The Adaptive Triplet: Integration of AI-based Learning into the Digital Twin

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Table of contents

1 Introduction

1.1 Motivation

Today's labor market is subject to ephemeral and disruptive changes. Employees in all sectors have to adapt quickly and effectively to evolving requirements as part of the digital transformation and a multitude of technological developments(Griep et al, 2021). This involves ensuring that the required employee skills are on hand when needed.

In addition, the expectations and needs of many employees are also changing. They demand a greater involvement in shaping their own career and development opportunities and want to take the initiative in promoting their individual skills and interests.

Personalized further training is therefore an important approach to meet these requirements. It enables companies to create individual learning paths that are tailored to the specific needs and goals of each employee. This is associated with an increase in the efficiency of corporate training programs in terms of costs and time, as tailred offerings are provided.

Learners have individual needs, skills, knowledge and learning styles. Personalizing the learning environment can also promote motivation and commitment. Among other things, this helps to improve users' learning outcomes. When learners learn in a way that suits them, they can absorb and retain new information faster and more effectively. A digital education space is created that meets the needs of every learner in the context of vocational training. This supports effective, sustainable, and holistic skills development and creates innovative teaching and learning opportunities. Doing so makes an important contribution to the continuous quality improvement and assurance of a company's existing training programs. The development and testing of personalization tools are accompanied by their usage and documentation of competencies, which in turn make important contributions to the understanding of qualifications and individual learning outcomes.

In order to continuously adapt this **personalization** to the changing needs and knowledge levels of employees, the learning content and recommendations need to be adaptable thanks to technical support.

The prerequisite for **adaptivity** is available and processed data at an individual level, which is pseudonymized within an interoperable system.

Another feature of holistic and personalized learning system is the progress via **conectivity** – through the integration and interconnection of various internet-based platforms and complementary offerings. The resulting exchange of learning technologies and content allows the needs of learners to be addressed individually and across a broad spectrum. This not only strengthens the benefits for learners, but also the visibility and reach of the individual services involved in a networked project.

AI-supported processes can be used for each of these target areas, which can intervene in a transparent and explainable manner and thus contribute to improving the quality and accuracy of digital offerings. The result is a socio-technical system that, depending on the area of application, allows automated feedback from the learning and work context, and independently initiates qualification measures.

To enable personalized and adaptivity even for already established systems on the market, it is necessary to develop an interoperable and expandable component that can be integrated quickly and easy and serves the individual target fields.

1.2 Demand & Research Gap

To make continuing education as successful as possible, sustainable learning opportunities for learners should be easily and swiftly accessible and adapt to individual needs (Krauss et al. 2018). This becomes particularly relevant as soon as learning opportunities are made available on different training platforms from different providers (Krauss et al. 2023). Such a distribution causes learners to constantly re-register and to have to go through the same learning paths, which can lead to frustration and possibly to the termination of the learning process (Krauss et al. 2017).

In traditional learning environments, learning processes are usually run through according to a statistical pattern without any reference to the learner's previous knowledge and abilities (Krauss et al. 2017). Adaptive learning systems can be used to adapt the learning offer to the individual learning needs of the learner, considering context-specific and personal preferences. These systems control the learning process based on data on learning progress and performance so that the level is neither too easy nor too difficult and the learner receives the support they need (Krauss et al. 2018). These systems observed the behavior of learners as an isolated phenomenon for a long time, which meant that learning processes could only be adapted to a limited extent.

To ensure that system boundaries are not an obstacle, and that the learner is optimally accompanied through the learning process, the interconnection of continuing education platforms based on common economic interests is therefore required, while at the same time the individual needs of the learner should be addressed adaptively. There are already several research efforts in this area (Streicher et al., 2016, Bakhouyi et al., 2017, Berdun und Armentano, 2018). Another important factor regarding sustainable learning success is the so-called intrinsic motivation to consolidate the acquisition of knowledge and skills (Looft 2010, Szentes, 2010, Atorf et al., 2019). This is promoted, for instance, by learners recognizing the meaning and purpose of learning or experiencing a sense of achievement, which can be achieved through gamification content for example. (Prensky 2007).

