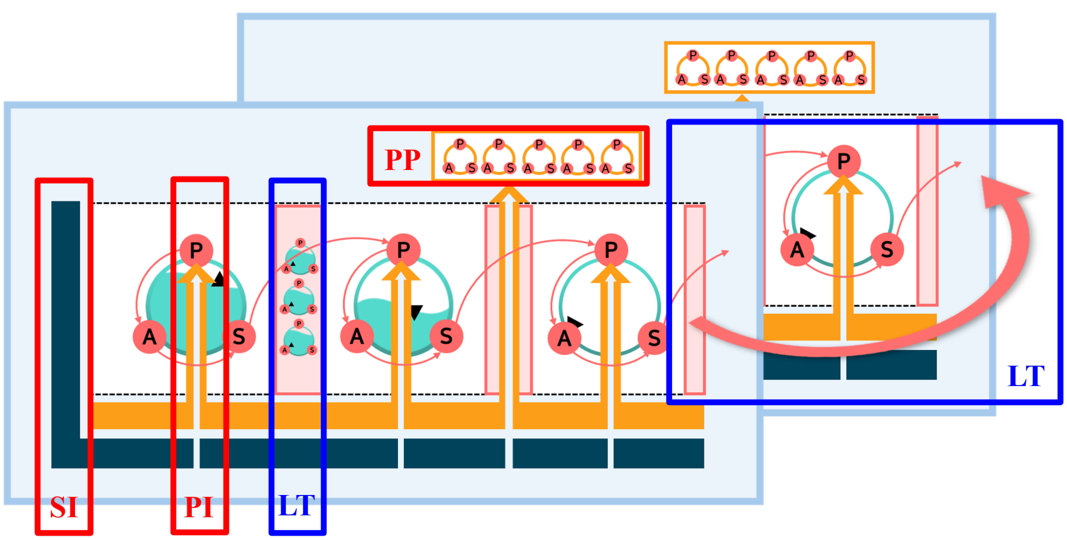

Figure 4: Four components integrated with learning analytics

learner performance data, and performance data from peers who have completed similar tasks. By providing such data, the dashboard supports learners in reflecting on their performance not only during task execution but also when selecting future tasks.

Next, procedural information (PI) is combined with LA by collecting data on learner performance during the execution phase (P) and analyzing errors. The model visually indicates this integration using a blue arrow overlaid on the traditional yellow arrow

Figure 5: Example polyhedron representing the individual learning paths

that represents procedural information in the 4C/ID model. This representation illustrates that the analytics process supports the learner's performance phase (P). By analyzing real-time error data and allowing learners to directly request help when they encounter difficulties, the system can provide timely procedural information. This enhances the support provided to learners during task execution, helping them overcome challenges more effectively.

Lastly, part-task practice (PP) is customized for each learner based on the history of previously provided procedural information and results from error analysis. Since part-task practice is a type of learning task, it is also governed by the P-A-S cycle, allowing learners to decide whether to engage in the recommended practice and how long to continue with it. Considering that the effectiveness of part-task practice can vary with the learner's prior knowledge and achievement level, providing personalized choices regarding engagement in part-task practice can significantly enhance the effectiveness of instruction.

Based on the 4C/ID_LA framework, individual learners can generate their own learning paths by selecting subsequent learning tasks and task classes as they progress through the instructional process. Each individual learner's learning path can be generated and visualized in the form of a polyhedron (Figure 5). Since each learner's polyhedron may differ, this can serve as a basis for exploring ways to compare learning paths across different learners.

3.2 Learner workflow and sample scenario

To visually represent how learners engage with the learning process and how LA interventions are integrated within the framework, we have developed a learner workflow. This workflow draws on prior research that clearly illustrates both learner experiences and the supportive technology interventions [9, 14]. The workflow is structured into six main stages of the teaching and learning process: (1) Before class, (2) During class: Performance (P), (3) During class: Assessment (A), (4) During class: Selection of subtasks (S), (5) During class: Selection of task classes (S), and (6) After class. As each stage unfolds, the specific learning experiences of the learner, as framed by the 4C/ID_LA approach, are depicted on the left side, emphasizing learner behaviors. Correspondingly, the right side illustrates the data that the LA system collects and analyzes to support these experiences and the interventions derived by the results of data analysis. This two-column structure elucidates how appropriate learning tasks and subsequent task classes are presented to the learner, along with the effective intervention consisting of supportive information, procedural information, and part-task practice. By presenting this workflow, we aim to clearly demonstrate the process of problem-solving teaching and learning within the context of the 4C/ID_LA framework.

To gain a better understanding of this framework, we have made a specific learner persona and a scenario in which the persona navigates the entire teaching and learning process as outlined by the framework. The example learner persona and the corresponding scenario we have established are as follows:

Kim is a first-year humanities major who has enrolled in an online general education course titled "Understanding and Utilizing Big Data Analysis for Problem Solving" offered through her university's teaching and learning platform. Kim lacks familiarity with statistics and is not experienced in using statistical programming software. The objective of the course is to present students with real-life tasks and to cultivate their ability to analyze provided data using appropriate statistical techniques.

