Best-of-Breed: Service-Oriented Integration of Artificial Intelligence in Interoperable Educational Ecosystems

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Abstract. Artificial Intelligence (AI) offers great potential for optimizing learning processes, teaching methods, learning content, or organizational procedures. However, the success of AI components in educational environments is by no means guaranteed and depends on several conditions in their respective learning settings. In this article, we analyze requirements that are often addressed prior to introducing AI features. We address organizational, methodological, didactical, content-related, and technical challenges. The research question of this work is how AI features can best be incorporated into modern educational system landscapes to create sustainable system architectures that are accepted and perceived as added value by users. Thereby, the article discusses two approaches to software architecture: Best-of-Suite (for monolithic architectures) and Best-of-Breed (for service-oriented architectures). Monolithic systems offer a wide range of functions, can be offered by a single provider but can become difficult to manage and create dependencies. Specialized and service-oriented systems, in turn, consist of modular functions handled by specialized services, are more flexible and scalable, and can be integrated with a wide range of tools and services, but require more effort to set up and manage. We explain why the Best-of-Breed strategy is a sensible approach to the use of AI components, how this can be implemented sustainably with the help of a middleware component, and we report on the user experiences from a field test. While in this work we evaluate the implemented system with a cybersecurity training as an on-the-job course, the middleware has been successfully used in other educational contexts, as well.

Keywords: Artificial Intelligence · Best-of-Breed · Learning Analytics · Didactic · Interoperability · Middleware · Best Practice

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1 Introduction

Artificial Intelligence (AI) not only shows tremendous potential in general but also in particular for increasing efficiency and effectiveness in learning environments [1]. The technological progress in the last few decades enabled the use of AI methods in a broad range of use cases from automatic signal processing to personalized recommendation systems. This progress also resulted in steadily improving accuracy and speed. The following text created by ChatGPT exemplifies the performance of modern AI-based systems, for it succeeds in describing the purposes of AI in educational settings:

"There are many ways that artificial intelligence (AI) can be used in educational environments to enhance teaching and learning. some examples include:

- *Personalized learning: AI can be used to create personalized learning experiences for students by adapting to their individual needs and abilities.*
- *Tutoring and feedback: AI can be used to provide one-on-one tutoring and feedback to students in real-time, helping them to better understand concepts and improve their skills.*
- *Content creation: AI can be used to create customized learning materials and resources for students, such as personalized study plans and interactive educational games.*
- *Grading and assessment: AI can be used to grade assignments and assess student performance, freeing up teachers to focus on other tasks.*
- *Student support: AI can be used to provide support to students outside of class, such as answering questions and providing guidance on assignments.*
- *Overall, AI has the potential to greatly enhance the education experience by providing personalized and interactive learning opportunities for students."*[1]

Reviews like the one from Guan et al. [2] identify similar themes in the scientific community. They examined over 400 articles in major educational journals from 2000 to 2019. Notable trends they found are learning analytics and user modeling for individual adaptive learning and aided teaching systems for grading and evaluation [2].

Conclusions and decisions can be made automatically by an AI, e.g., in recommender systems or in adaptive educational systems by generation of learning paths or dynamic difficulty adjustments of exercise difficulty levels [1]. Alternatively, the learners and teachers themselves interpret the results, typically by looking at pre-processed data visualizations in dashboards [3]. These visualizations can provide an overview by displaying relevant data as the average completion time per task and even indicate learning progress, weaknesses or learning needs. Additionally, AI approaches such as chatbots (recently the topic ChatGPT received a very high attention) used as virtual learning assistants may also lead to increased user satisfaction and, thus, promote higher user motivation and better learning outcomes.

Generally, AI systems are complex and research intensive, hence the integration and re-use of existing components is preferred over new developments. However, the integration in existing system environments poses organizational and technical challenges,

[1] This text was generated automatically by the AI-based Chatbot "ChatGPT" on the question "How can Artificial Intelligence be used in educational environments?"; https://chat.openai.com/chat (on January 5, 2023; ChatGPT Dec 15 Version. Free Research Preview).

for instance varying and changing public technical interfaces. The research question of this work is how AI features can best be incorporated into modern educational system landscapes to create sustainable system architectures that are accepted and perceived as added value by users.

The contribution of this work is a model for a middleware-based, AI-integrating software architecture and its application and evaluation in a public field test. The model has evolved over time from integrating various standard software in heterogeneous system landscapes. It formulates a so-called Best-of-Breed approach which describes the combination of well-tested, high-quality (AI) systems in a standardized manner for effective use in applications.

This article is organized as follows. Section 2 describes some of the most important data categories in educational systems and which are also central to our approach and to AI-based systems. Section 3 discusses the theoretical foundations for AI-supported educational systems, and we address requirements on organizational, methodological, didactical, content-related, and technical levels. Section 4 introduces the methodology and Sect. 5 pleads for the Best-of-Breed strategy instead of Best-of-Suite. Section 6 describes a modular, service-oriented environment based on an educational middleware that orchestrates external AI services.

