Enhancing Data Science Courses Pedagogy through GIFT-Enabled Adaptive Learning Pathways

Fadjimata I. Anaroua, Qing Li*, and Hong Liu
Embry-Riddle Aeronautical University, * University of North Texas

INTRODUCTION

Over the past decade, the educational landscape has experienced a surge of online learning and instructional platforms (Liu et al., 2020). This remarkable surge can be attributed to a confluence of factors, including the rising demand for higher education opportunities, the shortage of available teaching staff, and the rapid advancements in information technology and artificial intelligence capabilities. Artificial Intelligence (AI) remained a niche area of research with limited practical applications in education for over half a century (Bhutoria, 2022; Chen et al., 2020; Roll & Wylie, 2016) from 1950 to 2010. However, in recent years, the advent of Big Data and advancements in computing power have propelled AI into the educational mainstream (Alam, 2021; Chen et al., 2020; Hwang et al., 2020). Today, the rise of machine learning, deep learning, automation, together with advances in big data analysis has sparked novel perspectives and explorations around the potential of enhancing personalized learning, a long-term educational vision of technology-enhanced course options to meet student needs (Grant & Basye, 2014).

Fostering personalized learning necessitates the development of digital learning environments that dynamically adapt to individual learners' knowledge, prior experiences, and interests, while effectively and efficiently guiding them towards achieving desired learning outcomes (Spector, 2014, 2016). AI-powered technologies have made it possible to analyze data generated by learners and provide instruction that matches their learning performance. Through learning analytics and data mining techniques, large datasets collected are analyzed and processed to uncover learners' unique learning characteristics, often referred to as learner profiling (Tzouveli et al., 2008). Subsequently, leveraging artificial intelligence algorithms, the learning content is tailored, and personalized learning paths are designed to align with each learner's identified needs and preferences, thereby facilitating personalized learning experiences.

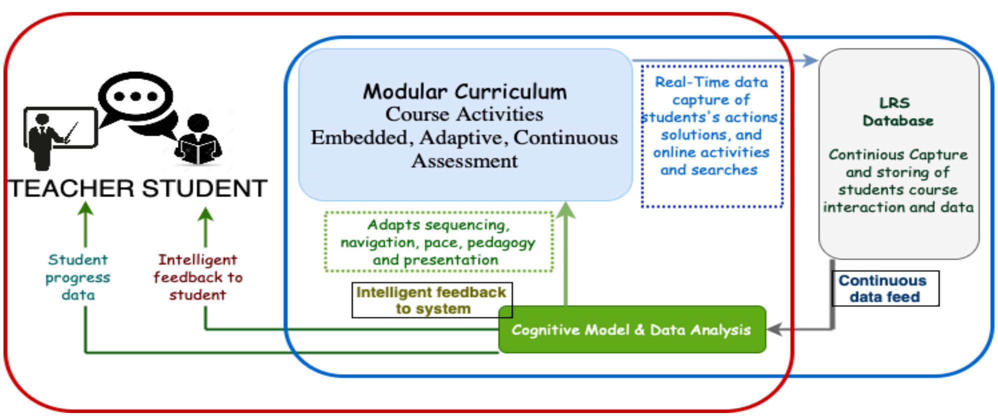

Figure 1: Advanced Digital Learning Environment

The data-driven personalization allows educators to create targeted interventions, address learning gaps, and provide enriched learning experiences for all students, moving from static learning environments to dynamic, adaptive systems that respond in real-time to learner data (Imhof et al., 2020). However, this AI-driven pedagogical shift requires profound transformations in conventional educational methodologies.

Educators must transition from a one-size-fits-all instructional model to a learner-centric paradigm, where teaching strategies, content delivery, and assessment methods are dynamically tailored to each individual's unique needs and learning trajectories. Such a shift requires a deeper understanding of learner characteristics, cognitive processes, and the effective integration of AI-driven analytics and adaptive systems into the classroom experience (Walkington & Bernacki, 2020). Moreover, the role of educators evolves from being mere content providers to facilitators and guides, leveraging AI-driven insights to create personalized learning pathways, provide targeted feedback, and foster self-directed learning (Kim et al., 2014; Kompen et al., 2019). Collaborative learning experiences, where AI systems augment and support human interactions, become increasingly important, enabling learners to co-construct knowledge and develop critical thinking and problem-solving skills.

