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Architecting Analytics Across Multiple E-learning Systems to Enhance Learning Design

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***Abstract*—With the wide expansion of distributed learning environments the way we learn became more diverse than ever. This poses an opportunity to incorporate different data sources of learning traces that can offer broader insights into learner behavior and the intricacies of the learning process. We argue that combining analytics across different e-learning systems can potentially measure the effectiveness of learning designs and maximize learning opportunities in distributed settings. As a step toward this goal, in this study, we considered how to broaden the context of a single learning environment into a learning ecosystem that integrates three separate e-learning systems. We present a cross-platform architecture that captures, integrates, and stores learning-related data from the learning ecosystem. To demonstrate the feasibility and the benefits of cross-platform architecture, we used regression and classification techniques to generate interpretable models with analytics that can be relevant for instructors in understanding learning behavior and sensemaking of the instructional method on learner performance. The results show that combining data across three e-learning systems improve the classification accuracy compared to data from a single learning system by a factor of 5. Our work highlights the value of cross-platform learning analytics and presents a springboard for the creation of new cross-system data-driven research practices.**

***Index Terms*—Cross-platform analytics, architecture for educational systems, distributed learning settings, distance education.**

I. INTRODUCTION

DIGITAL learning has grown significantly with the rapid expansion of Information and Communication Technology (ICT) and the concept of ubiquitous computing. This trend is a catalyst for learning to happen everywhere and at any time, across many different platforms and learning systems, situated and shaped by the tasks, the content resources, and the dynamics of distributed learning environments [1]. Although learning happens anytime and across many diverse learning settings, we still lack insights how to effectively optimize the learning context and the learner experience in these settings [2]. In addition, as learners are rapidly embracing the use of novel data-intensive learning technologies, they are becoming more demanding and critical, creating a challenge how to engage and support them when learning takes place in distributed settings [3].

One promising approach lies in a wider application of learning-related data collected from various e-learning systems, that once merged, can support a learning ecosystem of "dynamic, interconnected, and ever-evolving community of learners, instructors, tools, and content" [4]. The idea draws on the work presented in [5], who advocates that understanding learning and knowledge creation in distributed settings, requires multi-level analyses on learners' traces fragmented across time, numerous e-learning systems, and media (i.e., digital substrates where communication modes are encoded). However, mainstream methods and tools often rely on ***metrics derived from single and many times limited data sources*** such as grades, submission of assignments, self-reported data, or test performances [6]. On the one had, findings based on metrics extracted from limited data sources, represent only a small proportion of the learning process and the activities students engage with. This, in turn, only partially help educators to understand ***when and how students learn***, and ***how effectively they use the opportunities for learning as given in the learning design***. Thus, current approaches often display the ongoing limitations in the learning analytics field, in which many researchers and educators miss the opportunity to make effective and meaningful refinements in the learning designs that can encourage, enable, and advance learning.

On the other hand, learners often make decisions (e.g., whether and what technologies to use) based on the perception of what might maximize their chances to succeed [7]; hence, their focus is often on assessment [8], [9]. However, changes in the instructional methods (i.e., adding personalized feedback) can change learners' single focus on assessment [10] and usage of technologies for reasons other than solely succeeding in the course assessments [6]. Past research has shown that learning design and the instructional conditions strongly affect what technologies and tools students use [6], [11], as well as their level of engagement and performance [12]. Yet, we do not really know ***how to create and measure the effectiveness of learning designs that can maximize learning opportunities in distributed learning settings***. In that respect, learning analytics has the potential to provide insights into what is happening in each and across the different learning systems, and thus, examine the effectiveness of the learning design. For example, if educators have learning-related data from other

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systems learners use to master skills (e.g., GitHub for learning programming), rather then solely from the assigned tasks and the learning management system (LMS) in use, educators can have improved overview of learners' progress and potential misconceptions, and make pertinent decisions to (re)design the learning context when learning behavior deviates from the pedagogical intention.

Consequently, we designed and implemented a study to explore if ***architecting analytics across multiple e-learning systems can enhance the analytics capacities of the individual systems***, and discussed how the findings can support and enhance learning design practices in distributed settings [6], [13], [14]. However, developing cross-platform systems is a complex and data intensive process [15]. On the one hand, the procedure of standards development is inherently challenging [16] and there is a lack of data interoperability standards for handling and processing data generated from different systems [17]. On the other hand, cross-platform systems additionally increase the complexity of orchestrating learning activities in distributed settings, as educators need to deal with the requirements that steam from different learning designs [18], [19]. Therefore, it was also necessary ***to explore and define the minimum technical architecture requirements*** essential for setting the foundations to develop cross-platform systems.

To demonstrate proof of concept, we implemented a cross-platform architecture that integrates three independent personalized e-learning systems (i.e., ProTuS, MasteryGrids, and Visual Learning Analytics System for Programming–VLASP) into one learning ecosystem for data collection, integration, and harmonization. Since these systems automatically capture all user interactions, learning analytics was utilized to shed light and give rise to a larger phenomenon in digital learning and predictive modeling–***how to develop predictive models that not only predict performance and success, but also reveal significant elements for teaching practice*** (e.g., generic and specific), that can be applied to improve the quality of learning designs and instructional methods [20]. As a result, we present the potential of cross-platform learning analytics generated from behavioral log data, and utilized to show how predictive models can be constituted to inform teaching practices as a "diagnostic" tool that can support data-driven changes in the learning design, pertinent to the optimization of the various technologies used during the course. In that regard, we addressed the following research questions:

- **RQ1:** What are the benefits of implementing cross-platform architecture and harnessing cross-platform learning analytics for digital education?
- **RQ2:** What implications cross-platform learning analytics can offer to learning design?

In sum, the contribution of this paper is threefold: 1) ***Conceptual***–to present an ideational model of a digital learning ecosystem which supports and harnesses cross-platform analytics, 2) ***Operational***–to display the implementation of a cross-platform architecture, and 3) ***Empirical***–to validate the value of cross-platform data integration for building predictive models that carry the opportunity to reveal significant elements for teaching practice, rather than the long-standing focus on identifying learners at risk of failing a course or solely for predicting learner performance, as it is commonly done in the learning analytics and educational data mining communities.

II. Background

Optimizing the learning context and making valid and informed changes in the learning design utilizing learning-related data, was probably one of the first motivations for the emergence of learning analytics [21]. Nowadays, the wide proliferation of distributed learning environments gives rise to opportunities in learning analytics and predictive modeling, to explore how analytics from various learning systems (i.e., cross-platform learning analytics) can be harnessed to enhance the quality of learning designs and instructional methods.