(1) Before class: Before the class starts, instructors and instructional designers consider the overall learning objectives and design the subtasks learners will perform, organizing them into sequenced task classes. The learner profiles of enrolled students are utilized in forming this initial task database.

(2) During class—Performance (P): Kim begins the learning process by undertaking a subtask within the assigned task class. The first task class focuses on correlation analysis, where Kim is required to investigate the relationship between last year's salary increase rates and employee turnover rates. Lacking prior knowledge in correlation analysis, Kim first reviews the instructor's lecture videos, materials, and the textbook to grasp the fundamental concepts (support information—general information). These resources are pre-uploaded in the teaching and learning platform, allowing Kim to access them whenever necessary. After acquiring the basic theoretical knowledge, Kim proceeds to conduct the required statistical analysis for the task. Since this is the first subtask in the present task class, the data is well-prepared, requiring no additional preprocessing, and Kim easily follows the analysis steps described in the assignment. During the programming process for the correlation analysis, Kim encounters an unexpected error. Fortunately, a quick manual is provided, enabling Kim to identify and resolve the issue immediately (procedural information—corrective feedback). Upon completing the first subtask, feedback based on predetermined criteria set by the instructor, along with information on how other learners performed the task step-by-step, is displayed on the dashboard (support information—cognitive feedback). Using the data on her own performance and that of peers, Kim reflects on her previous task performance.

(3) During class—Assessment (A): After completing the task, Kim is presented with an evaluation section on the platform. The evaluation criteria are divided into self-assessment and task assessment. For self-assessment, Kim reflects on her satisfaction with her performance and considers what she learned from the previous task. The task assessment includes questions related to the perceived difficulty and complexity of the assignment, as well as whether the content and context is familiar with Kim's interests. Drawing on the information displayed on the LA dashboard, Kim reviews her performance and responds to the checklist and open-ended questions in the evaluation form.

(4) During class—Selection of subtasks (S): After completing the evaluation, a mini-quiz is activated focusing on the points where Kim made mistakes during performing the first subtask, specifically regarding the use of the Pearson and Spearman correlation coefficients. Recognizing her confusion in this concept, Kim chooses to complete the mini quiz. The quiz consists of several sessions, and after working through three of them, Kim gains a clearer understanding of the concepts that were previously confusing, allowing her to move on to the next task. Kim is presented with three options for the next assignment; considering the relative difficulty of completing the previous task, one option is similar in terms of complexity, while two others are slightly more challenging. Empowered by her newfound confidence, Kim decides to perform one of the assignments with more complexity. This cycle of assessment and task selection continues until Kim completes the final subtask of the first task class.

(5) During class—Selection of task classes (S): Upon completing the final subtask in the first class, Kim has developed the ability to effectively handle complicated data and apply appropriate correlation analysis methods to interpret and report results. The comprehensive performance data related to the correlation analysis task class is displayed on the LA dashboard, presenting Kim with three options for the next task class. Among these, Kim chooses the task class related to regression analysis, proceeding to tackle each subtask one at a time, similar to the previous task class.

(6) After class: After completing the final task class, Kim reflects on her performance based on the analysis results of aggregated data from the entire course. This compiled data, along with insights from Kim's reflective process, will be utilized to form the foundational learner profile for the subsequent course "Understanding and Applying Machine Learning," which Kim plans to take next semester.

4 Discussion

In constructing the framework presented in this study, we applied the P-A-S cycle [28] to create critical points for observing learner behavior and collecting data. This application enables the formulation of LA-based justifications for presenting personalized options for learning tasks and scaffolding strategies. By implementing the P-A-S cycle, the framework supports data-informed decision making, thus enhancing learners' autonomy and agency within the teaching and learning process.

While the original 4C/ID model emphasized performing learning tasks that were analytically designed by content experts [1, 2, 8, 10, 13], the integration of the P-A-S cycle and its corresponding LA structure allows learners' choices to influence not only the immediate tasks but also the overall path of the teaching and learning experience. In this data-driven decision-making process, it is essential that learners are provided with sufficient and appropriately presented information to facilitate their decisions. Additionally, feedback regarding the outcomes of their choices must be offered, creating a sense of responsibility for their decisions while allowing them to consider alternative options in a safe environment [31]. When these conditions are met, learners experience a process of discovering and solving new problems sequentially as they make choices based on data-driven decision-making in problem-solving contexts.

In this context, it is crucial to provide information about the overall teaching and learning process and decision-making through the LA dashboard in the form of cognitive feedback. This support facilitates learners' reflection on their decision-making processes. As a result, learners are empowered to establish their learning pathways, fostering a sense of control over their entire performance process. From the perspective of self-determination theory, this autonomy can enhance engagement and motivation in the learning experience [5, 21]. Although the learners' subjective choice processes may not explicitly align with the learning objectives outlined in the model derived from this research, they can serve as hidden educational goals.

