What to Learn Next? Designing Personalized Learning Paths for Re-&Upskilling in Organizations

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Abstract

The fast-paced acceleration of digitalization requires extensive re-&upskilling, impacting a significant proportion of jobs worldwide. Technology-mediated learning platforms have become instrumental in addressing these efforts, as they can analyze platform data to provide personalized learning journeys. Such personalization is expected to increase employees' empowerment, job satisfaction, and learning outcomes. However, the challenge lies in efficiently deploying these opportunities using novel technologies, prompting questions about the design and analysis of generating personalized learning paths in organizational learning. We, therefore, analyze and classify recent research on personalized learning paths into four major concepts (learning context, data, interface, and adaptation) with ten dimensions and 34 characteristics. Six expert interviews validate the taxonomy's use and outline three exemplary use cases, undermining its feasibility. Information Systems researchers can use our taxonomy to develop theoretical models to study the effectiveness of personalized learning paths in intra-organizational re-&upskilling.

Keywords: personalized learning, re-&upskilling, skill profile, learning paths, large language models

1. Introduction

Digitalization is creating new opportunities and challenges for re-&upskilling within organizations. As the OECD (2018) indicated, a massive demand for re-&upskilling could impact one-third of jobs globally, expanding the share of adult learners. Accelerated through the Covid-19 pandemic, online learning has emerged as the new standard, consequently amplifying the application and relevance of technology-mediated learning (TML) (Gupta & Bostrom, 2009). For instance, massive open online courses (MOOCs) used in the work context are rising, as they offer flexible learning hours and are widely accessible (Seaman et al., 2018).

However, dropout rates in online learning academies and MOOCS remain high, reaching up to 90% (Zhang et al., 2021). An eminently plausible rationale for this phenomenon resides in the indispensability of personalization within the design of such platforms. As affirmed by constructivist learning theories, learners require individual tutoring based on their experiences to acquire knowledge, thereby facilitating effective learning outcomes (Vygotsky, 1980).

Information technology offers new possibilities for re-&upskilling (Ritz et al., 2023), laying a foundation to attend idiosyncratic requirements and provide personalized learning paths in TML (Brinton et al., 2015). In this context, a learning path refers to a sequence of learning activities that help learners increase their knowledge and skills (Muhammad et al., 2016). The orchestration of personalized learning paths are facilitated by path-planning algorithms (Shou et al., 2020) and holds promise to increase learners' achievements, learning efficacy, intrinsic activation and motivation (Govindarajan et al., 2016). Organizational learning academies and MOOC platforms like Coursera, or Udacity offer excellent potential for personalization, owing to the availability of data that can be leveraged to tailor learning paths (Kabudi et al., 2021). Their pertinence is particularly conspicuous in the context of re-& upskilling, offering individuals distant from formal learning augmented guidance (Illanes et al., 2018), and reducing dropout rates while enhancing employee learning outcomes (Daradoumis et al., 2013).

However, despite the considerable potential of personalized learning paths, there is a great variety of methods for the generation for personalized learning paths (Raj & Renumol, 2022) and a paucity of guidance on how to design such personalized learning paths for the use in re-& upskilling. Thus, we pose the following research question (RQ): *What are design characteristics for using data to personalize learning paths in re-&upskilling contexts?*

We chose taxonomy development as our method to answer the research question (Kundisch et al.,

URI: https://hdl.handle.net/10125/106406
978-0-9981331-7-1

2022). Taxonomies can be a relevant input for developing theories (Iivari, 2007) and help to understanding a complex object of interest (Glass & Vessey, 1995). Due to the diversity of methods for facilitating personalized learning paths and the need for characterization and classification (Raj & Renumol, 2022), we follow the taxonomy development process by Nickerson et al. (2013) and conducted a structured literature analysis. We analyzed 35 papers in depth and classified them into four major concepts (learning context, data, interface, and adaptation). Next, we applied our taxonomy on three use cases with different personalization methods to prove its feasibility and elaborate how these methods can benefit employees and organizations, including (1) large language models, (2) knowledge tracing, and (3) CV and interest-based recommendations. Information systems (IS) researchers can use our taxonomy to develop theoretical models for studying the effectiveness of personalized learning paths in organizations. The use cases serve as a guide to designing and implementing personalized learning paths and offer new insights and methods on tackling the organizational challenge of re-&upskilling at scale.