A. Cross-Platform Learning Analytics

Current research often relies on metrics derived from data sources such as grades, submission of assignments, the time learners spent in e-learning, self-reported data, or test performances [6]. However, it often falls behind to consider data from more than one learning system, particularly when learning happens in distributed settings [22]. Nonetheless, the more complex data researchers capture across settings (e.g., interactions with learning materials via LMSs, learning trajectories via problem-based learning), the harder it becomes to synchronize and analyze that data [23], [24]. Although frameworks that describe how to capture and classify data from different sources exist [25]–[27], there is a lack of available tools that could assist researchers to easily establish cross-platform and sometimes multimodal systems [28]–[30].

Learning is distributed across multiple media, locations, and online environments; yet, researchers' scope is often limited to a single virtual learning environment (VLE) or LMS. This is a common drawback in the field of learning analytics that depicts the present-day reality where researchers depend on one-sided learning analytics measures due to the difficulties of extracting, harmonizing, and sensemaking of data from various sources [2]. In a previous work, a conceptual model named Group Learning Unified Environment with Pedagogical Scripting, Monitoring, Analysis, and Across-Spaces Support (GLUEPS-MAASS) was presented, describing how data from multiple sources should be collected and integrated, encompassing learning activities in the web, the physical, and the 3D virtual space [31]. However, to the best of our knowledge, this is still a conceptual model, that has not been placed into practice yet. Moreover, there are a few cross-platform patent models [32]–[34] that currently have a pending status.

Consequently, we try to overcome some of the ongoing issues (e.g., one-sided learning analytics measures, data integration, and interoperability) by *proposing a* ***cross-platform architecture*** *that automatically collects, integrates, and harmonizes data from several e-learning systems* (i.e., ProTuS, MasteryGrids, and VLASP). These data is then used to explore if *combining metrics extracted from multi-system log data can increase the predictive power* of the individual systems with respect to estimating student performance at the end of the course, as well as reveal significant metrics that can further *refine the personalization and the design of learning activities and instructional methods*.

B. Predictive Modeling in Learning Analytics

Data-driven approaches to further our understanding of learning are particularly relevant for e-learning and learning analytics research [35], with predictive modeling being an important topic [36]. Many researchers have already utilized predictive modeling techniques to identify students at risk and increase their retention [37], [38], to provide early insights about students' performance and to generate interpretable performance models [39]–[41], to improve the quality and to scale up feedback [42], and to create intervention methods that can improve students' mental health and their university experience [43].

Predictive modeling involves statistical models or data mining algorithms to find patterns in the data, and predict new or future events [44]. Most of the research in predictive modeling forecasts what may happen, and as such has shown opportunities for advancing the field of learning analytics. However, it has yet to mature to offer a wide-scale impact [45]. In other words, predictive models intent to offer actionable insights for learners and instructors, so that these groups of users can take further actions, rather than increase the frequency of feedback (i.e., informing students how they stand with respect to meeting the course list criteria) [46]. Hints (e.g., the traffic light metaphor in [37]) whether learners are at risk of not meeting certain course criteria, can help learners to be aware of their current progress, they do not offer much beyond that [45]. Therefore, learners and instructors do not always find much value and use of such predictive models, as these models are limited in provoking reflection and action [46], [47]. In the same vein, predictive models do not always generate actionable insights, resulting in limited information for instructors to improve their practices and the overall learning design [45], [46]. A step toward a more insightful and actionable information can be generated by combining predictive with explanatory modeling [44], to develop interpretable models with underlying variables that are relevant for instructors and learners in understanding learning behavior and making sense of instructional methods on learning performance [20].

To move beyond predictive analytics [20], [47]–[49] and to investigate and apply sophisticated and innovative approaches, we focused on *harnessing cross-platform learning analytics in predictive modeling*. This way we aimed to explore if combining analytics across various systems can increase the predictive power of individual learning systems with respect to estimating student performance (i.e., grades), as well as develop models that reveal significant elements for teaching practice, that in future, can *help learners, to understand the value of different learning resources* apart from solely maximizing their chances to succeed by getting good grades.

C. Standards, Integration, and Interoperability of Learning Systems

Systems operate by "understanding" the data structures they share [50]. Therefore, to perform meaningful analysis and produce applicable outcomes, interoperability of data format is paramount. The interoperability challenge is present in the learning analytics community, creating obstacles in implementing a standardized specification at scale that each "data supplier" or "tools developer" has to conform to [16]. In fact, "interoperability and scalability are evolution features embodied in the architecture of the software system" [16, p.32]. Considering this issue, much research in technology-enhanced learning has been focused on enhancing interoperability [51]. Thus, several conceptual frameworks [52] and software architectures [16], [53], [54] have been proposed to effectively store and retrieve large amounts of data generated in e-learning settings.

The interoperability issue is not a new one. Since 2001, several learning resource specifications have been developed, including ADL (Advanced Distributed Learning), SCORM (Shareable Content Object Reference Model) [55], IMS Learning Resource Metadata Specification [56], and IEEE LOM (Learning Object Metadata) [57]. These examples have been considered as drivers toward re-usability and interoperability of learning resources [58]. Furthermore, several industrial solutions, such as the Learning Tools Interoperability [59] and the Experience API (xAPI) [60], [61] are widely applied, to enhance the interoperability of e-learning systems and tools [16]. xAPI is a standardized approach that clarifies how the collection, storage, analysis, and exploitation of data are taking place. The prominence of xAPI consists of system independence, easy implementation, and the focus on learner activities [62]. Slowly, but effectively, xAPI specification [61] emerged as a standard vocabulary for communication with distributed data in learning systems, due to its inherent extensibility to accommodate unforeseen data collection needs.

Findings from past research present an architecture that tackles the challenge of collecting and managing data from a variety of services and feeds, and with a focus on simplicity and flexibility [30]. The work published in [30] emphasized the implementation and the importance of trackers as main connectors between the activity provider, the LMS, and the data storage component. To that end, our work aims to *set up a learning ecosystem consisting of several integrated e-learning systems that rely on distributed and diverse data, which will* ***satisfy the requirements for data format interoperability*** *and harness the potential of combining cross-platform learning analytics*. Moreover, with the *proposed* ***cross-platform architecture****, we aim to present a* ***proof-of-concept emphasizing the importance of holistic understanding*** *of learners' behavior and progress, relevant for supporting data-driven changes in the learning design*, and toward improving and sustaining student engagement utilizing personalized feedback methods [10].

III. Architecture of the Proposed Learning Ecosystem

Our motivation for designing and developing a cross-platform architecture lies in:

1) Offering a modular system that can be easily modified by adding new data sources;

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2) Exploring the trade-off between interoperability, flexibility, and scalability of the system;
3) Initiating communication among various stakeholders (designers, educators, students) to investigate how learning analytics might contribute to personalization and flexibility vs. scalability and standardization of learning;
4) Demonstrating proof-of-concept for the feasibility and the potential of combining analytics across various e-learning systems.