2 Foundations on Data in Educational Ecosystems

Data is the foundation that every AI-supported functionality relies on. Without loss of generality, data used by educational institutions can typically be divided into identity and profile data, activity data, institution data, content metadata, communication data, and application-specific data. These categories are explained in the following.

2.1 Identity and Profile Data

Users authenticate themselves as principals by means of their identity information stored within identity provider systems. Single sign-on describes a mechanism in which users must authenticate themselves only once for multiple software platforms. Irrespective of the authentication mechanism, personal data is usually collected and managed for an identity, e.g., name, birthday and place, address or contact data. Dynamic data that make up the personal educational biography, such as educational stages already completed or knowledge, skills or competencies acquired, are usually stored in user profiles.

2.2 Activity Data

Traditionally, activity data is understood as learning behavior data but can also include self-assessments, defined learning goals, or answers in exams. Typical formats for such learning records are Experience API (xAPI) or CALIPER which have their origin in general activity streams (e.g., W3C Activity Stream). Since profile data also results significantly from the activities of the users within the education stations, the boundary to activity data is fluent. Processed activity data can be stored as learning information in the user profile (e.g., competency level).

2.3 Institutional Data

Data that is typically generated or primarily processed by an institution. This includes administrative data, such as enrollments in classes or courses or assignments to instructors, rights, and roles of individual users for access to certain content, e.g., via the W3C's Open Digital Rights Language (ODRL). Exam questions or certificates and evidence are also usually created by or on behalf of the educational institution and subsequently made available to learners. Applications, enrollments, or learner files are usually managed by the educational institutions but are created almost exclusively through the actions of the individuals involved.

2.4 Content Metadata

Content metadata describe learning objects, their characteristics, creation and editing history, technical requirements, rights, educational characteristics, and pedagogical information, e.g., in the IEEE LOM format. It is also important to indicate the relation to other content. For example, learning objects can be nested within each other, linked to further objects, or combined to form entire courses. These courses should also be well described to make them easily locatable. The content metadata should be created at the smallest possible level of knowledge transfer and assessment. This metadata is aggregated for the combinations of new learning objects or complete courses.

2.5 Application Specific Data and Preferences

Such data is platform- or application-specific and does not belong to one of the previous categories. Obviously, each application produces its own data, typically proprietary. Here we focus on interoperable data accessible to and processable by other platforms either via an API or via export functions. Examples for application-specific data are individual preferences such as options of the personal start page, the font sizes, theming, design of an avatar, etc. Further data can be communication data between users, i.e., social interactions or chatbot inputs.

3 Literature Review on Challenges and Requirements for AI-Supported Educational Systems

While designing any AI-supported educational ecosystem developers face interdisciplinary challenges that impact the success and acceptance of AI to a great degree [4]. These challenges occur irrespective of the AI-functionalities and must be addressed before implementation. In the following, we highlight some of these aspects, ranging from organizational challenges (e.g., roles or regulations), to methodological (e.g., evaluation), didactical (e.g., course design), technical (e.g., interoperability) or aspects regarding content (e.g., digitalization and metadata).

3.1 Organizational Aspects

The introduction of artificial intelligence in educational environments requires the involvement of different stakeholders [1]. Above all, the responsible organizations must ensure that the application of AI is in accordance with applicable laws (in the EU, e.g., GDPR, data processing contracts), all regulatory requirements are met (e.g., naming of responsible persons, such as data owners, anonymization) and that IT and data security concepts are state-of-the-art. In this context, Flanagan and Ogata [5] discussed the increasing need for data and privacy protection throughout the entire AI workflow. Renz and Meinel [6] addressed the requirement to use pseudonymization for the GDPR-compliant collection of xAPI learning records and argue for the use of an appropriate middleware. An organization must additionally ensure that the role holders have sufficient resources, even after the initial launch of AI [3]. And for the general AI acceptance it is important to train the instructors and raise awareness for any AI particularities beforehand [3].

3.2 Methodological Aspects

Most AI applications in learning environments aim at optimizing learning by making it more effective (e.g., goal-oriented recommendations, learning path adaptations) or more efficient (e.g., less redundant, less already-known content). In the context of learning recommender systems, for instance, *efficiency* describes the quality of a learning path to achieve a personal (learning) goal. In a small-scale course setting, higher efficiency can save efforts and time to reach the course goal. *Effectiveness* directly affects the results achieved, e.g., a better mark in the exam or longer lasting knowledge [7]. Thus, the purpose of an AI function is essential for design choices, development of an appropriate methodology and selecting an optimal evaluation framework [8]. The user's interface, its usability and the user experience (UX) are integral for an AI-supported system to ensure user acceptance of the system [9].

3.3 Didactical Aspects

When organizers know how humans accomplish a certain task, such as analyzing learning groups at the beginning of a course or recommending appropriate learning materials, they can then consider having an AI component take on that task. We strongly believe that following a didactical concept instead of blindly replacing all classroom sessions would not only improve the learners' and teachers' overall acceptance of a system, but also result in better learning outcomes. The AI-based analysis provides additional information for creating and improving didactical concepts. As many AI applications are aimed at automating didactic activities [10], e.g., selection of learning material, it is necessary to decide on a robust didactic concept as a foundation [11]. As such, the didactic concept should be evaluated as thoroughly as the analytics' functionalities themselves.