Assessment practices must also adapt, moving beyond traditional summative assessments to incorporate continuous, formative, and adaptive assessments that provide real-time feedback and inform the personalization of learning experiences. The integration of AI-driven learning analytics and predictive modeling can help identify learners' strengths, weaknesses, and potential learning obstacles, enabling proactive interventions and targeted support.

To address these limitations, the Generalized Intelligent Framework for Tutoring (GIFT) was developed, adopting a modular, service-oriented architecture to promote modularity, reusability, and domain independence (Sottilare & Brawner, 2018). Originally designed for the US Army to understand and adapt to the needs of individual learners and to guide instruction in real time to optimize learning (Sottilare et al., 2017), GIFT aimed to improve scalability, enhance adaptivity through advanced learner modeling and instructional strategies, and enable interoperability with emerging standards like xAPI.

By providing a generalized and extensible framework, adaptive learning environments enabled by GIFT have facilitated self-regulated learning in an unobtrusive yet personalized manner, tailored to the unique needs of individual learners and small teams, enabling the necessary research and development leading to standardized, adaptive tutoring systems that are accessible, flexible, affordable, and easy to develop and utilize (Sottilare et al., 2023).

LITERATURE REVIEW

Adaptive learning technologies are grounded in the principle that education should be as unique as the individual learner. These systems dynamically adjust the educational content and instructional strategies based on real-time assessments of learner performance and behavior. This adaptivity is made possible through a combination of data analytics, artificial intelligence, and sophisticated algorithms. The goal is to create a personalized learning experience that aligns with each learner's cognitive abilities, preferences, and knowledge levels, catering to a wide spectrum of learning styles. In the ever-evolving realm of education, the advent of adaptive learning technologies marks a pivotal shift, heralding a new era in the delivery of educational content and instructional strategies (Martin et al., 2020).

Uniting the principles of personalized and adaptive learning, personalized adaptive learning emerges as a technology-empowered effective pedagogy that can adaptively adjust teaching strategies based on real-time monitoring of learners' differences and changes in the core elements of individual characteristics, individual performance, personal development, and adaptive adjustment (Peng et al., 2019). Adaptive learning technology provides personalized learning at scale by assessing learners' current skills and knowledge, providing feedback and content, and then constantly monitoring progress, utilizing learning algorithms that provide real-time updates and the necessary tools to improve student learning (Taylor et al., 2021).

The rise of personalized adaptive learning approaches is shifting the educational paradigm from a traditional instructor-centric model to a student-centric one. According to Dockterman's (2018) overview, learners tend to absorb material more effectively when the instruction is tailored to their individual requirements, and the pedagogy of personalization acknowledges that every student is unique. However, putting this learner-focused teaching methodology into practice necessitates the use of technological solutions and platforms capable of dynamically adapting to the distinct needs, capabilities, and learning preferences of each individual student.

Researchers have proposed frameworks and models for designing personalized learning paths and adaptive instructional strategies based on learner profiles, competency progression, and flexible learning environments (Peng et al., 2019). Efforts have also been made to design adaptive cloud-based educational systems to integrate adaptive learning with augmented reality (Marienko et al., 2020).

However, most existing studies on personalized adaptive learning instruction have focused on K-12 classrooms, with limited exploration of the reform effort in tertiary-level personalized adaptive learning (Christodoulou & Angeli, 2022; Taylor et al., 2021; Ryoo & Winelmann, 2021). Besides, there is a lack of targeted investigations into specific disciplines, which many have distinct pedagogical considerations. There is a notable research gap in exploring personalized adaptive learning environments specifically tailored to higher education contexts and disciplines like data science courses. This gap presents an opportunity for further research to address the unique needs and challenges of implementing personalized adaptive learning in tertiary-level data science education.