The digital representation of real-world objects and processes during learning (digital twin) are the first step in the digitalization of learning processes and the digital assessment of skills. However, the mapping remains the same regardless of who interacts with the system. Experienced users, on the other hand, need different information than novice. Therefore, there is a lack of adaption of the visualization to the individual needs of the users. As described above, this is particularly important in the teaching and learning context to create learning content adapted to the skills of the learners. This paper aims to add an adaptive level to the digital twin, the adaptive triplet. The digital images are to be extended by the knowledge so that the adaptive level transforms the digital information into personalized information and returns it to the learner.

This article has the following structure: Chapter two defines the digital twin. The third chapter discusses the concept of the adaptive triplet, naming its essential components, while chapter four describes the TRIPLEADAPT project and the use cases *Assemby Assitance* and *Cyber Security*, in which the implementation of the adaptive triplet is illustrated. The fifth chapter includes an assessment of the current potential, taking existing challenges into account. The sixth chapter then provides a conclusion and an outlook on adaptive triplets as a pioneer of holistic training.

2 Digital Twin

It is generally accepted that the term “Digital Twin“ was originally coined in 2002 by Michael Grieves as part of his work at the University of Michigan and has since become increasingly important in various disciplines, particularly in the manufacturing industry and engineering science (Tao et al., 2022, Maulshree, 2021, Eigner et al., 2019). Various definitions have evolved over time, most of which describe the digital twins as a virtual image of a real object (Klostermeier et al., 2020, Stark, 2020). The main differences lie in whether the digital twin can only depict physical or non-physical objects and whether the image must be complete or can be partial. However, there is agreement that the digital twin contains all relevant information of the real object and thus represents a comprehensive virtual representation that enables a deep understanding of the underlying real object.

According to Grieves and Vickers, the digital twin is defined as a set of virtual information constructs that fully describe a potential or actual physically manufactured product from the micro-atomic level to the macro-geometric level (Grieves et al., 2017). Ideally, all the information that can be obtained from the inspection of a physically manufactured product can be retrieved from this digital twin. This definition emphasizes the complete description of the physical product and the ability of the digital twin to act as a substitute for the physical object.

The digital twin can therefore be understood as a digital image of a real object, which can include physical objects such as machines, systems and buildings as well as non-physical objects such as processes and services. It provides a comprehensive collection of all relevant information and data required to fully describe the physical object. The data flows between the physical object and the digital twin enable real-time interactions and thus ensure that both twins are up to date (Grieves et al., 2017).

The digital twin construct consists of a physical object in real space (physical twin), a virtual object in virtual space (digital twin) and the data and information connections between the two objects. These connections are represented by the “digital shadow“ and the “digital pulse”. The digital shadow describes the information and data connection from the real to the virtual object, while the digital impulse represents the connection from the virtual to the real object (Grieves, 2014).

The specific properties of a digital twin are diverse and depend on various parameters. These include the specific design of the user, the infrastructure, the simulation methods used, the data procurement, the overall system and the use case. A precise determination of the use case is an important first step to be able to use the digital twin accordingly (Bolton et al., 2018, Frenz, 2020).

Exemplary areas of application for the digital twin can be found in industrial manufacturing, transportation, production and order control, and medicine. To develop a digital twin in production, suitable variables and signals are required that provide information about the process and can be measured. The digital twin therefore offers enormous potential for industry and other sectors, as it enables a comprehensive, data-based view of real objects and processes and can therefore contribute to greater efficiency, quality and safety. By comparing and analyzing the deviations between the real and virtual objects, real objects can also be adjusted and the process can be regulated accordingly. This makes it possible to increase the efficiency and quality of processes and products. An important point to note here is the real object must adapt to the virtual object in order to ensure a successful implementation of the digital twin (Boschert & Rosen, 2016, Klostermeier et al., 2019).

The digital twin offers many possible applications, ranging from the monitoring of products and processes to the optimization of planning and production. However, the digital twin is limited to mirroring real-world objects. Whether these meet certain requirements can only be checked by adding another, adaptive level to the twin.