2. Theoretical Background

2.1 Design of Personalized Learning Paths

A learning path consists of different courses with learning objects, which are sequenced to help learners achieve goals, such as learning a new skill (Nabizadeh et al., 2020). Learning objects, reusable for specific goals, combine into instructional formats like courses (Dharshini et al., 2015), shown in Figure 1. The pedagogical learning design is the domain of instructional designers, which aims to improve learning outcomes (Reigeluth, 1999). The pedagogical design of personalized paths can guide learners during their journey to achieve their learning goals (Vanitha et al., 2019). Two essential instructional design disciplines must be considered when designing adaptable learning paths: learning object design and sequencing theory.

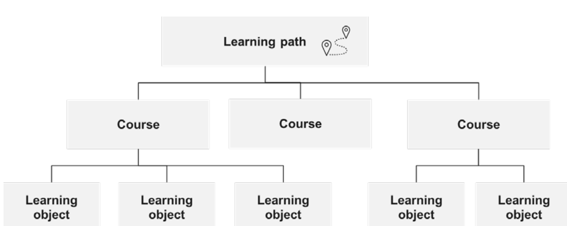

Figure 1. Course Structure

Regarding learning object design, Mowat (2007) argues that these must be non-sequential, self-contained and aim at a particular learning goal. There are many methodological approaches to sequence learning objects (Raj & Renumol, 2022). For instance, Wiley (2002) proposes a differentiation of sequencing based on a transforming or conforming learning type. While transforming learners receive multiple access to the material but no step-by-step instruction, conforming learners get general access and linear representations, but self-directed learning is avoided (Wiley, 2002). A requirement for personalizing learning paths is the representation and storage of learning objects. Adapting learning resources requires representing the whole library of learning objects and the conceptual relationships between these learning objects (Hwang et al., 2010).

As the deployment of TML continues to proliferate within organizational realms, there are new ways of personalizing learning paths by facilitating a selection, adaptation, and recommendation of learning objects. The technical personalization of learning paths encompasses four stages: (1) user data is collected within a TML system, (2) the system identifies and curates suitable learning objects for the individual, (3) the system arranges learning objects, adhering to guiding principles, and (4) the systems recommendation of the sequenced arrangement of learning objects, i.e., the learning path.

Nowadays, Artificial Intelligence (AI) applications are often implemented, affording an expanded terrain for the implementation of personalized learning trajectories. AI, as noted by Berente et al. (2021), represents the forefront of computational advancement, simulating human intellect to tackle diverse decision-making challenges. While the role of traditional TML systems was primarily to augment human instructors, AI-based learning systems are able to act autonomously and take over the role of track knowledge and adapt the learners' process (Abdelrahman et al., 2023). For example, AI applications can incorporate motivation levels and identify strategies (e.g., gamification) that boost and maintain motivation by incorporating engaging topics and interactive elements (Schöbel & Söllner, 2016). Similarly, the AI can analyze performance to track progress in skill development. Using this data, the AI applications can recommend appropriate learning materials and adjust the pace of learning, ensuring skill improvement over time.

However, research contributions expose different methods, algorithms, conceptual approaches, technological implementations, and user data parameters to personalize learning paths. Relevant work of Govindarajan et al. (2016) reveals that the effectiveness of learning can be increased when selecting and recommending content based on the learner's prior knowledge. Dharshini et al. (2015) propose a competence-based approach to sequence learning objects in e-learning, whereas Anselmi et al. (2021) rely on a skill-based model to store and arrange learning objects. Further, there is a variety of data input parameters ranging from learning data to personalize learning paths, including data about user's personality, knowledge background, and learning goals (Muhammad et al., 2016). Nevertheless, it lacks a clear overview of design characteristics of personalized learning paths in the context of re-&upskilling (Raj & Renumol, 2022).

2.2. Technology-Mediated Re-&Upskilling

To provide a solid understanding of how personalized learning paths are embedded in the re-&upskilling process, we examine TML as an overarching concept and outline the context of re-&upskilling in organizations. TML is anchored in IS and examines how information technology can be used for education (Janson et al., 2020). It is defined as "an environment in which the learner's interactions with learning materials, peers, and/ or instructors are mediated through advanced information technology" (Alavi & Leidner, 2001, p. 2).