However, it is essential to recognize that potential issues may arise if sufficient information is not provided when granting learners the freedom to choose. For example, since the evaluation process in the P-A-S model is based on self-assessment, there is a risk that learners may misjudge their performance and outcomes. Additionally, learners might tend to avoid challenging tasks when creating their learning pathways. To address these concerns, it is vital to establish objective performance indicators and guidelines set by instructors or instructional designers, along with an automated feedback system that appropriately delivers this information to learners. Most importantly, the process of learners creating their own learning pathways should itself be considered a learning experience. An environment must be established that supports the choices and evaluations aimed at achieving the instructional goals set by individual learners.

Moreover, the application of the P-A-S cycle also provides critical insights for instructional designers and system developers. As learning processes occur repeatedly and the data generated by individual learners accumulates, it becomes possible to adjust predesigned tasks or scaffolding based on this data, thereby facilitating the overall adaptation of the teaching and learning system. The fundamental principle of the 4C/ID_LA framework proposed in this study is to recommend the next task that best fits the learner based on data generated during the Performance (P) and Assessment (A) phases. However, there is a significant difference between a scenario where learners select from multiple options presented by the system (S) and one where the system offers what it deems the optimal choice. While both approaches utilize comprehensive analysis of learner data, the latter relies on predictive modeling to provide what is considered the most optimal choice, akin to point estimation. This predictive approach inherently has limitations as it cannot precisely cater to the diverse preferences of learners.

Therefore, rather than focusing solely on enhancing the model performance of the LA system, instructional designers should prioritize creating a safe environment where learners can exercise their autonomy and agency in making various kinds of choices. This shift is likely to more effectively facilitate learners' teaching and learning processes [5]. To achieve this, mechanisms that enable choice must be established, alongside the provision of sufficient information that supports informed decision-making and feedback on the outcomes of those choices.

In conclusion, through the 4C/ID_LA framework, instructional designers can collect data on how learners interact with learning tasks and the overall teaching and learning process. This enables micro-level adjustments to the sequence and complexity of individual tasks and task classes, while also supporting macro-level improvements to the adaptive environment necessary for effective problem-solving teaching and learning. This underscores the framework's potential as a theoretical basis for designing adaptive instructional systems.

The significance of this research lies in its emphasis on deriving workflows and scenarios that reflect the activities of teaching and learning stakeholders while integrating the 4C/ID model with LA. In other words, rather than starting with software design for system construction, the focus is on designing the data and learning activities that the system should collect and observe. This approach aims to enhance the interconnection between the LA system and the teaching and learning process. By visualizing the activities of teaching and learning stakeholders alongside the operational dynamics at the system level, this research not only conceptualizes the design of instructional systems based on educational theory but also enhances the practical applicability of the findings and provides important insights for system-level design.

5 Further work

This study contributes to building a theoretical framework for supporting learners' complex, real-world problem-solving using a LA approach. A key characteristic of the proposed framework is that it can be further refined through the process of the actual design and implementation of a LA system. For example, in addition to the data flows suggested in this study, there may be a need to collect unexpected types and forms of data during the implementation of problem-solving instructional processes. Moreover, determining when learners move to the next task or task class through the P-A-S process can also be changed in the context of actual system operation. As this framework is applied to various task contexts, certain components of the framework may need to be adapted based on specific instructional scenarios. Thus, the findings of this study are not a complete blueprint, but rather a collection of essential potential elements needed for operating a single system cycle effectively. Therefore, it is anticipated that the research outcomes will co-evolve with the development of the actual system and practical scenarios.

We are currently in the process of developing an actual platform based on cognitive load measurement, which will enable us to empirically validate the proposed model. The platform incorporates the sub-system layers necessary to run the entire LA system, including dashboards, databases, and analytics system layers, specifically designed for the context of complex problem-solving. Building on the theoretical framework developed in this study, we are constructing the system's structure and dynamic workflow to illustrate its operation across the P-A-S cycle. This includes detailing the data collected at each phase and the information presented to all agents involved in the teaching and learning process through dashboards, as well as illustrating how each sub-system layer functions throughout the whole process. Our efforts are focused on actively designing and developing the system to offer a comprehensive view of how the framework and its components function in practice. The next step of our research will include the validation of the proposed framework with a large dataset gathered from learners within the operating LA system.

6 Conclusion

This paper presents a novel theoretical framework as fundamental guidance for designing a LA architecture, encompassing data collection and the provision of scaffolding to support learners' complex problem-solving, based on the 4C/ID model. In other words, we revisit and reinterpret this established instructional theory to integrate a LA approach with the goal of designing an adaptive learner supporting system. This theoretical foundation not only informs the design process of LA systems but also provides deeper insights into how additional data can be captured to enhance our understanding of learners' problem-solving processes within such systems.

The newly proposed framework underscores the crucial point that LA and instructional system design can be systemically interlinked. Building the structure of collecting and analyzing learners' data from instructional design models can contribute to shifting the paradigm of LA processes from a 'data-driven' to a 'theory-driven' perspective [16], thereby enhancing the validity of the results. This shift allows LA not only to be used as a useful tool for prediction and prescription, but also to facilitate learners' instructional processes and support instructional designers in effectively creating intelligent instructional systems.

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