As a modular, open-source architecture that is designed to facilitate the development and deployment of adaptive instructional systems and intelligent tutoring systems (Sottilare et al., 2013), GIFT itself does not generate adaptive learning pathways, but provides a framework for integrating various components such as sensor, trainee, pedagogical, LMS (Hoffman & Ragusa, 2015), to enable personalized and adaptive learning experiences. Specialized authoring tools like Articulate can be used to create interactive and multimedia-rich learning content, built in three major tools – Presenter, Engage, and Quizmaker (Martin & Martin, 2015), which can then be integrated into GIFT-enabled adaptive learning systems. The content created in Articulate could be mapped to specific learning objectives, competencies, and instructional strategies within GIFT's domain model. This would allow GIFT to dynamically select and present relevant content based on the learner's performance, preferences, and needs.

The Moodle Learning Management System (LMS), widely used in online teaching and learning in STEM education (Gamage et al., 2022), can also be integrated with GIFT to facilitate the delivery and tracking of adaptive learning experiences (Despotović-Zrakić et al., 2012). GIFT could potentially interface with Moodle to retrieve learner data, such as performance metrics and progress, and use this information to generate personalized learning paths and adaptive instructional strategies. Conversely, GIFT could push adaptive content and assessments to Moodle for learners to access and complete.

While the framework of adaptive learning systems is helpful, it remains elusive how we can practically support the necessary multi-level and interdependent nature among systems to streamline their integration and tailor them to learners' needs at different levels and in different contexts. To address this, we explore the integration of the GIFT with learning and authoring tools, aiming to create a robust adaptive learning ecosystem for data science education. By harnessing the strengths of GIFT's adaptive learning engine combined with Articulate and Moodle's extensive repository of educational resources, we aim to deliver personalized learning pathways that are not only aligned with individual learning preferences and needs but also scalable across diverse educational settings. This paper introduces a novel adaptive learning model for data science education and presents analytical frameworks that enhance teaching practices. We demonstrate the integration of GIFT with Moodle and Articulate, showcasing how adaptive learning technologies can provide tailored and efficient learning experiences. Built on the GIFT platform, our findings highlight the transformative impact of these technologies in data science education and offer insights applicable to other fields. This research contributes to discussions on incorporating adaptive learning into existing educational frameworks, paving the way for personalized and effective learning experiences in the digital age.

INTITIAL DESIGN

The initial design for investigating the efficacy and impact of the integrated adaptive learning system, comprising Articulate, Amazon S3, GIFT and Moodle, adopts a mixed-methods approach to provide both quantitative and qualitative insights into its effectiveness within data science education. The quantitative component involves a controlled experiment where participants are divided into two groups: one using the traditional learning model and the other utilizing the new adaptive learning ecosystem. Key performance indicators such as engagement levels, learning outcomes, and time to competency, will be rigorously measured and analyzed. Concurrently, the qualitative aspect will employ surveys, interviews, and focus groups to gather in-depth feedback from students and educators regarding their experiences, perceived benefits, and any challenges encountered. This comprehensive approach aims to not only quantify the benefits of the adaptive learning system but also to understand the nuanced experiences of its users, thereby offering a holistic view of its potential to transform data science education.

INTEGRATION TOOLS AND PROCESSES

The main integration process of the proposed adaptive learning ecosystem, encompassing Articulate for content creation, Amazon S3 for content hosting, the Generalized Intelligent Framework for Tutoring (GIFT) and Moodle for content delivery, is a meticulously designed workflow that ensures seamless interoperability and maximizes the effectiveness of adaptive learning in data science education.

Content Creation with Articulate: The process begins with the development of interactive and adaptive learning materials using Articulate, a sophisticated authoring tool known for its ability to create engaging multimedia content. Educators and content creators design courses with adaptive pathways, incorporating various learning activities, assessments, and multimedia elements tailored to diverse learning styles and needs. In the context of e-learning, the concept of "branched" is frequently mentioned. This typically refers to "branched scenarios" or "branched e-learning," which describes a course structure that allows learners to navigate or be redirected through various pathways, also known as "branches. Courses with branching, or non-linear designs, offer a more tailored experience for learners. By integrating branching scenarios, learners can navigate through simulations of real-world scenarios, discovering how their decisions can result in diverse outcomes. Alternatively, a course design offering varied pathways to accommodate individuals/teams with distinct roles or varying degrees of background knowledge is also possible (Legault, 2024).