In the contemporary workforce, continuous skill enhancement is imperative. Accordingly, upskilling pertains to acquiring new skills relevant to one's current job. In contrast, reskilling refers to the acquisition of knowledge and skills to transition into different or novel positions (Li, 2022). Technology-mediated re-&upskilling is particularly crucial due to the rapid evolution of skills, driven by motivations like enhanced employability, career advancement, and adaptability in dynamic job markets. Accordingly, it is one of the organizations' significant challenges to develop suitable re-&upskilling initiatives that encourage employees. However, organizations struggle to respond to the learning needs of the individual (Illanes et al., 2018). In that vein, TML offers tremendous potential and can involve online courses, immersive training sessions, interactive virtual reality simulations, or even access to learning materials and training programs online (Xie et al., 2017).

Online learning platforms collect lots of data about the learning process, including learners' utilization of course materials, system access frequency and duration, and video consumption patterns. This data can be leveraged to develop tailored and personalized learning experiences for individual learners, fostering greater interactivity (Brinton et al., 2015). Given that adult learners are often self-directed, they still require professional assistance and social support to fulfill their re-&upskilling goals (Göldi & Rietsche, 2023; Knowles, 1990). The effectiveness of TML heavily relies on the support provided to learners and the instructional design (Bell et al., 2017). In order to tackle this challenge, learning platforms aim to comprise fully personalized learning experiences for the user (Ritz & Grüneke, 2022). Further, intelligent tutoring systems operate interactively and can personalize tasks fitting personal requirements, characteristics, and pace of learning (Anselmi et al., 2021).

3. Research Method

Our goal was to classify design dimensions and characteristics of personalized learning paths. Therefore, we used the method of Nickerson et al. (2013) for our taxonomy's rigorous development and evaluation process. The meta-characteristic for the taxonomy is to systematically identify design, method, and analysis characteristics for personalizing learning paths. Further, we conducted an empirical-to-conceptual approach to include a broad empirical foundation and then moved on to conceptual-to-empirical iterations. As shown in Figure 2, four iterations were required to develop a first version of our taxonomy.

Empirical-to Conceptual Approach. Herein, we comprehensively examined personalized learning paths through a structured literature review. Following the approach of Webster and Watson (2002) and vom Brocke et al. (2015), we initiated a search involving AISel, IEEE Xplore, and Science Direct as databases to include input from IS, technical engineering, and pedagogical perspectives. Our search encompassed journals since 2010 and a keyword-based search was conducted to grasp relevant contributions. Therefore, we identified different keywords used to describe the personalization of learning processes. This resulted in the following search terms: ("individualized" OR "individualization" OR "personalized" OR "personalization" AND "learning path"). The initial search led to 555 articles. We then applied inclusion criteria by screening titles and abstracts and scoring the articles for relevance in alignment with the research question. The scoring ranged from "low" (1=not connected to research question) to "high" (4=clear connection to research question). Only 71 articles, scored four were included. After full-text screening, we excluded 39 articles not being thematically relevant. A backward and forward search enriched the article set, culminating in 35 research contributions, as displayed in Table 1.

Table 1. Literature Review Process

Data bases	Initial set	After title/ abstract screening	After full-text screening
AISeL	3	2	1
IEEE Xplore	317	21	5
Science Direct	236	49	27
Total	556	72	33
For- & backward search			2
Final article set			35

We coded all articles using the software Atlas.ti to inductively find shared design characteristics. In our preliminary results, we derived a list of 34 characteristics in alignment with our meta-characteristic. Then, we iteratively classified the characteristics and identified dimensions with selective coding techniques. The procedure was repeated iteratively, where one author compared and associated characteristics and discussed results with another author. To identify when to end, we defined the following four objective ending conditions. First, all identified papers in the literature review have been examined and categorized. Second, at least one object is categorized under each dimensions' characteristic. Third, no dimension or characteristic was added, merged, and split in the most recent iteration. Fourth, all characteristics and dimensions are differentiable.