3 Concept

3.1 Context

The concept of the adaptive triplet that we propose describes the additional level to the physical and digital triplet (also known as the physical and digital twin). It is based on the use of real-world data, that is collected for example via system tracking and sensors. This data is then processed to derivate relevant information. The main idea behind the adaptive triplet is to use this processed information to generate adaptive recommendations. To generate customized recommendations, the individual skills, experience and knowledge of the learners are taken into account. The adaptive nature of this approach enables the context-specific adaption to the individual needs and abilities of learners. The ability to generate recommendations based on collected data and its processing offers new possibilities to increase work and learning performance, and efficiency.

The adaptive triplet is an artifact that provides recommendations in two different areas. First, process-based and product-centered assistance system recommendations are derived within the employees' digital work environment. In addition, learning assistance recommendations are generated in the digital learning environment via adaptive learning paths to promote learning and impart knowledge. The working and learning environment represent two interlinked fields of application of the adaptive triplet, with people at the center. In both fields, the learning process and content of employees can be addressed by different learning management systems (see Figure 1).

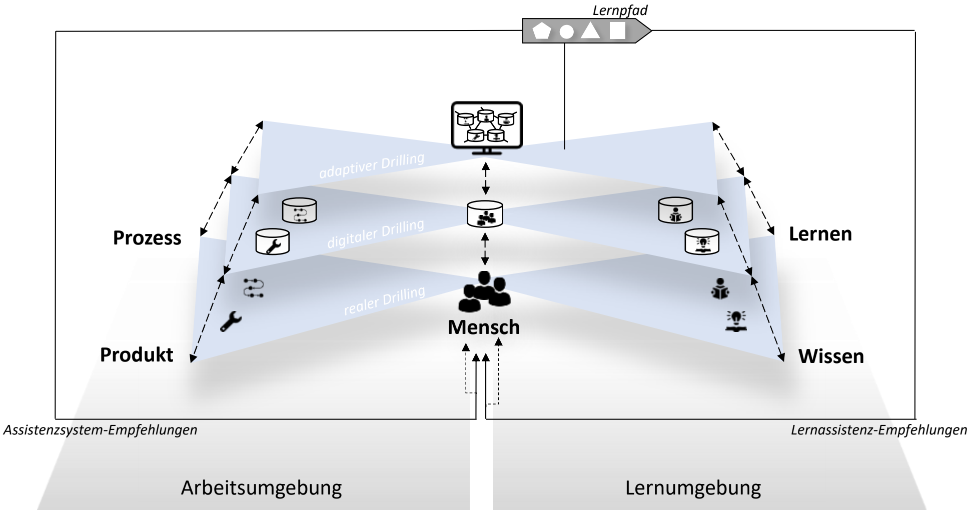

Figure 1: Concept of the layers of the Triplet

3.1.1 Human

The human takes a central role and unites the areas knowledge, learning, product and process. The focus is on people's individual needs and requirements, as the adaptive triplet aims to generate personalized recommendations and to improve the performance. Personalization enables tailor-made recommendations based on the learner's skills, experience and knowledge. This results in more effective knowledge transfer and word process design.

The adaptive triplet uses personal data to achieve this goal. It is important to protect the data and the privacy of learners, and to ensure that the data is only used for the purpose of learning improvement and work performance under applicable law and company agreements. The integration of people, technology and data creates an adaptable environment that continuously responds to the individual needs and abilities of learners and thus sustainably improves work and learning performance.

3.1.2 Working Environment

The adaptive triplet plays a decisive role in the working environment by providing process-based and product-centered assistant system recommendations on the digital level for learners. Relevant information can be derived through the integration of real-word data to design work processes more efficiently and effectively. The personalized recommendation of the adaptive triplet helps learners to manage their

tasks better, to optimize their work processes, and to increase their understanding of the product and the process.
In the working environment, a **process** refers to the active execution of work steps on the product within the workflows. The adaptive triplet aims to optimize these processes with the help of personalized recommendations and increase learner performance and ensure the quality of their work.

The relevance of the adaptive triplet for learning in the work environment lies in the fact that recommendations do not only optimize work processes, but also promote learning. Specific knowledge content is conveyed by adaptive learning paths, which help the learners to cope with their tasks better and to expand their competencies.