We utilized Articulate Storyline 360's robust features, specifically variables and triggers, to develop customized branching scenarios that respond to a learner's progress within the e-learning course. The method employed involves leveraging the platform's quiz and results slides to establish scoring variables. Subsequently, we implemented conditional triggers to navigate users to different course branches based on their accumulated points, effectively modifying variable values to create a tailored learning journey.

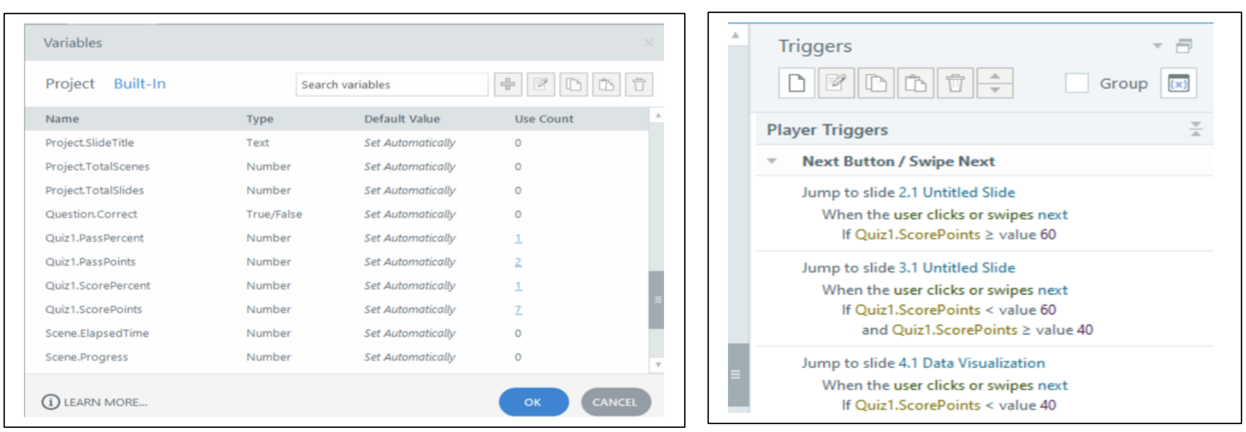

Figure 2: Storyline 360's Variables and Triggers for Adaptive Course Concept

Hosting on Amazon S3: Once the content is developed, it is uploaded to Amazon Simple Storage Service (S3), a reliable and scalable cloud storage service and managed through CloudBerry Explorer. This step involves configuring storage buckets in S3, ensuring the content is securely stored and readily accessible. Amazon S3 serves as a centralized repository for the adaptive learning materials, offering robust data protection, high availability, and seamless content delivery. According to Slim (2021), CloudBerry Explorer is used as an intuitive file explorer that helps manage Amazon S3 account just as if it was one more folder on the local drive. The program features a double-pane interface and works like an FTP client, with each window devoted to a location. CloudBerry Explorer supports multiple S3 accounts and lets users open multiple connections, which can then easily be managed through interface tabs. A web URL for the hosted content on amazon S3 for our initial design is generated from CloudBerry interface: https://lesson1eda.s3.amazonaws.com/porfolio/Ethisindatascienceadaptive/story.html.

Integration within GIFT and Moodle Platform: The final step involves integrating the hosted content with GIFT, as our advanced adaptive learning engine. This integration is facilitated through APIs and specific integration protocols that enable GIFT to fetch and present the adaptive content stored in Amazon S3 to learners. We have deployed our GIFT software on an Amazon AWS EC2 instance and integrated our adaptive content. The web URL generated from Amazon S3 will be embedded within the GIFT platform using the "Web address" course object. The subsequent step involves connecting our hosted GIFT as an “External Tool” to the Moodle LMS platform using Learning Tools Interoperability (LTI). This integration will enable students and teams to access the adaptive content, facilitating the initial design and assessment of teamwork competence. GIFT dynamically adjusts the learning content based on real-time analysis of learner interactions, performance data, and feedback, providing a personalized learning experience for each student or team. Moreover, the Learning Record Store (LRS) will capture the xAPI statements of interactions from our GIFT-Moodle integration, ensuring detailed tracking and recording of all learning activities.