Then, we conducted semi-structured interviews with six experts (E) for the evaluation of our ending conditions. E1 is a serial entrepreneur of organizational learning platforms, E2 is a professor and co-founder of an intelligent writing systems, E3 is founder of an organizational learning platform in the construction industry, E4 is CEO of a learning analytics platform, E5 is senior researcher in the field of organizational AI management, and E6 is a senior researcher in the field of conversational agents. We applied the guidelines of Myers and Newman (2007) for qualitative interviews and conducted expert sampling to select interviewees (Bhattacherjee, 2012). Within the interview, we asked open-ended questions to grasp relevant characteristics of learning paths, e.g., "how would you imagine your optimal learning path when learning a new skill on a learning platform and which design elements are important?". Afterwards, we let experts evaluate the taxonomy regarding the five subjective ending conditions by Nickerson et al. (2013) concise, robust, comprehensive, extendible, and explanatory (e.g., "are all dimensions and their characteristics clear and unambiguous?"). Hence, we questioned about future research and the taxonomy's applicability. The interviews lasted on average 32 minutes. We then consolidated the interview statements using transcripts and evaluation criteria.

Conceptual-to-empirical approach. We iteratively enhanced the taxonomy through expert insights and evaluation outcomes. New dimensions emerged, influenced by expert perspectives, and integrated theories. Figure 2 illustrates taxonomy changes post-evaluation. Revisiting the initial classification and verifying end conditions, the authors ensured rigor. Employing an empirical approach, the finalized taxonomy emerged as concise, robust, comprehensive, extensible, and explanatory. The conclusive taxonomy is presented in the fourth chapter.

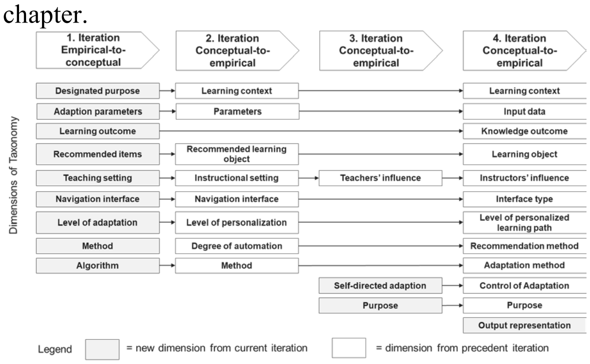

Figure 2. Taxonomy Development Iterations

4. Results

4.1. Taxonomy

This section presents the revised and consolidated version of the taxonomy. The unit of analysis for the taxonomy development was a single learning path system application. The proposed design characteristics can be categorized into four main groups: learning context, data, interface, and adaptation. Learning context pertains the purpose and type of knowledge acquisition. Data refers to the sources required for implementing personalization. Interface contains dimensions for user experience and front-end design. Lastly, adaption relates to the methods and output of the personalization.

The cluster "*learning context*", distinguishes between knowledge creation (learning something new), knowledge retention (preserving learned content), and knowledge transfer (applying learned content practically) (Argote et al., 2003). Although companies often state that transfer is the most important part (Argote et al., 2003), we argue that all three parts are equally important for a holistic re-&upskilling process. The *instructors' influence* defines if the instructor can change the learning path planning. A hybrid setting indicates that the instructor controls the learning resources and objects while an automated setting means no influence the learner's progress. We further identified that different *knowledge outcomes* should be considered within the path sequencing. Following coding and re-iteration, Krathwohl's (2002) framework differentiates four knowledge types: factual (involving basic elements like terminologies), conceptual (encompassing topic relations and contextual embedding), procedural (pertaining to subject-specific skills and methods), and metacognitive (impacting self-awareness and cognition knowledge). We recognized different *learning objects*, which shed light on the display of learning content. Most application cases included learning videos (Dharshini et al., 2015), texts (Brinton et al., 2015), or graphics (Anselmi et al., 2021). Further, reference links, navigating to other explanatory websites or reading material can be used. Exercises are also contributing to problem-solving activities and skill development (Anselmi et al., 2021).