A **product** is in the context of the working environment the object on which process steps are carried out. Especially in the case of multi-variant production, the adaptive triplet plays a key role by using digital images and simulations of the product. The use of digital images and simulations enables a better understanding of the product and its different variants and designs. The adaptive triplet uses these virtual models to provide recommendations for learners that are specifically tailored to the respective product variants. This allows work processes to be optimized and ensures a more efficient and accurate production.

The link between the product and the adaptive triplet lies in the combination of digital data and real work processes. By collecting and processing data, personalized recommendations can be derived and directly tailored to the product and its production. This enables the seamless integration of knowledge and findings into work processes.

3.1.3 Learning Environment

3.1.3.1 Learning

In the following, the learning process is understood as the sequential processing of a wide variety of learning content. As part of the learning process, people acquire knowledge that is compressed into the smallest learning units, so-called “learning nuggets”. A section of the learning process with certain prerequisites for implementation and clearly defined success criteria is referred to as a learning path. The learning success can be determined with the help of partial tests or an overall exam at the end of the learning path.

Currently, these learning paths, including the learning nuggets, are compiled manually for a specific target group, and then run through along the path independently of the targeted achievements. Figure 2 illustrates this using a specific selection of learning nuggets from four categories (circles), which must be completed in a predefined sequence by each of the learners (A, B and C). With increasing individualization and the associated multiplication of defined target groups, the number of learning paths that are required also increases. This leads to considerable development effort, as a learning path has to be created for each target group. Furthermore, static learning paths do not take the individual learning progress of the learners into account, which can lead to the inefficiency of the learning paths.

Our concept starts at this point by generating adaptive learning paths through an automated comparison between actual skills (measured by digital learner assessments) and desired skills. This means that a learner who has been assigned to a predefined learning path can break out of it, if another learning path proves to be more efficient in terms of their individual learning success. Figure 3 illustrates this using the alternative learning paths of learners “A“, “B“ and “C“, which all start from the same starting point but take a different course based on the learner‘s individual abilities. In this example, the adaptive triplet sees itself as a recommender which is always informed about the learner’s skills profile and generates the further learning path individually accordingly.

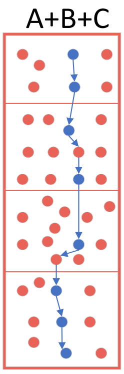

Figure 2: Static learning path

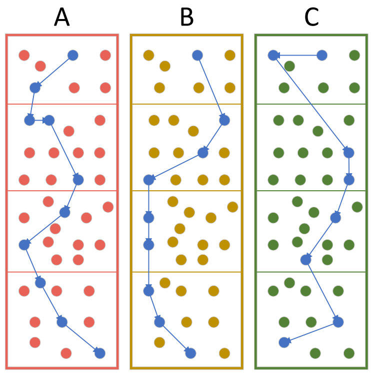

Figure 3: Dynamic learning path

3.1.3.2 Knowledge

In the learning environment, knowledge is both the goal and the means of the learning process. It serves as the basis for understanding and applying skills in real-life situations and as a reference point for assessing learning progress.

Knowledge can be defined as the totality of facts, information and skills acquired through experience or education. It is not just about having information, but also about how this information can be interpreted, applied and used in different contexts.

Types of knowledge

There are different types of knowledges, including:

Declarative knowledge: This refers to “knowing that“, i.e. facts or information that one can know.

Procedural knowledge: This is the “knowing how“, i.e. how to perform a particular task or activity.

Metacognitive knowledge: This refers to the awareness of one’s own knowledge and learning.

Acquisition of knowledge

Knowledge can be acquired in different ways:

Direct learning: This happens through formal education processes, such as teaching in a school or university.

Self-directed learning: Here, the learner determines the content, pace and methods of their own learning.

Informal learning: This takes place outside of a formal educational environment and can happen through daily experiences, interactions with others or self-study.

Significance in the adaptive triplet

In the context of the adaptive triplet, knowledge serves as the basis for creating personalized learning paths. By understanding a learner’s existing knowledge and learning goals, the adaptive triplet can provide effective and customized learning recommendations. In addition, monitoring knowledge acquisition helps to track progress and adapt learning paths accordingly.