CONCEPT IMPLEMENTATION AND TESTING

The implementation of the adaptive learning ecosystem, integrating Articulate for content creation, Amazon S3 for hosting, GIFT for adaptive learning delivery, and Moodle for additional resources and activities, encompasses several successful key phases. Each phase focuses on a specific aspect of the system's deployment, from the technical setup and configuration to the creation of adaptive learning pathways and the enhancement of user experience.

Through Articulate's intuitive interface, users can design intricate branching scenarios that present learners with decision points, leading to different paths based on their responses. This capability enhances the interactivity and personalization of courses, making learning more engaging and closely aligned with each learner's needs.

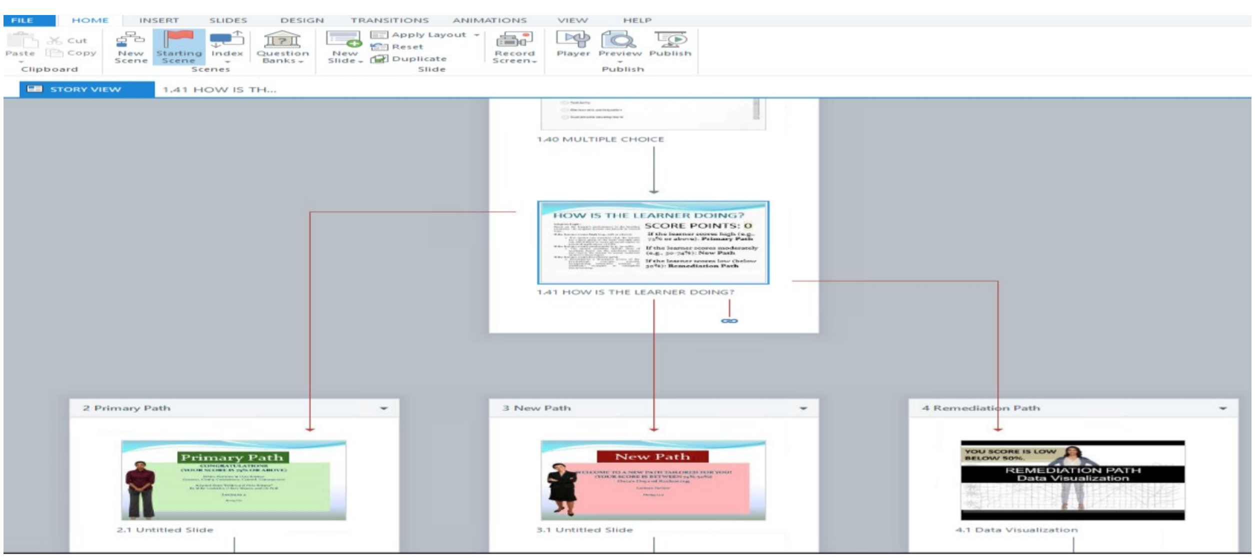

Figure 3: Initial Adaptive Path Branching Course Content with Triggers and Variables

Moodle's extensive repository of learning resources and interactive activities is integrated to enrich the ecosystem. Key steps include content synchronization to ensuring that GIFT resources are accessible within the Moodle platform, providing a unified learning experience. The activity tracking is for Integrating Moodle's activity data into the adaptive learning analytics to be captured by Learning Record Store (LRS), allowing GIFT to adjust learning pathways based on interactions within Moodle. Overall, the implementation of this adaptive learning ecosystem is a multi-faceted process that requires careful planning, coordination among various technology platforms, and a steadfast focus on the learner's experience. The ultimate goal is to create a dynamic, engaging, and personalized learning environment that effectively supports the diverse needs of data science students and teams.