The *data cluster* describes the learning data types used to facilitate path personalization. First, *CVs and resumes* serve as comprehensive documents that summarize an individual's educational background, work experience, and career goal information. This data can help to consider learners' motivations, enabling algorithms to incorporate relevant content and is already used to personalize career planning (Guo et al., 2016). *Skill data* grounds on already acquired skills, so that employees can be suggested suitable upskilling materials to enhance their skill set (Gugnani & Misra, 2020). The relevance of this input was highlighted by E3 who mentioned his organization introduced employee skill profiles and plans to accordingly provide individual, digital re-&upskilling training. *Assessment* is one of the most applied data sources to detect the learner's current knowledge level. Xie et al. (2017) confirm that taking learner's prior knowledge into account is significantly more effective than a randomly sequenced path. In that vein, E2 mentioned that "*I would actually like to be asked at the beginning what I might already know, what my previous competencies are […] and then on that basis the system suggests learning content to me […].*" Assessments are used in all stages of the learning paths, including pre-, during-, and post-assessments (Meng et al., 2021). However, pre-assessments are the most prominent approach to determining the learner's knowledge level (Lin et al., 2013). Next characteristic is *learner interest data*, where the learning path is adapted to learning habits, schedule, or satisfaction. Azan et al. (2019) collect feedback on learners' current satisfaction or cognitive complexity after finishing the adapted path. E3 additionally highlights that this should include general interest regarding a topic and current motivation. *Behavior data* can be collected within the TML environment and analyzed to adapt the learning process. This includes the viewing behavior of the learner (Brinton et al., 2015) or the employee's motivational attitude (Dietrich et al., 2021). In this context, E3 raised the huge opportunity of tracking emotions through sentiment analysis and determining the current motivation level as a data input for personalization.

Dimensions		Characteristics				
Learning Context	Purpose	Knowledge creation	Knowledge retention	Knowledge transfer		
	Instructors' influence	Instructor-managed	Hybrid	Learner-managed		
	Knowledge outcome	Factual	Conceptual	Procedural	Metacognitive	
	Learning object	Video	Text	Graphics	Reference Links	Exercises
Data	Input data	CV data	Skills data	Assessment data	Learner interest data	Behavior data
Inter face	Interface type	Web-based	Mobile-based	Mixed		
	Control of adaptation	Self-regulated Influence	No Influence			
Adaptation	Adaptation method	Evolutionary algorithms	Reinforcement learning	Large language models	Mixed	
	Recommendation method	Course generation	Course sequencing			
	Level of personalized learning path	Learning process	Course	Learning object		

Figure 3. Design characteristics of personalized learning paths

The *interface cluster* describes dimensions of the user experience in the TML systems. The cluster includes two dimensions interface type and control of adaptation. There are different types of interfaces to provide the navigation of personalized learning paths, including web-based, mobile-based, and mixed interfaces. These interfaces also determine which data can be collected for personalization. Brinton et al. (2015), for instance, use a mobile-based application to collect sensor data, e.g., when was the last user touch and activity during the learning process, the device angle, or device movement. The majority of learning paths use a web-based interface to personalize the learning process (van Seters et al., 2012). Web-based interfaces are often used to provide personalized learning content on MOOCs. A third characteristic is the combination of web- and mobile-based navigation, which can increase the usability for learners, and it helps educational designers to collect a greater variety of data. The dimension *control of adaptation* describes if the learner can intervene within the proposed learning paths. According to the self-regulated learning theory developed by Zimmerman learners should apply their metacognitive abilities to gaining academic skills (Zimmerman, 1990). He further argues that self-regulation of learners can increase their self-efficacy. In alignment with this theory, E2 proposed the locus of control dimension. In this context, the design of the learning path can also be differentiated. One characteristic is self-directed adaptation, indicating that learners can adapt the proposed learning paths to their needs and determine the degree of adaptation (Ritz, et al., 2023). Other applications propose that the path is adapted autonomously for the learner, e.g., to ensure that the learner still reaches the individual learning goal.

The last cluster of dimensions describes the technical design and *adaptation* for personalization. The cluster contains three dimensions, the adaptation method, recommendation method, and level of personalized learning path. We identified different *adaptation methods* used to select suitable learning objects and sequence them accordingly. The first characteristic, evolutionary algorithms, are heuristic search methods to solve complex problems. In the learning path planning context, a population of possible learning objects is first created based on the data input of the learner, then learning objects are scored to find the most suitable. Applications used in research designs are genetic algorithms, ant colony optimization, or partical swarm optimization (Christudas et al., 2018). Reinforcement learning is a sub-field of machine learning, in which the intelligent agent aims to take direct actions within a system to maximize a numerical performance measure. Reinforcement learning optimizes the allocation of learning objects to maximize learning gains (Bassen et al., 2020). Large Language models are of high importance for personalization of text classification and generation tasks (Salemi et al., 2023). For personalizing the outputs of the language model, a simple approach is to integrate the user profile directly into the language model prompt. The mixed characteristic combines all methods to facilitate an adapted learning path. There are two general types of *recommendation methods*. Course generation is a recommendation that cannot be changed based on the learner's performance and behavior data. Consequently, the entire learning path or course is recommended as a whole (Nabizadeh et al., 2020). A course sequencing approach enables to incorporate real-time feedback of the learner in the TML system learner and adapts the path step-by-step (Bhattacharjee et al., 2018). According to E2, course sequencing is of major importance as it enables to *"respond optimally to the needs of the learner"*.