To summarize, knowledge is central to the learning environment. It serves as the basis for learning and as a benchmark for progress and development. In the adaptive triplet, this understanding of knowledge is used to create personalized and effective learning experiences.

3.2 Levels

Our concept of the “Adaptive Triplet“ compromises a further development of the familiar digital twin, which not only imitates a physical object in the context of a digital image, but also supplements it with an adaptive view. This idea behind this innovative approach is to confront and align the actual state with the target state on an adaptive level. Based on the “Digital Twin“, a customized and adaptive path is developed to transfer the physical object from its current state to the desired state.

The construction of the digital twin describes a physical object in real space (physical twin) and its digital image in virtual space (digital twin) as well as the data and information connections between the two objects, which are referred to as “Digital Shadow” and “Digital Impulse”. The digital shadow describes the information and data connection from the real to the virtual object, while the digital impulse represents the connection from the virtual to the real object. These connections ensure the constant congruence of both objects. We add a third level to this construct, which not only represents the actual state in virtual space, but also the expected state of this object. In the case of a deviation between the two states, the adaptive level offers situation-dependent recommendations to compensate for this. The real-time checking of the relevant states and the subsequent tracking of the paths offered thus ensure an adaptive view of the state.

By adding the adaptive component, we will therefore no longer speak of twins, but of triplets. In this context, it makes sense to consider three levels:

The first level of the “Adaptive Triplet“ contains the “Physical Triplet“. The concrete interaction with the real object takes place at this level. Data about the physical object is collected here using appropriate sensors and serves as a starting point for comparison with the target state. In the case study of a learner in the further train process, for example, the learner’s skills are recorded here. At this level, the learner also receives learning recommendations if one of their skills does not correspond to the expected state: If necessary, the learning paths can be adapted to a new learning level. The first level is therefore crucial, as it determines what data is collected, how it is collected and what formats and standards are used to ensure a smooth flow of information.

The second level of the construct contains the “Digital Triplet“. Here, the real-world state of the object, which was detected by sensors, is processed and digitally mapped. The digital image comprises a collection of all relevant information and data required to fully describe the physical object. These can be recognizable within the first level, such as the nature of a material or a position in the room, but also characteristics that are not immediately recognizable, such as the skills of a learner or process indicators. The digital triplet adapts dynamically to changes in the real world, thus digitally processing the actual state of the real world in real time and forming the bridge between the physical and digital worlds. In the context of a learner, this could be their individual skills profile or the key figures of the instance of a process step being carried out.

The „Adaptive Triplet“ is on the third and crucial level. This extends the „Digital Triplet“ presented to include various requirements for the object and thus primarily maps its target state. In the case study of a learner in the further training process, this could be the competency profile that the learner is trying to achieve or a series of key figures that should be met. The next step involves confronting the actual state that has been collected with the corresponding target state. Based on this comparison, personalized learning recommendations can be generated based on individual user data. Relevant information from the five areas (product, process, knowledge, learning and people) is incorporated into the recommendations, both for higher-level learning paths and for individual work steps in production. This enables holistic and tailored (adaptive) support for learners. These go through learning paths with the help of digital learning assistance recommendations. The insights gained from the users‘ learning process make it possible to continuously adapt and supplement the learning paths. By integrating knowledge from other learning platforms, the “Adaptive Triplet“ becomes a comprehensive tool that offers users an optimal learning experience and provides them with target supports them on the way to achieving their goals.

The developed concept of the “Adaptive Triplet“ offers an innovative approach to the further development of the “Digital Twin“. The combination of physical, digital and adaptive levels creates a comprehensive system that offers users optimal support in their learning and development journey. This holistic approach promises increased efficiency, better adaptability and an individually tailored learning experience that can be seamlessly integrated into the work environment. Personalized recommendations are the central means of bridging the identified differences between the target and actual status.

3.3 Recommendations

In the learning and working environment, adaptive recommendations help learners to accurately convey work processes and adapt it to individual knowledge or context-specific events (disruptions). These recommendations are provided in the form of assistance recommendations and learning assistance recommendations and vary depending on the user level and context.