The proposed architecture is developed addressing five core functionalities (see Table I) that *the next generation of learning ecosystems* should have [4]. In addition, considering the nature of the learning setting, the following are the requirements that have been taken into account during the design of the architecture, as suggested by [63]:

- **Data accessibility**. Accessibility and data latency are two crucial factors that affect data usage for instructional improvement [64]. Therefore, the architecture model integrates heterogeneous data using APIs for mining and retrieving common data formats such as JavaScript Object Notation (JSON), comma-separated values (CSV), or database storage. This way, the infrastructure can support and promote standardization, while facilitating data integration and harmonization [65], [66].
- **Extensibility**. The design needs to follow modular architecture with clearly defined and separated components. This approach increases the extensibility of the system and decreases the level of effort required to implement future functionalities [67].
- **Scalability**. Although scalability is a growing concern for e-learning systems [68], majority of these systems are implemented to support their current users, with less consideration for future user-base growth. The model of our proposed architecture aims to provide a better code structure, ability to run as a distributed application with faster resource usage, and thus, support future scaling of the user base.

To reach the goals of the proposed architecture, the design and development stages followed approaches defined in system development research [69], best practices in software design [66], and principles of software engineering for learning systems [70]. Thus, the architectural design decisions have been emphasized through two views [71]:

- **The conceptual view** shows the composition of the concepts necessary for system execution. This view represents the conceptual model of the system and explains the communication and data aggregation processes between the different components.
- **The implementation view** shows the topology of the implemented solution, the architectural layers, and the physical connection between the three e-learning systems.

The conceptual view represents the generic overview of the system and contains the elements required for collecting cross-platform data and analytics, while the implementation view presents the actual execution of the proposed architecture with the use of several existing systems as data providers. Since the purpose of the study is to demonstrate proof-of-concept of the feasibility and applicability of analytics across learning systems, this paper presents only the overall idea that lies behind the proposed cross-platform architecture.

A. Conceptual Model of Cross-Platform Architecture

To minimize challenges (e.g., data formats, undocumented data, or noise in the data) when working with multiple data streams, we propose a conceptual model that promotes and supports integration and interoperability among various data sources. The aim is to develop an integrated ecosystem, that would eliminate the need to manually log in, gather, and synchronize data from different systems. The proposed integration encompasses several functional layers as shown in Fig. 1:

- **The data processing layer** imports, aggregates, transforms, normalizes, and processes data. This layer is responsible for collecting and preparing data for further use and analysis.
- **The data analysis layer** interacts with the stored data to extract business intelligence.
- **The report generator** visualizes data and generates reports based on educators and designers' preferences.
- **The data source layer (i.e., learning record store)** stores data in standardized and consistent format.
- **The application front end (i.e., learning analytics dashboard)** accommodates different reports, visualizations, and solutions, for report customization and personalized feedback.

B. The Implemented Architecture of the Integrated System

This section presents the implemented learning ecosystem that encompasses three e-learning systems, i.e., ProTuS, MasteryGrids, and VLASP. The proposed architecture of the learning ecosystem aggregates data from four different data providers, and thereby, supports cross-platform learning analytics. The following are the e-learning systems we integrated:

- **ProTuS** is an intelligent e-learning system for learning programming basics. ProTuS allows educators to design and implement their own learning content, in addition to the option for easy integration of learning content from third-party providers, such as wiki pages or YouTube videos. For this study, lectures from Confluence wiki pages were used to cover the basic Java concepts. ProTuS also provides personalization techniques and several methods for recommending learning content [72].
- **MasteryGrids** is an open social learner modeling interface, written in JavaScript [73]. The interface shows learners' progress in different topics compared to other learners or the class. It also provides adaptive navigation support for learning content with stars indicating recommendations. The system tracks learners' activities and updates learner knowledge levels in a centralized user modeling server. This allows MasteryGrids to report the progress level (i.e., based on activities) and the knowledge level (i.e., based on estimated learner knowledge). MasteryGrids collects activity data from two data providers:

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TABLE I
THE CORE FUNCTIONALITIES OF A LEARNING ECOSYSTEM

Goals	Core functionalities
Identify learners' characteristics, goals, skills, strategies, and needs.	Personalization
Monitor, assess, and predict students' behavior, progress, and performance.	Analytics and learning assessment
Process, interpret, and utilize data across learning systems.	Interoperability and integration
Provide real-time actionable feedback.	Advising and support
Visualize metrics based on cross-platform analytics and educational theories.	Explanation and interpretation

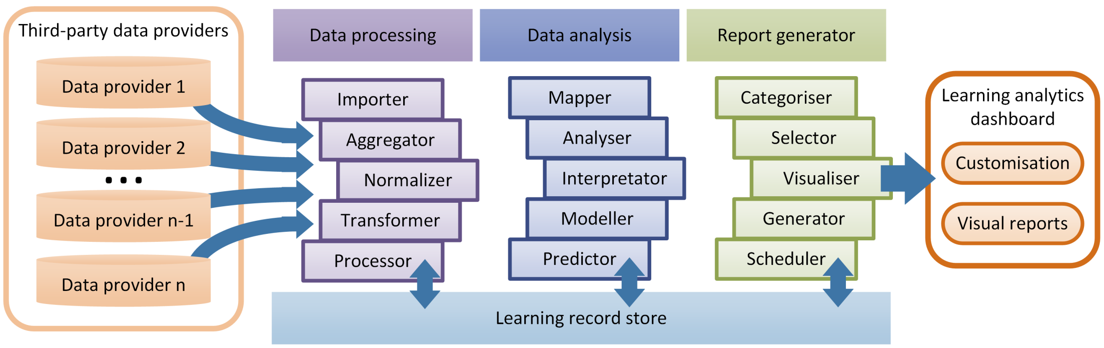

Fig. 1. General architecture.

– **PCLab** includes interactive examples and challenges developed at University of Pittsburgh [74]. The system tracks learner activity, including students' trial and error approaches.
– **Programming Course Resource System (PCRS)** includes coding exercises developed at University of Toronto [75]. This system tests learners' solutions against a set of unit tests for a particular problem, while the results are stored in the data source layer.

- **Visual learning analytics system for programming (VLASP)** is an Eclipse plug-in that monitors learners' progress in programming, tracks learner behavior while learners develop/debug code in Java, and reflects progress to learners as a mirroring tool [76]. The environment monitors progress and visualizes metrics (e.g., how many times a student has run an individual test, how many times the code has been compiled) associated with learner behavior and performance during programming/debugging activities. The main goal of the system is twofold: 1) to collect data about learner activities, so that educators can better understand how learners program/debug; and 2) to mirror learners' own actions back to them, as a way to increase awareness and motivation, foster self-reflection, and facilitate improvements in their programming habits [77].