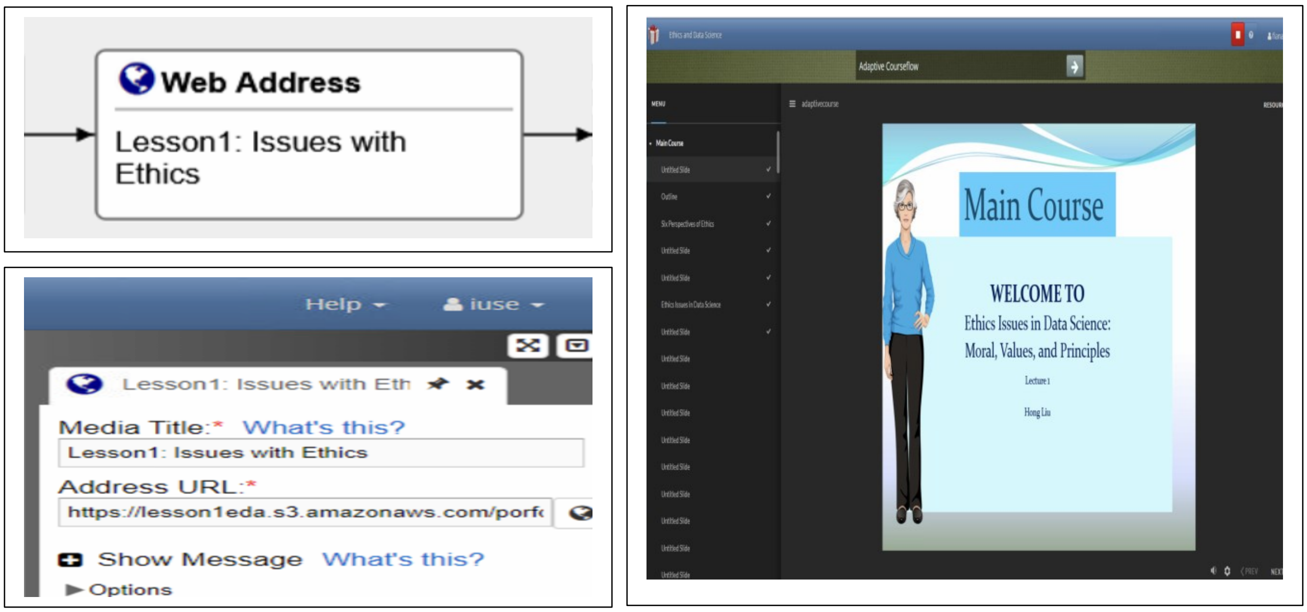

Figure 4: Adaptive Content Integration to GIFT

EVALUATION AND ANALYSIS

Evaluation Framework and Data Collection Methods

An integral component of our adaptive learning ecosystem is the Learning Record Store (LRS), a specialized database designed for storing, retrieving, and analyzing learning data in compliance with the Experience API (xAPI) standard. The LRS serves as the backbone for data-driven decision-making within the system, enabling a nuanced understanding of learner interactions, behaviors, and outcomes. This section delineates the strategic incorporation of the LRS into our ecosystem, detailing its role, configuration, and the benefits it brings to adaptive learning in data science education.

Setting up the LRS involves selecting a robust and scalable LRS platform that can support the anticipated volume of learning data and integrate seamlessly with our existing infrastructure. The chosen LRS (Veracity Learning), https://erau.xapi.io is configured to communicate with GIFT, Moodle, and the content hosted on Amazon S3, ensuring that learning activities are accurately captured and logged in real-time.

The LRS plays a pivotal role in shaping adaptive learning pathways within GIFT. By analyzing the comprehensive dataset stored within the LRS, the identification of patterns, trends, and learning gaps at both individual and cohort levels can be possible through GIFT. This data-driven insight allows GIFT content creators to dynamically adjust learning pathways, content recommendations, and instructional strategies, ensuring that each learner receives a personalized and optimally challenging learning experience. Figure 5 and Figure 6 illustrates the overview of a class of learners' learning activities and an individual learner's learning activities, respectively.