3.4 Content Aspects

When well-structured data on learning content and usage is available, learning analytics can offer additional, clearly visible value for many users. However, it is not enough to just describe the content. Learning analytics (LA) is digital and hence, content must be available in a digital and compelling format, ideally following an established standard. For interoperability purposes, we encourage the use of standards, such as IEEE Learning Object Metadata (LOM) or IMS Common Cartridge (CC) - ideally also IMS Content Packaging (CP) and IMS Question & Test Interoperability (QTI). The required metadata for AI functionalities depends on the respective application's purpose and overall didactic concept. From our experience, the implementation and maintenance of metadata standards for one's own content involves a great deal of effort, which, in the best-case scenario, is automated or already realized during the creation of individual content.

3.5 Technical Aspects

Finally, a successful implementation and integration of LA into corporate learning environments – especially in environments of multi-institutions with distributed services – requires the use of widely accepted interoperability standards [3]. To address typical technical challenges such as IT security and network limitations (e.g., CORS) while still adhering to given data-privacy and data-protection regulations, we identified and implemented multiple core technologies and protocols which adhere to established specifications. Notable standards include the learning record specifications xAPI and CALIPER, which can be persisted in distributed Learning Record Stores [12] or user-controlled Data Wallets [13], LTI (Learning Tools Interoperability) or cmi5 (computer managed instruction, 5th attempt) launch specifications, as well as standards for the exchange of content metadata, such as CC, LOM or Question and Test Interoperability specification (QTI). However, not every service in a complex educational ecosystem follows the same standard and many direct links between individual adaptive services are difficult to maintain. Therefore, a middleware architecture for service orchestration is often recommended [14]. This middleware can either be standards-agnostic and allow communicating services to agree on a particular form of communication, or act as a standards-translator, e.g., between LTI and cmi5 [15]. A specific challenge arises, however, when decentralized storage or replication of learning record data becomes necessary. We observed a standard corporate requirement: multiple as well as decentralized Learning Record Store (LRS) instances. Each subsidiary can have its own data handling constraints, resulting in the need for individual stores. This motivates LRS replication strategies, control of the data flow, and operating dashboards under customer sovereignty.

4 Methodology for Developing an Interoperable AI-Supported Educational Infrastructure

This article focuses on the development of an AI-supported educational infrastructure in the context of the interdisciplinary research project TripleAdapt[2], funded by the German Federal Ministry of Education and Research (BMBF) as part of the INVITE program. TripleAdapt develops cross-platform digital learning opportunities by interconnecting learning platforms from different institutions as well as AI-supported teaching and learning options.

[2] TripleAdapt Project: Sponsored by BMBF; Funding Number 21INVI1306; Duration: May 2021 to April 2024; See: https://www.fokus.fraunhofer.de/en/fame/projects/tripleadapt.

TripleAdapt uses the concept of an adaptive triplet to expand the digital learning environment in such a way that employees can be supported in real challenges in their work processes. The learning concepts emerge from the analysis and modeling of process data based on developed competence profiles, which are anonymously matched with actual competence profiles. In this way, actual learning needs can be identified, which transparent and comprehensible systems recommend differentiated learning content. The result of the implementation should be a perceptible increase in learning success, considering various aspects such as workload in variant-rich production.

The project focuses on a total of nine use cases in the three categories: Networking platforms, platform-related innovations, and AI-supported teaching/learning offerings. The networking use case on cybersecurity, for example, envisions public testing of a networked online educational landscape on IT security with a focus on cryptography and hacking. For example, a portal shall serve as a central entry point for retrieving digital media from an ILIAS LMS, from a company's proprietary learning management system, and from learning platform for further professional training. The difficulty levels of the offered exercises shall adapt to the users and micro certificates shall be issued at the end via blockchain-based technology.

To combine these independent functions into a common offering without interruption for the users, a suitable infrastructure solution must be designed that also makes it simple to add further functions. For this purpose, possible monolithic and service-oriented solution approaches and interoperability standards have been analyzed. The most suitable approach in the authors' view, a middleware-based solution, was deployed and tested in a large-scale field test. In a first field trial, users were asked to evaluate their experience in using the services after attending a cybersecurity course whose content and AI functions were distributed across different platforms.

5 Considerations for a Sustainable System Architecture

Monolithic systems offer a wide range of functions and can be managed by a single provider. They are relatively easy to use and can offer a high-quality experience for users in small systems. However, they can become difficult to manage as they become more complex and need to be integrated interconnected with other services. They also create dependencies and can be less flexible and futureproof compared to specialized and service-oriented systems. Specialized and service-oriented systems, on the other hand, consist of modular functions handled by specialized services. They are more flexible and scalable and can be integrated with a wide range of tools and services. However, they require more effort to set up and manage, and may not offer the same level of user experience as monolithic systems. This section discusses monolithic systems and service-oriented architectures (SOA), classified as Best-of-Suite (for monolithic) and Best-of-Breed (for SOA).