The level of *personalized learning path* can be either a process, proposing that learners aim to acquire new knowledge or a particular skill, a course which can be part of such a large learning process or a learning object (see section 2).

4.1. Use Case Applications

To provide further guidance and evidence of the taxonomies' feasibility, we present three exemplary use cases relying on case study evaluation practices (Yin, 2013). Within these cases, we undertake an in-depth examination, each underscored by different personalization methods. The use cases have been discussed as part of reviewed research papers and are informed by the expert interviews. Thereby, we aim to increase the applicability of our taxonomy.

Use Case 1: Large Language Models to Design Personalized Course Recommendation

In this use case, large language models are used to provide personal course recommendations in form of reference links. Learners have full responsibility to use such models and can influence the given outcomes according to their preferences. When they provide prompts, they can actively shape the outcomes. The *goal* of this use case is to get targeted re-&upskilling courses for the learner that are tailored to what the learner aims to get skilled in, or to their current knowledge level. Regarding the *benefits for organizations*, research has shown that one major reason for employee turnover is lacking educational re-&upskilling opportunities (Mitchell et al., 2001). In that case, it might be beneficial for organizations to provide sufficient in-house programs, but also external development possibilities. Such an application can empower employees to think about future career aspirations and interests and thus, can lead to increased employee satisfaction and retention. Current *organizational challenges* include, that the use of such technology is completely self-directed and employee-driven, wherefore employees require underlying knowledge in prompt engineering so that they get accurate recommendations that fit their needs. At the same time, organizational may have difficulties in evaluating the courses and conducting quality assessment before an employee starts a recommended course. *Requirements for successful implementation* comprise solid prompt engineering skills of employees, as well as a comprehensive library of training courses that can be evaluated according to their suitability for an individual. E1 mentioned additionally that "*instead of telling learners that a certain course would benefit them, they must first experience at first hand why they learn to create a sense of relevance for them*". A *successful example* for this use case is the study of Bahja et al. (2023), who developed a CV-based recommendation systems that parses resume to extract the pieces of information, sends these extracts to a classifier model to classify into categories and then displays top courses suitable to the CV data. Through the integration of OpenAI's ChatGPT via API, employees have the chance to ask questions about the recommended courses.

Use Case 2: Knowledge Tracing to Design Personalized Re-&Upskilling Learning Paths

Bayesian Knowledge tracing is one method of adapting learning objects to the individual. It is the algorithmic task of modeling learners' latent knowledge state as a set of binary variables (e.g., when answering a knowledge assessment right or wrong) over time (Piech et al., 2015). Based on these variables, the model can estimate the probability of learning a new skill in future interactions (Yudelson et al., 2013). One main purpose is knowledge retention and therefore focusses on assessing and monitoring knowledge. This allows learners to reach metacognitive knowledge outcomes. As knowledge retention is a major component for knowledge management and organizational success (Levy, 2011), this use case can *benefit organizations* by implementing strategies that ensure that employees retain the knowledge they learned earlier during their trainings. E2 stated that the use of such a system could improve the attention of learners: "*if you have eight hours of content, but part of it doesn't interest me, I will kind of diminish my attention and then I maybe miss interesting things I didn't know yet*". *Challenges* of this approach include that knowledge tracing as a method yields at mastery learning, meaning that learners work on similar questions until they can answer everything right. At the same time, employees cannot control the personalized assessments as this is solely designed by learning managers of the organizations. *Requirements for a successful implementation* requires small-scale assessments aiming to assess the current knowledge for a certain skill, as well as integrated knowledge tracing algorithms. A *successful example* for this use case is the study of Piech et al. (2015), which applies a deep knowledge tracing to model the learning of an employee or students. Their approach allows not only the tracking of multiple-choice question answers but can capture more complex representations of learners' knowledge. One application was mentioned by E4 refers to genetic algorithms for personalizing quizzes: *"There are evolutionary algorithms where the genetic algorithm tries to perceive sequencing so that different suitable sections are selected from a capacitor".*