ProTuS, MasteryGrids, and VLASP are separately designed and implemented systems; thus, their data models are different. The integrated learning environment has to provide access to different data structures, combine those data structures, and harmonize the data formats. Therefore, Visualized Education NTNU (VENT) [78] has been created and presented as a layer on top of the modules of each data source, consisting of a VENT system object notation (VSON) model and a VENT controller. This layer contains the data source controllers that act as conversion layers from the source model (e.g., JSON format) to VSON format which is then exposed by the VENT controller. Finally, because three e-learning systems were utilized in this study, we selected ProTuS to be a portal for seamless integration of different content providers. The overview of the data sources and integrated learning environments employed in the study is shown in Fig. 2.

IV. METHODOLOGY

A. Research Approach

The approach adopted in this study is based on design-based research (DBR) [79]. DBR utilizes an iterative process of design, implementation, analysis, and revision of models, with two primary goals: to construct knowledge and to develop solutions [80]. Hence, a series of DBR cycles were performed to develop the learning analytics component (i.e., first DBR cycle) [72], the adaptability feature, i.e., adaptive assessment (i.e., the second DBR cycle) [81], and the cross-platform architecture (i.e., the third DBR cycle) [82].

In the first DBR cycle, a focus group was organized with 12 teaching assistants (TAs), to understand and generate the best practices they had accumulated over the last few years, by closely working with students from introductory programming courses. The TAs were computer science (CS) majors, that were in their third or fourth semester of bachelor CS studies at the Norwegian University of Science and Technology (NTNU). The focus in the first DBR cycle was on participatory [83] and human-centered [84] design approaches in the development of the learning analytics component. These approaches were employed to support the design of seamless user experience in personalized e-learning systems [3].

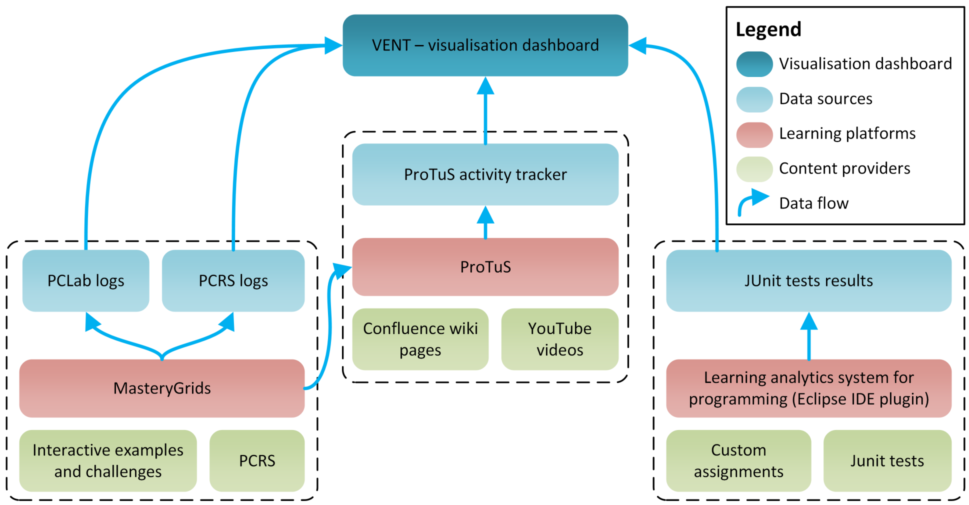

Fig. 2. Aggregated data sources.

Applying affinity diagram technique and usability survey, we transformed the generated best practices into design guidelines and applied them in the second DBR cycle.

In the second DBR cycle we focused more on learners' behavior and requirements, because personalized e-learning systems need to acknowledge and model users' natural behavior, so that the interaction is intuitive and minimizes users' cognitive workload. Therefore, we designed an experiment to explored how students interact with the new learning analytics module in ProTuS. The purpose of the second DBR cycle was to explore learners' trajectories during five quiz activities. A total of 66 students participated in the study and each student was asked to fill out one quiz at a time. After every quiz, the students were asked to reflect and monitor its own progress with the help of the generated reports utilizing learning analytics, and then continue to the next quiz assignment. All 66 students were CS majors in their second semester of bachelor studies. The insights generated from this study were used to develop the adaptive assessment feature in ProTuS.

The last DBR cycle is the focus of this study, which is the development, the implementation, and the evaluation of the proposed cross-platform architecture. All three DBR cycles have used the framework for modeling personalization dimensions proposed by [85]. This framework was selected to develop personalization features in ProTuS following six personalization dimensions in intelligent tutoring systems (ITSs) and adaptive educational hypermedia [85].

B. Implementation

1) Context and Participants: The research context for this study was an introductory object-oriented programming (OOP) course offered to undergraduate students at NTNU. The course content was delivered online (e.g., reading materials, assignments, examples) and once a week in a classroom setting (e.g., lectures and labs). During the course (which lasted for 3 months) the students were required to submit ten individual assignments and undertake a final mandatory exam. The grade students get at the end of the course is based only on the final exam. The instructor used the university LMS to distribute the relevant course materials and Eclipse integrated development environment (IDE) for the submission of the individual assignments. In addition, the instructor introduced ProTuS and MasteryGrids, as non-mandatory learning systems, that students could use to practice and learn Java.

The sample was comprised of 153 participants, freshman CS majors, who were in their second semester. All participants had already taken an introductory programming course in Python in their first semester; thus, it was assumed that they have already mastered a basic knowledge in procedural programming. The study focused on a set of online activities and participants' interaction with the educational content. ProTuS has been used as a portal for seamless integration of content from different content providers, while both ProTuS and VENT have been used to access, record, and collect activity data. The data were collected over the academic year 2018-2019 from logs of the three e-learning systems: ProTuS, MasteryGrids (PCLab, PCRS), and VLASP (see Table II).

2) Study design and data collection: Before the start of the study, the participants were introduced to the NTNU policy for ethical and data privacy issues, as well as with the purpose of the study and the e-learning systems that they could interact with. The learning content encompassed four types of activities that support individual work aligned with self-regulated learning practices [86]. Participants that used the system signed up with their university email address; however, in the system they got an ID number (e.g., StudentID001) that has been linked across the three systems. The three systems provided five types of learning content, which are briefly described in the following:

1) ***Explanations (ProTuS)***. ProTuS contains reading content (i.e., tutorials) on 15 topics that are aligned with the curriculum presented in the course. These learning materials help students to master concepts in OOP (Java language) based on their existing knowledge in procedural programming (Python).
2) ***Examples (MasteryGrids-PCLab)***. For each topic learners can start with a worked-out example from Program

TABLE II
OVERALL DATA COLLECTED

Academic year 2018-2019	Value
Overall number of users	389
Number of active users	153
Number of user sessions	2.727
Number of student activities (content visits, submissions, etc)	906
Data sources	ProTuS, PCLab, PCRS and VLASP

Construction EXamples (PCEX) set [87], which explains why certain programming constructs are used in the code. Explanations are available for almost all lines of code in the example, and are hidden until a learner clicks on the lines of interest.