Assistance recommendations serve to support the learner during a session by showing which steps should be taken to successfully complete a task or process in the specified time and to the required quality. These recommendations may vary in level of detail depending on user level and skills. The adaptive nature of these recommendations allows the adjustment of difficulty levels to individual needs in real time and to provide personalized guidance. The relevant information is displaced within a suitable display medium (e.g. monitor or AR glasses) to give the learners clear orientation and ensure that the session is carried out effectively.

In contrast to the assistance recommendations, the learning assistance recommendations do not aim to directly instruct the learner what to do next. Instead, they are focused on the learning success and show how and why certain content should be learned to impart knowledge and promote the medium to long-term development of skills. These recommendations can occur in the middle of a learning session, for example a complex process flow or to generate additional learning content. The learning assistance recommendations help to optimize learning progress and deepen the understanding of what has been learned.

The generation of recommendations is based on linking information from various sources and data. Data about the learner, their skills and experiences, as well as the current context and progress of the session, are taken into account. By incorporating adaptive, personalized and real-time difficulty adjustments, recommendations can be tailored precisely to the individual needs and requirements of the learner.

Adaptive recommendations in digital learning and working environments provide powerful support for learners. The distinction between assistance recommendations and learning assistance recommendations enables targeted guidance during the session as well as effective promotion of learning progress . By intelligently generating these recommendations, learning and work processes can be continuously optimized to ensure personalized and efficient learning.

4 Projects and Activities

4.1 TRIPLEADAPT & context

The TRIPLEADAPT project (adaptive, interoperational training platforms through the adaptive triplet), funded by the Federal Ministry of Education and Research, addresses three areas of development in particular: The interconnection of further education platforms, the development and testing of platform-related innovations as well as the linking of AI-supported teaching and learning offers in a socio-technical system. The main goal of the project can therefore be understood as the effort to provide a digital learning environment that holistically supports learners and employees with the help of innovative learning and teaching methods. The desired solutions go beyond isolated learning environments. This creates connections between different learning platforms, ensuring an integrated learning experience. With the help of artificial intelligence, the project partners will also develop personalized learning content and recommendations that adapt to the individual needs of the learners.

The objective of TRIPLEADAPT can therefore be divided into three main aspects. Firstly, the implementation of educational innovations within the learning platforms to give learners access to modern teaching methods, interactive content and innovative learning tools. Secondly, the provision of cross-platform learning paths to take advantage of the interconnection of further training platforms. We want to ensure that learners can switch seamlessly between different platforms to design their individual educational path. This flexibility makes it possible to respond to the needs and preferences of users. The third goal is to develop a collaborative business model that includes all training platform providers, relies on partnerships and synergies, and thus creates a sustainable basis for the TRIPLEADAPT project.

4.2 Application of the adaptive triplet and exemplary use cases

4.2.1 Assembly Assistance

The Assembly Assistance use case describes the manual production of a cylinder piston at a physical manual workstation supported by the visual instructions of an assistance system. Manual assembly includes several activities such as removing parts, screwing, measuring and assembling. After each completed activity, process data (e.g. activity name, timestamp, resource, etc.) is generated by the system itself and by a sensor structure. This is created for the users before the scenario begins. Depending on the nature of the data, real-time recommendations are generated that take the history and skills of the user into account, i.e. the level of information provided by the assistance adapts to the needs of the users. Two main components that communicate with each other are responsible for this:

- The **basic component** compromises the visualization of the instructions, data acquisition and communication with the hardware components of the manual workstation (e.g. screwdriver, caliper gauge and pick-by-light system) and with the recommendation component. User input should be avoided as far as possible so as not to disrupt the workflow.
- The **recommendation component** receives the process data from the base component and data from the sensor setup and puts them into a common context. Considering other data sets, such as historical user data and data from other users, the recommendation component determines the infor-

mation requirement and forwards it to the base component. This adapts the visualization of the instructions accordingly. In the assembly chassis scenario, the levels of information are divided into four categories: easy, medium, difficult and expert, whereby learning content from different learning platforms can be recommended at the same time.