5.1 Monolithic Systems – Best-of-Suite

Learning Management Systems (LMSs) such as Moodle have become very popular and thus widespread in recent years[3]. Over time, numerous professional communities have been involved in expanding these systems for various use cases and functions. In addition to these open-source communities, there are also various, mostly closed-source LMS solutions that address the needs of paying users as comprehensively as possible.

Best-of-Suite (BoS) describes systems consisting of functionality and infrastructure from one source or provider. The biggest advantage and at the same time the biggest disadvantage of the BoS approach is that the developer or software architect is responsible for all parts of the system. In systems with a small scope, this promotes well-coordinated, high-quality services and great experience for the users. However, the more extensive the functions become, and the more existing services need to be integrated, the more difficult it becomes for a single institution to manage the various aspects. Whether intended or not, complex systems also cause dependencies (to 3rd party plugins as well as to the rights holder) to increase over time, often creating so-called lock-in effects. These effects are particularly apparent, for example, when individual modules of an overall system must be accessed separately so they can be reused in other independent systems. Vice versa, it can be a big challenge to integrate data, identities, or content from external sources into the existing system. In these cases, the developer must add functions and data flows to extend software modules of the monolithic LMS with often only limited software documentation available. Especially when numerous existing systems (i.e., identity providers, authoring tools, or already established processes) must be integrated or connected to the LMS, the effort needed to build necessary interfaces and to translate between various, often proprietary, data and exchange formats quickly becomes unmanageable, especially for larger institutions with growing user-bases and expanding course-portfolios. On top of that, monolithic systems tend to be less futureproof compared to their alternatives. While they might satisfy immediate needs and pain points, relying on monolithic systems often leads to incompatibilities or other problems in the future. In most of these cases, this means considerable effort for the developer to implement workarounds or to reimplement specific modules, in the worst case this could even mean a replacement of the entire system.

5.2 Specialized and Service-Oriented Systems – Best-of-Breed

Complex interconnected artificial intelligence systems are likely to exceed the maintenance capabilities of one organization. Relying on a one-fits-all solution would not be sustainable, since the number of additional functions and modifications would make it very difficult to maintain and expand monolithic systems. For this reason, service-oriented architectures (SOA) increase in popularity. A key aspect of SOA is that each modular function is handled by a specialized service. In this architecture approach, services can also either be integrated as flexible Software-as-a-Service (SaaS) solutions (e.g., cloud-based), or hosted entirely or in part on premise, usually when deeper integration with existing services and architectures is needed. This results in a shift towards

[3] See: European LMS Market Report: https://eliterate.us/new-release-european-lms-market-report/.

a Best-of-Breed (BoB) approach which describes the strategy to utilize the best possible component to take care of a specific problem. Compared to monolithic systems, SOAs tend to be more complex during the initial setup phase. However, the modular nature of the SOA approach allows several developer teams from different organizations to work on different parts of the overall system in parallel. The entire system, as well as parts of it, can be better operated and maintained, or quickly replaced if necessary. This leads to parallelizable, scalable systems. However, for the corresponding services to offer users transitions that are as seamless and imperceptible as possible (e.g., users want to open the next appropriate content, the video conference, or the associated forum with just one click), the services must exchange information efficiently. To achieve this, all services involved must agree on a common understanding of the exchange mechanisms, data formats and semantics. For this reason, it is highly advisable to use established interoperability standards when opting for the SOA approach.

5.3 Interoperability Standards

BoB architectures and their services need to have compatible interfaces and protocols to communicate with each other. Several specialized standards and specifications from different initiatives and consortia exist for this purpose. Global initiatives that push the creation of new interoperability standards are prevalent in the learning community. Internationally established are the initiatives ADL (Advanced Distributed Learning; e.g., SCORM or xAPI) or the 1EdTech Consortium (formerly “IMS Global Learning Consortium”; e.g., LTI, Common Cartridge or LOM). Many learning platforms support formats from those initiatives.

ADL’s Sharable Content Object Reference Model (SCORM) was for a long time the most suitable and thus most widely used format for managing, linking and representing learning content. The monolithic character of SCORM has proven to be too inflexible for modern service-oriented educational technologies. The following strategies have been considered more promising for building sustainable educational ecosystems:

- Standardized content launch approaches to enable uniform access to learning materials and services: 1EdTech Learning Tools Interoperability (LTI), ADL cmi5 (Computer Managed Instruction, 5th attempt; part of the ADL xAPI specification).
- Well-structured definitions of learning records: ADL xAPI, 1EdTech CALIPER.
- Persistence of well-structured metadata: Common Cartridge, Content Packaging, and QTI from 1EdTech and IEEE LOM.