3) ***Challenges (MasteryGrids-PCLab)***. Following the pedagogical reasoning that examples are more effective when a learner solves a problem immediately after the example [88], we presented a challenge after each example. Each challenge shows a problem similar to the one presented in the example, and blank lines that need to be filled in by dragging and dropping the pieces of code to the blank fields [89].
4) ***Coding exercises (MasteryGrids-PCRS)***. The Programming Course Resource System [75], whose content server resides at the University of Toronto, provides coding exercise with a problem description and a baseline code. When learners submit their code, the code is tested against a set of unit tests developed for that particular problem, and the learner receives an immediate feedback on whether the tests were passed or not.
5) ***Course assignments (VLASP)***. The ten individual assignments learners solve in Eclipse IDE, as they are able to test the code against a set of unit tests developed by the instructor. Learners' Eclipse installation has been extended with a plug-in that collects data from the learners' solutions.

All three systems keep a track of every click and store data as logs with time stamps in the learning record store. ProTuS collects data about ***learners' actions*** in the system. The collected data for our study included the number of actions in the system, the time spend in each session, what topic a learner selected, and the level of difficulty of the coding exercise. According to the level of difficulty, the coding exercises (PCRS) have been grouped in ProTuS in five categories (e.g., novice, skillful, confident, proficient, and expert). MasteryGrids collects ***progress data*** from learners' interactions with the learning content. The generated data included clicks on lines of explanations in the examples, attempts to solve a challenge, coding exercises solved in the first, second, or third attempt, distinct challenges seen, etc. The challenges and the coding exercises could be attempted multiple times, or until the learner is satisfied with his or her performance. Finally, VLASP collects ***activity data*** related to a programming assignment. In our study we collected the number of submitted assignments, the number of incorrect and incomplete submissions, and the number of assignments not submitted at all. A full list of the generated variables is presented in the Appendix A.

3) Data processing: The data were extracted from the learning record store and as .cvs file placed in R Studio, to extract features from all three systems (ProTuS, MasteryGrids, and VLASP). In total, 142 features were extracted from the three e-learning systems, of which after removing the columns that had SD = 0, the final data set included 55 features. Appendix A includes a table with all 55 features plus explanation for each. The data collection and the respective e-learning systems abide by the European data privacy regulations that allow data to be collected and anonymized before use.

4) Variables: To answer the research questions, we selected learners' performance to be our dependent variable. Learner performance was computed from the score participants achieved on the individual assignments they submitted, transformed into a grade. The performance from the individual assignments summarizes participants' development over the course, considering the applied learning design, and therefore, it is timely, available during the course run-time, and more granular and representative. The learner performance includes values between 0 and 1000, which was discretized into six levels (i.e., A to F) with the help of the instructor, to resemble a grade that a learner would receive if the instructor assigned grades based on the assignments (i.e., formative assessment perspective) rather than based on the final exam (i.e., summative assessment). The rest of the 54 features that were all extracted using the R language, were considered to be the experimental/predictor variables. Appendix A provides a summary of all features.

5) Data analysis: To demonstrate proof-of-concept for the feasibility of the implemented cross-platform architecture, we applied both, inference and prediction. A statistical model will help us infer the relationship between the data variables to a degree of statistical significance, and use prediction to identify the best course of action. Our aim was to explore how can we incorporate hybrid approaches that combine statistical methods with machine learning techniques in education, particularly when combining analytics across systems and data sources.

First, to get an initial understanding of the measures, a descriptive statistic was calculated and the Shapiro-Wilk test was used to check for data normality. The Shapiro-Wilk test showed that the data did not have a normal distribution (p values were significant) but a highly skewed nature. However, because linear regression does not assume normality for either the predictor or the outcome variable, the lack of normal distribution of the collected data was not an obstacle to perform a linear regression (for more information please look at the GaussMarkov theorem) [90]. We also checked for other

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assumptions important for linear regression to ensure that the inferences are appropriate: 1) *multicollinearity*–there was no perfect linear regression between two or more predictor variables. We calculated the variance inflation factor (VIF) and following the rule of thumb, in order to consider problems with collinearity the VIF value should exceed 10, which was not the case in our data [91]; 2) *homoscedasticity* or homogeneity of variance, refers to the constant variance of the residuals [92]. We checked for homoscedasticity by plotting the data and exploring the residuals vs fitted and scale-location (or Spread-Location) diagnostic plots, as well as running the Levene's test (p values were not significant) [93]; 3) *normally distributed errors*–we checked if the residuals in the model are normally distributed by generating the quantile-quantile (Q-Q) plot. The Q-Q plot from our data shows that each observation roughly falls on the straight line, indicating that the residuals are roughly normally distributed.

Second, we looked into several ways how variables can be entered into a model, but because we were conducting an exploratory study on all generated variables that does not have SD=0, we decided to go with the stepwise method (backward direction), which has a lower risk of making Type II error (i.e., missing a predictor that does in fact predict the outcome) due to supressor effects [91]. The backward method starts by placing all predictors in a model and based on Akaike Information Criterion (AIC) the model removes predictors that cause AIC value to increase. The stepwise methods is usually used for exploratory model building and when researchers do not know which predictors can create the best model [94]. Thus, because there was no previous research that we could consider and built upon with respect to reported significant variables, we decided to build the models on a purely mathematical criterion. Due to the selection of the stepwise method, we performed a 10-fold cross validation.

Third, we evaluated the performance of each of the selected features that are shown in Appendix A in predicting learner performance (i.e., student grades), using Random Forest [95]. Random Forest (RF) as a decision tree-based algorithm, is suitable for large numbers of features that are strongly correlated [96]. Moreover, RF offers easy extraction of feature importance, and has been found to be a top performing algorithm in a large comparative study [97]. To build a predictive model (not a representative) when dealing with an imbalance dataset (which is a common problem in the education field) in a multiclass classification problem, we first performed a stratified sampling with respect to the majority class, i.e. grade B, used to control the sampling process. This step was necessary to avoid creating a train and test set with totally different data distributions. Then, we divided the dataset into training (70% of the students) and testing (30% of the students) sets, and applied a hybrid re-sampling technique (i.e, SMOTE) to the training set [98]. Using SMOTE we down-sampled the majority classes and synthesize new data points in the minority classes, using k-nearest neighbours for the new data [98]. This was an important step in the analysis, because RF algorithm is sensitive to the proportions of the classes, tending to favor the majority class. Finally, to remove the selection bias in the training set, we used 70% of the data to train the model using a 10-fold cross-validation. This reduces the variability and presents more accurate estimates of learners' performance.