With regard to the levels described in chapter **Fehler! Verweisquelle konnte nicht gefunden werden.**, the use case of Assembly Assistance can be derived as follows:

The **real level** compromises the concrete sequence of the process and all the physical components it contains. Here, the real user actively carries out the assembly of a cylinder piston at the physical manual workstation. The user generates process and sensor data that depict the real-world processes on the **digital level** and thus represent the digital twin. This level includes the storage, processing and visualization of data as well as interfaces for data transfer, such as the transfer between the basic and recommendation components. At the same time, the digital level already contains stored data such as user competence profiles, their process history, data on the cylinder piston to be manufactured and retrievable learning content on specific activities in the assembly process. This data is analyzed at the **adaptive level** and results in a recommendation tailored to the user (adapted visualization on the assistance system). In this use case, user behavior is recorded via process discovery and used as input for the recommender system. The current work step and user-specific data such as the skills profile and history are considered for this purpose. These are transferred into a user-item matrix with data from others and the product data and similarities are determined using a distance measure. This generates recommendations for the user that have led to an improvement in performance (e.g. faster, fewer errors, etc.) for other similar users. The recommendations are then retrieved in the digital layer, orchestrated and forwarded to the base component so that the user ca view the information on the assistance system in the real layer.

4.2.2 Cyber Security

The Cyber Security use case is about a networked educational landscape on the subject IT security, with a focus on cryptography and hacking. A portal serves as a central point of contact for accessing digital media from an ILIAS-LMS, a company's own learning management system and a learning platform for further vocational training. The difficulty levels of the exercises offered are adapted to the users, and at the end a blockchain-based micro-certificate is issued after an exam.

To combine these independent functions into a joint offering without interruption for users, a suitable infrastructure solution was designed that also enables the simple addition of further functions. For this purpose, possible monolithic and service-oriented solution approaches and interoperability standards were analyzed. The most suitable approach a middleware-based solution, was implemented and successfully tested in a large-scale field test (Krauss et al. 2023).

With regard to the levels described in chapter **Fehler! Verweisquelle konnte nicht gefunden werden.**, the Cyber Security use case can be described as follows:

Real level: Physical triplet

The interaction of users with the educational landscape takes place on a real level. In the context of cybersecurity, this means:

Users access the learning portal via various devices (computer, tablets, smartphones). Interactions that take place via physical devices and input media (mouse, keyboard, touchscreen) are recorded. User progress and actions, such as completing modules or exercises, are tracked in real time. The security protocols on these devices are also part of this layer, as they ensure physical access and the integrity of the learning environment.

Digital level: Digital triplet

The digital level maps the status of learners and the content they use digitally.

Sensors in this context are tracking tools and analytics systems within the LMS that monitor the behavior and progress of users. The digital level includes the ILIAS-LMS, company-owned LMS and other digital resources. This is where user data is processed, including their interaction, performance and progress. The content, such as course materials and exercises, are digitized at this level and made available to users.

Adaptive level: Adaptive triplet

On the adaptive level, the learning content and paths are adapted to the individual needs of the users:

Personalized learning paths are based on the performance and interests of the user by comparing the target state of learning progress with the current state. Adaptive difficulty levels of the exercises are adjusted according to the progress and performance of the users. Blockchain-based micro certificates are issued at the end of exams, providing an individual, secure and verifiable form of performance documentation. The middleware solution that was implemented ensures the necessary flexibility and interoperability between the different platforms and supports the adaptive learning process.

For field testing:

Users provide feedback here on the use of the services and the effectiveness of the adaptive learning paths. The experiences from the field test help to further refine the adaptive level by identifying and adapting any discrepancies between the users' expectations and the learning paths offered. AI capabilities analyze user behavior and results across platforms to improve recommendation algorithms and promote personalized learning (Krauss et al. 2023).

In summary, the Cyber Security use case leverages the three layers of adaptive triplet to provide a seamless, personalized and interactive learning experience that recognizes and addresses users' individual needs in real time while ensuring the security and integrity of the learning process.