There is usually not only one de facto standard for each application area, but several alternatives (e.g., xAPI and CALIPER, or LTI and cmi5). A dossier by Reichow et al. [16] provides a good overview of the most important standards and recommendations for implementing digital professional development platforms. While it is focused on the field of vocational training, it also shows great applicability beyond this. In 2021, the authors of this article analyzed the 53 most popular LMSs and found wide disparities in support for certain interoperability standards. While 72% of the LMSs supported the outdated SCORM, only 64% supported a current launch mechanism such as LTI (62%) or cmi5 (13%). Nevertheless, a development towards current interface standards can be observed. Thus, it can be assumed that hardly any LMS is currently working on

SCORM support, but many have planned support for cmi5 which was first released in 2016. Cmi5 is based on the xAPI specification which is already supported by 58% of LMS and enables consumer-side control of collecting user interactions vs. provider-side control in LTI by requiring the LRS endpoint to be passed in the launch URL. It is also interesting to note that only 25% of the LMSs surveyed were made available under a common open-source license and only 30% can be used without license fees.

6 Implementation of AI Use Cases

We have developed the Common Learning Middleware (CLM) [15] and successfully applied it in various contexts[4]. In 2021, the CLM was selected by the German Federal Ministry of Education and Research as one of three prototypes of the German National Education Platform within the framework of the "mEDUator" project[5] to demonstrate the successful concept of an interoperable middleware for connecting distributed education ecosystems. In the "EXPAND+ER WB^3" project[6] the middleware is used to interconnect the learning platforms of education providers with a superordinate continuing education search platform without making them directly dependent on each other. Moreover, the CLM was used in an investigation of the prototypical use of artificial intelligence techniques (learning recommendations, chatbots, adaptive assignments, learning analytics dashboards for educators) using the example of course-based individual training in the German Army[7]. Here we outline a use case for distributed adaptive training on cybersecurity in context of the TripleAdapt project. In the following, we describe the way in which the most important distributed components interact and their typical data flows, followed by some evaluation results from public user tests.

6.1 Middleware-Based Approach

Following the reasoning given above, we developed the orchestrating, standard-enabling Common Learning Middleware that promotes the BoB strategy as well as the usage of standard-compliant interfaces and data sources. The users (learners) are placed in the center, and all the services and data flows are designed for and built around them. They can access content and services from different providers without interruption, and their data (e.g., tracking data, tokens) is handled by the middleware approach in the background. As a service, the middleware provides interfaces for decentralized connections of different platforms, i.e., coupling and orchestration. Providers of learning content can register their systems – and hence their learning material – with the help of the middleware, i.e., regarding LTI as a tool or service provider (Fig. 1).

4 See: Fraunhofer Common Learning Middleware: https://www.fokus.fraunhofer.de/en/fame/clm/.

5 mEDUator Project (Sponsored by BMBF; Funding Number: 16INB3006): https://www.fokus.fraunhofer.de/en/fame/project/meduator/.

6 EXPAND+ER WB3 (Sponsored by BMBF; Funding Number: 21INVI31): https://www.fokus.fraunhofer.de/en/project/fame/expander_2021-12.

7 AI in Learning Management Systems (German): https://kilms.fraunhofer.de/ki-funktionen/.

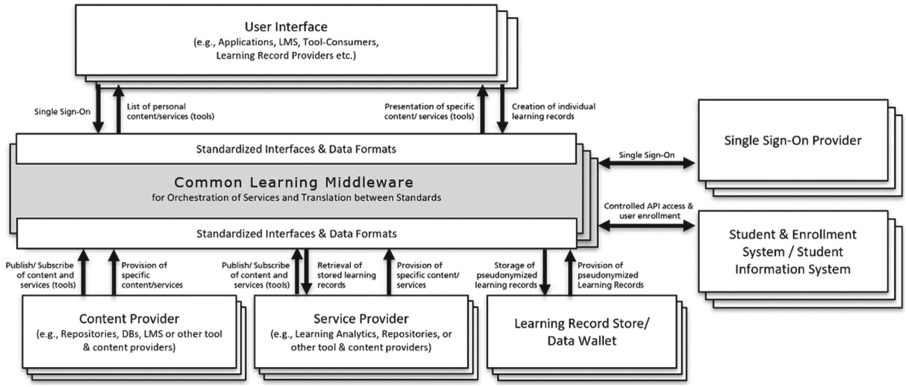

Fig. 1. Architecture of the AI-enabling Interoperable Infrastructure

A repository acts as a digital asset store that essentially contains course structures, learning objects and their metadata (e.g., as IEEE LOM, 1EdTech QTI, CC or CP). Learning objects, i.e., learning content, media and services, can be integrated into platforms and applications of the end users. Specifications such as cmi5 or LTI can be used to interconnect learning objects. It is a secure launch of learning objects and reflects the trust relationship between a client, also called tool consumer, platform or application for end users, and a service, also known as tool or tool provider. A retrievable learning object may contain either pre-rendered HTML elements or content metadata based on specifications such as LOM (also considering CP or QTI) which must then be appropriately rendered by the application. In the case of a launch request, the request data is signed with the user's information (as with LTI) or based on the user's token (as with cmi5) and transmitted to the content provider.

The middleware checks the user data, the associated role and access rights for each interface request. In the case of a launch request (i.e., the request for the application to present a launchable object to the user), the request data is signed using the user information (LTI) or based on the user's token (cmi5) and transmitted to the launchable object via the service provider. The middleware also makes it possible to translate between different launch mechanisms, such as LTI v1.1, LTI v1.3, LTI Advantage, and cmi5. This means that providers can, for example, make cmi5 objects available in their applications by utilizing LTI (or vice versa).