At the end, we used RF to measure the importance of the individual features for learner performance (i.e., student grades). While importance of individual classification features might be calculated in many different ways [99], we used Mean Decrease Gini (MDG) which is based on the reduction in Gini impurity measure. Gini impurity measures how often a randomly chosen data point from the data set will be incorrectly labeled, which is essential for correctly classifying new data points. Classification accuracy (ACC), which is the ratio of the total number of correct predictions and the total number of predictions, is a reliable measure but it is not sufficient to evaluate machine learning classification algorithms [100]. Hence, we employed precision, recall, f-measure, and Cohen's kappa, as additional measures to evaluate the robustness of the classifier. Precision is the ratio between the true positives and all the positives (true positives + false positives), and gives us the measure of relevant data points; while recall shows the classifier's potential to find all the positive outcomes. Thus, we calculate the average precision and recall, weighted by the number of true instances for each label, to account for the label imbalance. F-score aggregates precision and recall under the concept of harmonic mean that summarizes the model performance. Finally, Cohen's k shows how the classifier is performing over the performance of a classifier that guesses at random with respect to the frequency of each class.

V. RESULTS

Table III shows the results from the stepwise multiple regression (backward direction) in building the exploratory model based on a purely mathematical criterion. In fact, we were interested in identifying variables that have a scientifically meaningful and statistically significant relationship with the learner performance (i.e., the number of points 0-1000). This step was required to explore if architecting analytics across multiple systems can improve the explanation power over the individual systems, and because there is no theoretical grounding that can be used as a starting point for specific predictors (i.e., features/variables) to create the best model. The model combination selected with AIC = 1088 is significant (F(8,168) = 4600, p ¡ 0.001) and explains 87% of the variance in learners' performance.

The ProTuS model is not significant (F(3,173) = 0.688, p = 0.561) and on its own explains only 12% of the variance, while MasteryGrids model although not significant (F(46,130) = 1.22, p = 0.193), accounts for 30%. The VLASP model (F(3,173) = 1200, p ¡ 0.001) is significant and with total, incomplete, and incorrect submissions as predictors, accounts for 80% of the variance in learners' performance.

Table IV presents an overview of the main results, listing the classifier's accuracy, Cohen's k, the average precision, recall, and the f-measure for RF. The features coming from the separate systems (e.g., ProTus, MasteryGrids, and VLASP) have lower accuracy (and Cohen's k) than the combined features from the integrated system. The best classification accuracy of 0.81 (95% CI[0.67, 0.91]) and Cohen's k 0.79

TABLE III
STEPWISE MULTIPLE LINEAR REGRESSION COMBINING FEATURES FROM ALL 3 LEARNING SYSTEMS

Model	**adj.** R^2	**B**	**SE B**	β	**p**
Model Zero					
(Intercept)		648	23		0.000
Model Combination	0.871				
(Intercept)		-4.10	5.31		0.446
level_of_coding_exercises		0.02	0.01	0.65	0.025
mastery_grids_durationseconds		1.21	0.71	0.42	0.033
pcex_ch_attempts_success		-9.66	6.34	-0.16	0.095
pcex_ch_success		9.95	6.56	0.16	0.090
total_sub_ass		99.95	0.56	0.99	0.000
incom_sub_ass		-33.44	2.50	-0.17	0.000
incor_sub_ass		-90.07	4.0	-0.32	0.000
not_sub_ass		1.19	0.85	0.41	0.095
Model ProTuS	0.117				
Model MasteryGrids	0.301				
Model VLASP	0.801				

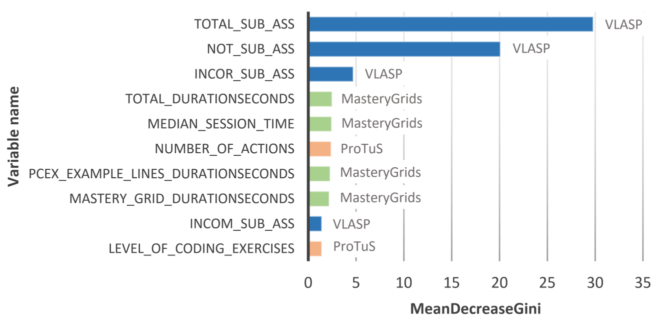

Fig. 3. Top ten feature importance - Random forest.

comes from the classifier which considers the top 10 features (i.e., RandomForest Top 10 features), and was obtained with mtry value of 6. Mtry is a parameter of RF which shows the number of variables randomly sampled as candidates at each split. In our case, the mtry value of 6 means that each decision tree took into account only 6 features out of the 54 features.

At the end, we performed a feature importance analysis and we present the top ten most significant variables shown in Fig. 3. We also present the top ten variables across the six classes (i.e., grades A to F) as shown in Table V.

VI. DISCUSSION

A. Interpretation of the Results with Respect to the Research Questions

Since the nature of this study was exploratory, in which we used both inference and prediction, we provide insights into association relationships and not causality [100]. Considering the results, we outline the positive findings from the analyses, as a reinforcement toward the positive findings reported by [82].

1) Insights derived from cross-platform learning analytics: With respect to the first research question, the regression results presented in Table III show that learning analytics derived from the separate systems, ProTuS and MasteryGrids, are not significant and they explain less than 30% of the variance, while learning analytics generated from VLASP explain 80%. The analytics from VLASP are directly related to student assessment outcomes, and as such, support the previous research findings [7]–[9], which reported that students often focus on assessment and technologies that can maximize their chance to succeed (e.g., get a high grade at the end of a course). Moreover, assessment was a major focus of the learning design in the OOP course in which our study was implemented. From past research [11], we know that learning design and the instructional conditions strongly affect what technologies and tools students use. Thus, students' decision to focus on VLASP more than on ProTuS or MasteryGrids, was based on their perception that can help them to maximize their chances to succeed. In fact, students were required to achieve more than 750 points on the individual assignments to qualify for the final exam, although this score from the individual assignments was not counted in the final grade.

Nonetheless, we observed that combining data collected across several distributed learning systems accounted for an additional increase (i.e., 7%) in the explanation of the variance of learner performance. The 7% increase is coming from the following analytics: *the level of complexity of a chosen coding exercise*, *the time students spend navigating in mastery grids to monitor and reflect on their progress*, *the successful attempts on challenges*, and *the distinct challenges successfully solved*. Although the additional increase in the explanation of the variance is not very large and is with an overall effect of 9%, it is still a significant step (e.g., demonstrating proof of concept) toward building learner models that can explain higher portions of variation in the outcome (e.g. student's grade performance) by combining analytics across different platforms. Some of these analytics (i.e., *correct attempts to problems*, *distinct problems attempted correctly*, and *time in mastery grids navigation*) have also been found significant for student engagement, usage, and attitude in the open social student modeling (OSSM) compared to the open student modeling (OSM) interface in technology-based learning [89]. The authors [89, p.459] have reported these three analytics/features and additional eleven, as "very attractive for contexts where motivation and retention are critical, such as modern MOOCs.“

After describing the data using a statistical framework, and

TABLE IV
RANDOM FOREST CLASSIFIER. COMBO: COMBINING FEATURES FROM ALL THREE LEARNING SYSTEMS. TOP10: USING ONLY THE TEN BEST FEATURES. PROTUS, MASTERYGRIDS, VLASP: USING FEATURES SOLELY FROM ONE SYSTEM