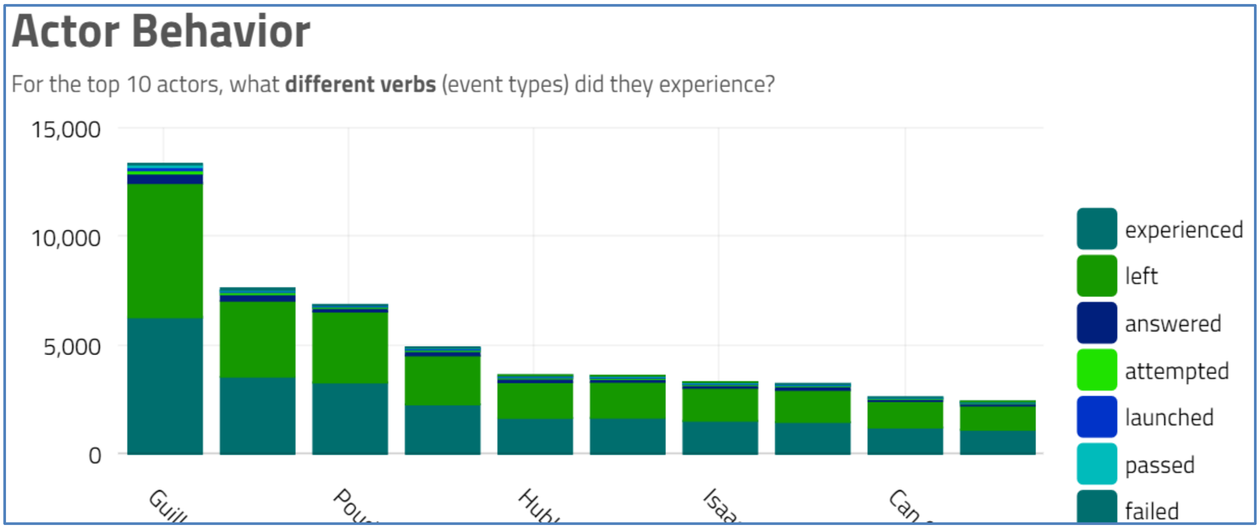

Figure 5: LRS overview of the learners' learning activities sorted from the most active to least active learners.

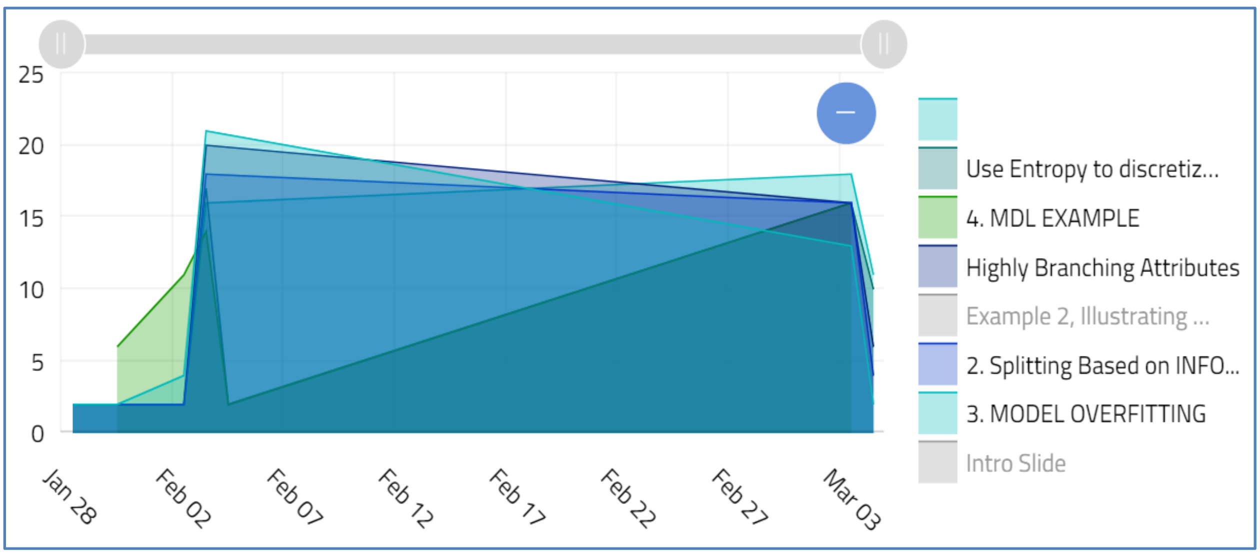

Figure 6: LRS overview of an individual learner's learning activities and content details.