The learning records can be recorded in the application or in the respective learning objects. To enable the tracking in a launchable object, the application is required to supply the user information to this object - this is transmitted with the two "launch" mechanisms. For the capturing of learning records, xAPI and CALIPER are supported. These learning records can be persisted in LRSs, where educational institutions can register their own LRS with the middleware. Institutions can configure which users send which type of learning records to which LRS when interacting with which tools. The middleware orchestrates and ensures the trustworthy interaction between learning record providers (which produce new learning records from the interaction), learning record stores (as databases for managing pseudonymized interaction data) and learning record consumers (which process stored learning records e.g., AI services). The middleware manages the permissions of services and their access to the learning record stores. However, it is also possible that users hold their personal in a local data wallet. From the perspective of the middleware, storing data locally at the user's site, for example, makes no conceptual difference, since the accessing services handles the required access information independent of the endpoint providing the data. In scenarios where the tools themselves are not (yet) able to generate xAPI statements, but support the LTI Assignment and Grade Services, the middleware can be actively used to translate these learning state callbacks send to the middleware into a minimal set of activity data reported to the according LRS.

All interfaces of the middleware are RESTful APIs[8] which follow the paradigm for software architectures of distributed systems. The interfaces have been specified according to the OpenAPI specification. Relevant interfaces, such as the provision of LTI-based tools as tool providers, have been implemented with validating functions. The middleware checks new learning objects according to their specification when being integrated into the middleware.

6.2 Integration of AI Services

AI services process different data with the aim of analyzing, evaluating, and reacting to it. Examples for usable data are learning records, learning content descriptions (for example as LOM, QTI or CC), learning objectives, learning progress, competencies, skills & qualifications. Just like repositories, AI services are connected to the middleware in the form of encapsulated services and can present their results directly in the applications via the presented launch mechanisms.

In the case of AI components, it should be noted that in addition to personal learning records, anonymized learning records of other, similar participants often need to be evaluated - for example, to identify and transfer successful learning behavior (collaborative filtering in recommender systems). Learning path generators and learning analytics services also require this advanced data evaluation. Accordingly, concepts for handling, releasing, and disclosing other users' data (for example, user-adjustable or always anonymized after release) must also be considered when designing user-sovereign data stores.

Search engines can also be easily integrated into the applications. For the findability of content for the search service, the learning objects registered in the middleware are accessed, called up individually and indexed for the search index like the work process of popular search engines. To ensure that users only receive results for content that they can access, the access rights stored in the administrative data are compared and all restricted content is removed from the results lists.

One AI component frequently used in our ecosystem provides dynamic difficulty adjustments (DDA, also called Rubber Banding). The DDA AI has been integrated into an educational game for gamified training and it controls the game's difficulty setting, e.g., number and semantic complexity of answer options or available time budget. The

[8] RESTful API: Representational State Transfer Application Programming Interface.

AI functionality has been implemented using an AI adaptivity framework which provides adaptivity responses as a service (adaptivity-as-a-service). Information primarily from xAPI observation data is made available through the middleware when calculating target difficulty levels. This specifically includes the measured performance value, i.e., how well an individual user performed on a task. The target value for the control loop is implicitly assumed to be one hundred percent which means that the aim is to continuously improve the users' performance. DDA is calculated based on the performance trend using a harmonic sum. The AI adaptivity framework is designed using established interoperability standards and generalized models, hence it is easily applicable to other assistance systems. The gamified trainings component was also used in the context of the public field trial.

7 Findings of the Public Field Test

In the TripleAdapt Project, a public field test was carried out in December 2022. In the field test, we presented an adaptive training course on cybersecurity that unites different learning platforms and learning technologies into a common infrastructure with the help of the proposed middleware architecture approach. Participation in the test was free of charge and open to all interested parties. Registered users received a personal certificate of participation upon request after the test. During the test 186 visitors were observed, 650 accesses took place, and 48 people took part in a subsequent formal survey. Most of the survey participants fall in the age category of 30–39 and worked in the education industry.

The adaptive training on cybersecurity offered participants a choice of four different learning paths: beginner with plenty of time, beginner with limited time, expert with plenty of time and expert with limited time. The AI is part of the interconnected, middleware-based architecture, and the respective services offered adaptive learning paths as well as recommendations.

The subsequent survey included questions about the participants' experience with the different learning platforms and tools, the ease of switching between them, their satisfaction with the navigation and the layout of the combined platforms, suggestions for improvement, and their demographic information. While many participants (31 out of 48) noticed that they were using multiple platforms during their learning path, most participants (44 out of 48) felt that they were able to navigate all offerings well and that they were able to handle visual changes in the layout of the platforms. 17 out of 48 participants even found it to be a very pleasant experience.