Classifier	ACC	Kappa	Precision	Recall	F-measure
RandomForest combo	0.79	0.69	0.90	0.77	0.87
RandomForest Top10	0.81	0.79	0.92	0.81	0.89
RandomForest ProTuS	0.23	0.01	0.14	0.23	0.37
RandomForest MasteryGrids	0.42	0.05	0.79	0.42	0.59
RandomForest VLASP	0.70	0.65	0.88	0.77	0.78

TABLE V
FEATURE IMPORTANCE ACROSS CLASSES

Variable	A	B	C	D	E	F
total_sub_ass	53.88	100	43.97	51	33	87.47
not_sub_ass	47.56	78.22	44.62	41.55	34.11	56.26
incor_sub_ass	19.58	60.73	32.38	36	5.21	25.51
total_durationseconds	7.15	20	10	8.50	12.30	15.25
median_session_time	9.51	23.10	14	20	4.31	10.12
number_of_actions	4.48	9	15	10	8.76	3.51
pcex_example_lines_durationsec.	8	30	11.43	15.67	4.22	5.72
mastery_grid_durationsec.	6.12	9	24.62	3.18	12.55	10
level_of_coding_exercises	6.10	2.10	2.50	3.46	7.20	20
incom_sub_ass	7.14	9.75	5	17.30	6.31	34

characterizing the relationship between the variables and the learner performance to a degree of statistical significance, we utilized machine learning to build different models with various features to predict a label, i.e., i.e. student grade. RF used the associations between the predictors and the learner performance to validate the benefits of cross-platform learning analytics in generating accurate predictions for future outcomes. In addition, we also investigated if cross-platform learning analytics can build predictive models that carry an opportunity to reveal significant elements for teaching practice.

The results reported in Table IV are aligned with the findings from the regression analysis, i.e., harnessing cross-platform learning analytics can improve the classification accuracy in predicting learner performance (i.e., student grade). The baseline performance for the proposed learning ecosystem that differentiates between 6 different classes (i.e., students' grades) is 1/6 or 16.7%. We argue that when reporting machine learning results, a baseline performance should also be reported, due to the importance of discussing performance in relation to the complexity of the machine learning task [100]. Thus, the results from the analysis show that our learning ecosystem achieved accuracy of 79% (RandomForest combo) and 81% (RandomForest top 10), exhibiting an improvement in the baseline by a factor of 3.73 and 3.85 respectively. In other words, the RandomForest Top10 performance exhibits a 5-fold increase over the baseline. Also, looking at the f-measure for RandomForest combo and RandomForest Top10 classifiers, one can notice that these classifies have demonstrated better robustness (do not miss a significant number of instances) and precision (how many instances it classifies correctly) measures than the rest of the classifiers.

In a study presented by [101], prediction models have shown that combination of mastery data (i.e., mastery score) and use intensity data (i.e., number of attempts, time on task) from e-tutorial systems that students used to practice homework exercises, constitute a good second best information source (after assessment data) for predicting performance. Their findings [101] strongly support the integrative approach to learning analytics as advocated by [102]. Moreover, our findings also align with these previous findings, that combining analytics across systems in distributed learning environments can provide insights into what is happening in each and across the different systems, and thus, be used to predict performance more accurately.

By harnessing cross-platform learning analytics, our predictive models also disclosed the potential for building future models that can reveal significant elements for teaching practice, which can be utilized to further refine the design of learning activities and instructional methods. In fact, the advantages from analytics generated across various e-learning systems lie in the support that educators will have, to shape teaching and learning with data that is timely and available during the learning process. We posit that in future, such insights can assist educators to examine the effectiveness of their learning designs and assessment practices in relation to serving the intended educational objectives and pedagogical intent, and maximize the learning opportunities in digital education.

2) Cross-platform learning analytics to support learning design: Compared to previous studies on predictive modeling that have investigated academic success [20], [39], [103], our intention was not to build a high performing prediction models that outperform other machine learning models, but to explore how predictive models can be constituted with practical value for educators, to inform teaching and learning practices as a "diagnostic" tool, pertinent to the optimization of various technologies.

Based on the positive findings reported in Table III and in particular Table IV, we posit that although the best predictor for performance is performance itself, there are other features also relevant for learner performance (but not all of the features) that can be extracted from behavior log data. Our findings are supported from previous research [104]–[108], which demonstrated that not all analytics that can be collected in a learning environment are equally relevant for learning, nor the same learning analytics are relevant for every student. If we look at Fig. 3, which displays the top ten features by importance (generated with RandomForest Top10 features classifier), we can observe that in addition to the activity data generated from the VLASP system (directly related to the assessment outcomes), other analytics at different granular levels are also significant for learner performance. Therefore, in this paper we present the value of more granular data to monitor and assess learner progress, which can be utilized to develop interpretable predictive models based on cross-platform learning analytics. Such models can reveal significant elements from the learning designs for understanding behavior and progress in distributed settings, in addition to data generated from summative assessment or LMS, and instructor's tacit knowledge, that can be harnessed to identify best course of action in making reliable and informed decisions.

Table V shows the top ten features across the six classes (i.e., students' grades). For example, if we look at grade B, we can notice that although the assignment submissions are very important (we explained the role of VLASP in the learning design), the time spend on practicing learning tasks and the time spend on reading examples before practicing exercises, can also be important indicators for a learner performance. Examples with explanations for the code are commonly used learning resources in learning programming that help students grasp various programming structures and concepts [109]. To optimize the support for learning from examples, instructors can benefit from insights derived from interpreatable models as presented in this study, to guide students to access the right example at the right time [87], [110]. This is an important decision that instructors can make, because past studies demonstrated that the effect from worked examples is stronger in the early stages of learning, and declines gradually as students' knowledge grows [111].

For grade C, another important indicator can be the time a learner spend navigating in mastery grids to monitor and reflect on their progress. In other words, if learners spend time monitoring and reflecting on their progress, such information can assist the instructor to help those students improve their self-regulation skills and the decisions they make. From a self-regulated learning perspective, learners are considered to be active participants in the learning process, who construct their own meanings and goals, and can potentially monitor and regulate certain aspects of their own metacognition, motivation, and behavior, from the information available to them [112]. Thus, more granular data from interpretable models can assist instructors to work toward development of personalized feedback to support students' self-regulated learning skills, thereby helping their students to become independent professionals, who can shape their own learning. In addition, sharing learning analytics from such interpretable models with students, can enable them to understand the state of their knowledge and use this knowledge to plan their learning [113].