5 Assessment of the current potential (discussion, challenges)

The concept of the adaptive triplet takes the digital twin to an adaptive level. In the context of learning, this links data about the learner, the learning object and the process with knowledge and relates it to current explanations. This allows the learner's needs to be adaptively adjusted during a learning session by displaying or recommending tailored learning content. In this way, learning content should be individually adapted to the skills and learning needs of the learners in order to achieve the best possible learning progress.

The potential of the adaptive triplet is therefore very high. As the use cases show, both digital and real-world learning sessions can be supported, but also combined. Digitally conducted versions of a real-world learning session, such as cylinder assembly, can also be included in the adaptive level. Another potential of the adaptive triplet lies in the choice of AI algorithms used to analyze and predict learning paths. The algorithms can be tested and chosen depending on the use case to get the best results. The adaptive triplet can also be applied to other application domains, such as medicine, which is why the target group is very variable. The focus does not have to be on learning, since, for example, the personalization of visual content in assistance-supported processes can also be covered by the adaptive triplet. Although the adaptive triplet can be used specifically on each platform, the full potential of the adaptive triplet is only achieved when the processes can be run independently of the platform. This creates a larger database that can be used and allows even more specific paths to be generated. This is where the goal of linking further education platform providers should start. The development of a collaborative business model could help to offer cross-platform learning and thus holistic learning processes. Such a collaborative business model is characterized by the fact that it goes beyond the boundaries of cooperation between different players. Rather, the focus is on creating value as a group based on a common objective that goes beyond what individual companies in the group could achieve independently.

However, achieving platform independence is also a challenge. Platform providers must provide interfaces, while users should not notice the change of platforms in order not to impair the learning experience. Although the concept of the adaptive triplet is generally valid, its characteristics are highly dependent on the respective use case. This means that each use case requires either partially (e.g. unchanging domain) or completely new data and the actual potential can only be achieved with larger amounts of data. Data protection guidelines must be observed here, particularly due to the creation of user and skills profiles.

Overall, the adaptive triplet concept closes the gap between the digital representation of real-world processes and knowledge about them to fulfill user-specific learning needs, especially in the teaching and learning context. In this respect, platform independence is particularly important and is already being successfully implemented as part of the TRIPLEADAPT project. The problem of the database is also a general problem for AI-supported approaches but can also be partially circumvented with the right algorithms. Less data-driven algorithms can be used until sufficient data is available. Adjusting the AI algorithm at an adaptive level is therefore a way of always using the most efficient solution.

6 Conclusion & Outlook

In the context of digital continuing education, the concept of the adaptive triplet represents an essential extension to provide learners with tailored support. By extending the concept of the digital twin to include an adaptive level, digital information is expanded to include knowledge about it. Contextualizing this data and applying intelligent algorithms allows learners to receive tailored support on their learning path. As a result, the adaptive triplet takes the role of a digital teacher so that learners can learn with support regardless of time and place.

The potential of adaptive triplet is high and domain-independent, as the use cases in chapter 4.2 show by example. In particular, the cross-platform use of the adaptive triplet offers the potential for the optimal use of learning content to achieve learning objectives. In an increasingly digitalized environment, the adaptive triplet can create more and more use cases. Through digitalization in schools, for example, pupils can also benefit from adaptive learning recommendations and thus be optimally guided through school learning content.

Nevertheless, there are challenges that need to be considered, particularly in the technical implementation of the adaptive triplet. Data protection and security are a critical issue, especially when it comes to platform independence, whereby user data is essential for the successful use of the triplet. The actual implementation of the concept also depends on the application, as shown in chapter 4.2. For the Cyber Security use case, xAPI statements had to be evaluated, while in the Assembly Assistance use case, tracking was carried out using system and sensor data. However, both approaches were able to respond to user behavior and make adaptive adjustments during the learning unit.

With ongoing digitalization and the associated standardization measures, such as data protection, the adaptive triplet can exploit its full potential. By orchestrating and contextualizing user behavior, competency profiles, historical data as well as knowledge, courses and learning units, intelligent algorithms are used to create a digital teacher who can support each learner in a personalized way and at any time. This can sustainably improve the learning progress of learners, but also relieve the burden on teachers.

7 Literature

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