The responses to the question "What did you like about the learning path and content?" are generally positive, with many participants noting that they appreciated the variety of tasks and media used to present the content. They liked the design of the platform and the way the information was organized in an orderly manner, which made it easy to navigate. They also enjoyed interactive components like a crypto-quiz and an interactive hacking lab. Some participants commented that they liked the multimedia offerings of text, videos, and quizzes. They also liked the way the platform adjusted to their progress and the fact that the content is up to date and relevant. Some people found the course basic and repetitive, but overall, the positive feedback was consistent.

We asked participants what they would improve in the interaction of the learning platforms. From the responses provided, it appears that users have several suggestions for improving the way that the different learning platforms interact with one another. Some common themes that appear include:

- Navigation and user feedback: Five users would like to see more information provided in the navigation sidebar, such as which learning content they have already viewed or completed. Additionally, two users found the branding or menu bars of certain platforms to be distracting.
- Consistency between platforms: Eight users found it difficult to switch between platforms and suggested that more information about the type of content (e.g., videos, learning modules) or a more consistent layout would help with this.
- Loading times: Seven users noted that the loading times for certain elements or platforms were slow and suggested that this could be improved.
- Login issues: Two users reported issues with logging into certain platforms and suggested solutions such as automatic retries or warning messages.
- Quiz formatting: Five users suggested that the quiz could be better integrated into the overall layout of the platform.
- Consistent design: Four users suggested that a more consistent design across platforms would be beneficial to the overall user experience.
- Navigation to next point: Six users suggest having better navigation structure after completion of a course or a chapter.

In general, it seems that users are seeking a more seamless and consistent experience across the different learning platforms, with clearer navigation and faster loading times. They also want better integration between different platforms and more consistency in design and layout.

In conclusion, the field test proofs the technical feasibility of such a middleware-based architecture and highlights the importance of user experience and ease of navigation when integrating multiple learning platforms. The feedback provided by the participants in terms of their experience with the different learning platforms and tools, and their suggestions for improvement, can help guide future developments in the TripleAdapt project and similar endeavors.

8 Discussion on the Challenges of Developing Educational Infrastructures

Challenges for the development of sustainable AI-supported educational infrastructures are diverse: On the one hand, the interests of the users should always be in the foreground and efforts should be made to adapt the technical systems to their needs as efficiently and effectively as possible. On the other hand, there are also many challenges on the side of the content providers and course leaders. These usually concern the sustainable use, accessibility, and reuse of content, which is increasingly taking place across institutions.

Due to market fragmentation and the diversity of data, technologies, and interoperability standards, it seems almost impossible to combine different learning repositories and advanced technologies directly into a central learning experience. Equal access to educational services, on the other hand, is essential and must be ensured by considering national and international initiatives.

However, educational ecosystems usually need to process diverse categories of data, which have different characteristics - for example, in terms of the frequency with which new data is generated and the possibility of subsequent changes: Certificates are created once and usually not changed, competencies, on the other hand, change regularly, and activity data/learning records are regenerated very frequently. The corresponding characteristics have a direct impact on the suitability of certain solution and architecture approaches - for example, using centralized or decentralized data structures, data vaults or data wallets, and so on.

The proposed CLM represents a middleware-based solution for orchestrating data flows in service-oriented educational architectures. It translates between different interoperability standards and thus serves the sustainable networking of services. A middleware is not directly perceptible to end users but performs many essential tasks of modern educational ecosystems in the background. It eliminates the need to manually switch between different apps and websites: All content and functions can be presented in one place - for example, via a central access point of the provider. Searching for the specific login credentials for a particular service becomes unnecessary: The same global identities can be used for all services connected to the middleware. And end users benefit from full protection and control of their personal information: Data is processed throughout the ecosystem in a privacy-compliant manner, and users can determine for themselves which services they grant access to their data.

For the providers, the middleware-based solution is accordingly not to be understood as another separate ecosystem, but rather as an additional enabler and multiplier for reaching new customers and realizing new educational journeys. A key requirement here is that the connection of existing systems can be realized without major technical and organizational hurdles, i.e., with little effort. Providers who also rely on the single sign-on offered or the concept of user-sovereign data management will benefit from more secure and satisfied end customers in the future. In this way, the middleware contributes to an established, sustainable, and self-sustaining platform economy to offer both users and providers long-term added value.

Especially in the field of education, it is important to point out that a well-thought-out didactic concept is required for cross-platform data processing, as well as a strongly independent use of technology [17]. In the future, computer systems will not take over human learning, nor should learners blindly trust every feedback from an assistance service - even if this can already be very precise nowadays. An undifferentiated acceptance by users of AI-driven decision systems can be problematic. The computer system would also be to blame if, for example, learners fail their exams because they rely unquestioningly on the recommendations of the AI-driven learning platforms.

Well-networked learning technologies cannot and will not replace teachers but should rather be understood as supporting regular processes that lead to an increase in efficiency and effectiveness in the learning process. Modern, networked architectures in educational ecosystems help to shift the focus away from the technology to the learners, which on the one hand promotes self-activating and self-determined learning and on the other hand can better support the independent organization of the learning process according to individual inclinations and interests.