Finally, the last example for grade F, shows that other important features for learner performance can be the level of complexity students choose in the coding exercises and the submission of incomplete assignments. One explanation can be the potential association between these two, suggesting that learners who get grade F, might have trouble selecting assignments that match their current knowledge, so they failed to learn meaningfully. Students' lack of knowledge (and potential development of misconceptions) is later demonstrated in the submission of incomplete assignments. In fact, these learners need an intervention through proper scaffolding, to guide them gradually to master skills and learn concepts, by aligning the complexity of the assignments with their current knowledge proficiency. This is an action, much in line with the existing research in adaptive learning and intelligent tutoring systems [114].

In this study, the insights generated from cross-platform analytics through feature importance, depict a different approach where more granular data can offer additional information (not easily observable in digital settings) on top of the information educators have from the LMS in use, their tacit knowledge, or the summative and formative assessment data. Such additional information still does not reveal the whole picture how students learn, but discloses significant elements for teaching and learning practice about how students use the opportunities as given in the learning design, which can assist educators to further refine the design of learning activities and instructional methods in digital education.

In sum, we argue that our approach can overcome some of the ongoing issues (e.g., one-sided learning analytics measures, strong focus on summative assessment) in learning analytics by collecting, integrating, and harmonizing data from several learning systems and at different granular levels. This approach can generate data that represent a larger proportion of the learning process and the activities students engage with. Thus, educators can make effective and meaningful refinements in the learning designs that can encourage, enable, and advance learning. At last, although the technological advancements increased the interest for performance-based, formative assessment [115] and e-learning systems that can effectively support that [116], the biggest challenge is that there are many aspects (e.g., reliability, validity) of assessment in online settings that are yet to be comprehend in relation to serving the intended learning purposes [117].

B. Theoretical and Practical Implications

The presented study provides useful insights for learning technology researchers, designers, and developers, by introducing the concept of cross-platform analytics architecture that could measure the effectiveness and fine-tune learning designs, to maximize learning opportunities in distributed settings. The findings support the importance of harnessing data across various learning systems by emphasizing the potential of leaving the exclusive focus on single source data. By quantifying the usefulness of cross-platform learning analytics, we would like to invite learning technology designers to focus on the development of valuable interconnected functionalities, affordances, and resources.

One of the most important implications of this paper is related to how learning technology and user experience researchers and practitioners can employ analytics across platforms and build cross-platform methodologies to make sense of the requirements that steam from different learning designs, as well as take design decisions for various learner groups. The 21st-century learning systems are expected to become more interconnected and personalized (e.g., Khan Academy, Udacity), and incorporate smart and adaptive behavior (e.g., Adaptemy, Dreambox, SmartSparrow). However, there is a lack of the state-of-the-art empirical approaches that can combine and identify what analytics can measure the effectiveness of learning designs, and how various stakeholders can benefit from those combinations. Taking a cross-platform analytics approach provides a unique opportunity to enrich the contemporary capacities of the current learning systems, by using statistical and machine learning techniques as a "diagnostic" practice that educators can utilize it, to improve the quality of the instructional conditions. This will allow contemporary learning ecosystems to leverage the capacities of their learning analytics and maximize their innovation potential.

On the practical side, we managed to propose and implement in practice a cross-platform architecture that integrates and interconnects analytics capabilities, and enhances the present analytics capacities of ProTuS. As elaborated in the related work, currently there are many conceptual frameworks and software architectures that emphasize the need for a cross-platform methodologies; however, none at present completely solves the problem of collecting, integrating, and harmonizing learning-related behavioral log data from several distributed environments. The proposed architecture presents the minimum technical architecture requirements and provides solution for data format interoperability and integration issues.

Despite the limitations of this study, we obtained positive and encouraging results, that developing cross-platform architecture and combining data across several learning systems can advance the state-of-the-art in developing an ecosystems of "dynamic, interconnected, and ever-evolving community of learners, instructors, tools, and content" [4], as well as toward predictive models that can provoke reflection and action among learners and instructors. The humble analysis approach braces the proof-of-concept in furthering the understanding of how cross-platform analytics can add value to enrich the contemporary learner models and leverage the capacities of their analytics. Finally, one of the most significant contributions of this study is the demonstrated feasibility of the defined concept, where the learner model is gradually built based on integration of data from three e-learning systems.

C. Limitations and Future Work

One of the limitations in our analysis is related to the size of the data set. Although we have 153 students using the integrated system, not all of them are using the system frequently. Another limitation is the lack of comprehensive set of feature extraction, especially the features that can be extracted from the main tasks or activities related to a programming exercises. For example, how many times a student has run an individual test, how many times the code has been compiled, the number of errors and warnings resulting from the compiler's analysis of the code, etc. These features can lead to improvements in designing programming instructions, assignments, and scaffolds, and reveal directions for future research on curriculum design and analytics in computing education. Third, the interpretation of the importance and significance of the results for learning design for researchers and practitioners (e.g., instructors) is limited and difficult to estimate, because it is mainly based on our understanding and knowledge in learning design and learning analytics. Therefore, in the future these findings need to be investigated with instructors who would utilize the learning ecosystem in their course. Finally, because all of our participants are coming from a single university with a particular pedagogical and instructional approach, the results from the classification algorithms might have effect on the generalizability of our findings. Thus, in our future work, we are planning to extend the content by developing a programming course for Python. We also plan to implement the integrated ecosystem in collaboration with a other universities that offer introduction courses in Java and Python, to increase the generalization power of our analyses, to further validate our findings, and to account for other important features that might have been overlooked in this analysis.

VII. Conclusion

To demonstrate and validate real-life examples of how and when learning is taking place, educators and researchers need to embrace the complexity of the learning process and its distributed nature across various learning settings and contexts. In that regard, we tried to capture and explore authentic learner-generated behavior log data coming from three different e-learning systems (each system resides on different server at different university). Our objective was to integrate analytics across e-learning systems with the aim to explore and understand how to create and measure the effectiveness of learning designs that can maximize learning opportunities in distributed learning environments. Consequently, we proposed and implemented a cross-platform architecture for interactive courses and analytics support. While most of the previous work handles data from one source, this study aims to present a cross-platform architecture for simple automatic integration and ease of data collection from four different data sources. To that end, this study takes a humble approach to analysis, comparing learning analytics metrics across three e-learning systems, using both inference and prediction. The proof-of-concept is envisioned to be the first step toward utilizing the potential of cross-platform learning analytics as an added value in (re)designing and evaluating learning and teaching activities in distributed learning environments. This approach should aid users (e.g., educators, learners, instruction designers, and researchers) to engage in informed decision-making, considering relevant metrics that align with their goals and needs, and toward personalized and scaled feedback practices in digital education.

APPENDIX
EXPLANATION OF ALL OF THE 55 FEATURES

The Appendix A contains a full list of the generated variables. It includes a table with all 55 features and an explanation for each.

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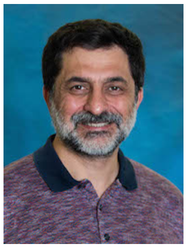

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