Moodle's vast repository of educational resources and interactive activities is leveraged by feeding data on learner interactions within Moodle into the LRS. This integration ensures that learners' experiences with Moodle's resources contribute to the adaptive learning pathways in GIFT, creating a cohesive and comprehensive learning experience that spans multiple platforms.

The LRS functions as the central repository for learning records generated by learners as they interact with the adaptive learning content hosted on Amazon S3 and delivered through GIFT. These records encapsulate a wide array of data points, including learner responses, time spent on activities, assessment scores, and navigational paths, among others. By adhering to the xAPI specifications, the LRS ensures that learning data from various sources, including Articulate-authored content and Moodle activities, are uniformly structured and semantically rich, facilitating advanced analytics and insights.

CONCLUSIONS AND FUTURE WORK

This paper provides a comprehensive framework for integrating an adaptive learning system utilizing Articulate, Amazon S3, GIFT, and Moodle to enhance data science education. The mixed-methods approach used in the study effectively combines quantitative and qualitative data to assess the system's impact. Quantitatively, the use of controlled experiments helped measure engagement levels, learning outcomes, and time to competency. Qualitatively, surveys, interviews, and focus groups offered valuable insights into the users' experiences, benefits, and challenges encountered. This holistic approach not only quantifies the benefits but also deeply understands the nuanced experiences of learners, making a strong case for the potential transformative impact of this integrated adaptive learning system on data science education.

To date, two adaptive courses, Data Visualization and Data Mining were developed and delivered to the 56 students at Embry-Riddle Aeronautical University. Future research could expand in several directions such as a broader implementation for scaling the system to include a wider variety of courses and academic disciplines beyond data science to examine its adaptability and effectiveness across different educational contexts. Longitudinal Studies can also be conducted for long-term studies to assess the sustained impact of adaptive learning systems on students' academic performance and retention rates over time. Advanced Analytics is another focus where utilizing more sophisticated data analytics techniques will help to delve deeper into the data collected through the LRS, which could help refine the adaptive learning models further and AI enhancements. Incorporating more advanced AI technologies, such as machine learning and natural language processing may help enhance the personalization capabilities of the learning system.

Finally, the Team Competence Assessment will be further explored for developing and integrating metrics and tools within the adaptive learning system to assess and enhance team competence systematically. This involves creating frameworks that not only measure individual learning outcomes but also evaluate collaborative skills, communication, and problem-solving abilities in a group setting. Future studies could explore the dynamics of team-based learning environments and devise methods to optimize team interactions and performance in real-time. This could also include the use of AI to analyze team interactions and provide feedback to improve group cohesion and effectiveness.

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ABOUT THE AUTHORS

Fadjimata I. Anaroua *is a Ph.D. student and research assistant at Embry-Riddle Aeronautical University. She was awarded a master's degree in software engineering at Embry-Riddle Aeronautical University, a bachelor's degree in Aeronautical Science, and a bachelor's degree in industrial engineering.*

Dr. Qing Li *was awarded a Ph.D. in Learning Technologies from the University of North Texas in 2024. She is currently a lecturer at Chongqing University of Science and Technology. Her primary areas of research interest include technology-enhanced foreign language learning and teaching, as well as computer-aided translation and interpreting theory and practice.*

Dr. Hong Liu *was awarded a Ph.D. in Mathematics and MS in Computer Science at the University of Arkansas, Fayetteville in 2000. He serves as a professor in Mathematics and Computing at Embry-Riddle Aeronautical University. He served as PI and Co-PI of 14 sponsored projects and published numerous articles in mathematics, data science, and STEM education. His current research interest is to develop a smart learning environment to promote peer learning.*