9 Conclusion

This article discusses two approaches to designing educational technology systems: monolithic systems ("Best-of-Suite") as well as specialized and service-oriented systems ("Best-of-Breed"). The research question of this work is how AI features can best be incorporated into modern educational system landscapes to create sustainable system architectures. The contribution of this work is the model for a middleware-based, AI-integrating software architecture and its application and evaluation in a public field test. The model has evolved over time from integrating various standard software in heterogeneous system landscapes. It formulates a so-called Best-of-Breed approach which describes the combination of well-tested, high-quality (AI) systems in a standardized manner for effective use in applications. We describe how to create a technically seamless learning experience for the users, an interoperable and flexible educational infrastructure, and how to incorporate widely used standards and specifications. These approaches have been applied in various contexts, including professional training and public education. The middleware-based approach involves the use of standard-compliant interfaces and data stores to facilitate the exchange of data between different platforms. Thereby, learning object repositories as well as AI services register their functions to the middleware, which, in turn, can be integrated into platforms and applications using specifications such as xAPI, cmi5 or LTI. An important result of the field test is the need for a uniform appearance of the various platforms and service offerings, which will be considered in future work through the use of common style sheets.

References

1. Chen, L., Chen, P., Lin, Z.: Artificial intelligence in education: a review. IEEE Access **8**, 75264–75278 (2020)
2. Guan, C., Mou, J., Jiang, Z.: Artificial intelligence innovation in education: a twenty-year data-driven historical analysis. Int. J. Innov. Stud. **4**, 134–147 (2020)
3. Ifenthaler, D., Drachsler, H.: Learning analytics. In: Niegemann, H., Weinberger, A. (eds.) Handbuch Bildungstechnologie, pp. 515–534. Springer, Heidelberg (2020). https://doi.org/10.1007/978-3-662-54368-9_42
4. Altun, D., Krauss, C., Streicher, A., Mueller, C., Atorf, D., Rerhaye, L., Kunde, D.: Lessons learned from creating, implementing and evaluating assisted e-learning incorporating adaptivity, recommendations and learning analytics. In: Sottilare, R.A., Schwarz, J. (eds.) HCII 2022. LNCS, vol. 13332, pp. 257–270. Springer, Cham (2022). https://doi.org/10.1007/978-3-031-05887-5_18
5. Flanagan, B., Ogata, H.: Integration of learning analytics research and production systems while protecting privacy. In: The 25th International Conference on Computers in Education, pp. 333–338 (2017)
6. Renz, J., Meinel, C.: Can pseudonymized xAPI-Tracking solve data privacy issues in German schools?. In: SAILA-ECTEL 2018, Leeds, UK (2018)

7. Krauss, C., Merceron, A., Arbanowski, S.: The timeliness deviation: a novel approach to evaluate educational recommender systems for closed-courses. In: Proceedings of the 9th LAK19 Conference, pp. 195–204. ACM, New York (2019)
8. Wise, A.F., Vytasek, J.: Learning analytics implementation design. Handb. Learn. Anal. **1**, 151–160 (2017)
9. Gunesekera, A. I., Bao, Y., Kibelloh, M.: The role of usability on e-learning user interactions and satisfaction: a literature review. J. Syst. Inf. Technol. **21**, 368–394 (2019)
10. Chaudhry, M., Kazim, E.: Artificial intelligence in education (AIED) a high-level academic and industry note 2021. Available at SSRN 3833583 (2021)
11. Ciolacu, M., Tehrani, A. F., Binder, L., Svasta, P. M.: Education 4.0-artificial intelligence assisted higher education: early recognition system with machine learning to support students' success. In: 2018 IEEE 24th International Symposium for Design and Technology in Electronic Packaging (SIITME), pp. 23–30. IEEE (2018)
12. Samuelsen, J., Chen, W., Wasson, B.: Integrating multiple data sources for learning analytics—review of literature. Res. Pract. Technol. Enhanc. Learn. **14**(1), 1–20 (2019). https://doi.org/10.1186/s41039-019-0105-4
13. Kagermann, H.: European public sphere: towards digital sovereignty for Europe. National Academy of Science and Engineering (2020)
14. Folsom-Kovarik, J.T., Jones, R.M., Schmorrow, D.: Semantic and episodic learning to integrate diverse opportunities for life-long learning. In: MODSIM World Conference (2016)
15. Krauss, C., Hauswirth, M.: Interoperable education infrastructures: a middleware that brings together adaptive, social and virtual learning technologies. In: ERCIM News 120 - Special Theme: Educational Technology, pp. 9–10 (2019). ISSN 0926-4981
16. Reichow, I., Hochbauer, M., Goertz, L.: Standards und Empfehlungen zur Umsetzung digitaler Weiterbildungsplattformen in der beruflichen Bildung: Ein Dossier im Rahmen des INVITE-Wettbewerbs. Bundesinstitut für Berufsbildung, Bonn (2021)
17. Rerhaye, L., Altun, D., Krauss, C., Müller, C.: Evaluation methods for an ai-supported learning management system: quantifying and qualifying added values for teaching and learning. In: Sottilare, R.A., Schwarz, J. (eds.) HCII 2021. LNCS, vol. 12792, pp. 394–411. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-77857-6_28