Use Case 3: CV- and Interest-Based Recommendations on LinkedIn Learning

LinkedIn Learning (LiL) is a learning service embedded in LinkedIn, a leading social networking platform (Healy et al., 2023). LiL offers 15,000 MOOCs on workplace skills (LinkedIn, 2023). After completion, the certificates are integrated into learners' profiles. Referring to our taxonomy, LiL aims to create knowledge by offering courses and learning paths for its users. The courses are managed by the learner. LiL educates on factual, conceptual, and metacognitive levels and refers to several media types depending on courses or learning paths. It utilizes an online CV and interest data to offer personalized content to professionals. LiL provides tailored recommendations for relevant courses and learning paths by leveraging user-generated data and machine learning algorithms (LinkedIn, 2023). However, the exact adaptation method remains company internal. Such an approach can *benefit for organizations* as such recommendations on LiL in the work contexts might help employees to identify current skill gaps for their job position and pursue targeted learning opportunities, leading to improved performance without extra efforts by the organization. This was also highlighted by E3, who states that we may face be a lack of educators in the future and should depend more on external learning platforms for re-& upskilling. *Challenges* for implementing CV-based recommendations include that accurate assessment methods are required. Moreover, the quality and relevance of course content needs to be ensured. Data privacy and security are important considerations when using an external service and especially by using user data for recommendations. *Requirements for successful implementation* are robust data, a comprehensive library of high-quality learning resources, and machine learning algorithms for accurate recommendations. *Success Criteria* are increased user engagement, higher completion rates, and improved alignment of employee skills with organizational needs.

5. Discussion and Conclusion

AI-based TML systems enable the collection and analysis of vast amounts of personal data for the adaption of learning paths based on the learner's characteristics. However, it lacks guidance on how to design and embed the personalized learning path within TML environments. In our study, we analyzed 35 research papers in-depth and followed a rigorous taxonomy development process to classify design characteristics of personalized learning paths. The final iteration of our evaluated taxonomy includes ten dimensions and 34 characteristics. While iterating and evaluating the taxonomy, we observed several re-occurring combinations of design characteristics. For instance, the use of behavior data as input and facilitation of a dynamic recommendation appeared frequently in learning path adaptation applications. Further, the characteristic of self-directed adaptation, which enables learners to control their learning paths, is particularly taking place in re-&upskilling (e.g., Morris & Rohs, 2021). Learning path personalization provides enormous opportunities on an individual and organizational level. These include, for example, the support of employees with disabilities or personalized interventions, such as the stimulation of learners to counteract negative learning behavior (Capuano & Toti, 2019). As the taxonomy outlines, the effectiveness of the learning path still depends on the moderating effects that influence the quality of learning objects, e.g., the structure of a learning object or the implementation of videos as learning objects. E1 added that they only adopt the personalization of learning paths if the path is embedded in a bigger context (e.g., learning a new skill for career planning) (Bauman & Tuzhilin, 2018). However, the design and embedding of such TML systems within the organizations require high ethical standards, for instance, the possibility of evaluating learning performance data solely on the team but not on individual employee level (Azan et al., 2019).

Our research contributes to the academic discourse by consolidating state-of-the-art knowledge on personalized learning processes facilitated through IS. Our research aims to support organizations facing re-&upskilling demands in professional contexts by showing personalization methods in TML system. We acknowledge that this research study is not without limitations. First, our taxonomy development relies on a limited data set, for instance current research on large language models and personalized learning is just at its infancy and publications are added daily. Thus, repeating the search and extending the set of literature samples could increase the generalizability of our research. Second, the three exemplary use cases have been derived from reviewed research papers and the expert interviews but focus on use cases for the individual and thus neglects other learning paradigms, such as peer learning processes. Future research could evaluate a broader context and can result in a more diverse set of use cases and thereby enrich the taxonomies' applicability. To elucidate more of the implementation of personalized learning paths, future research should conduct interviews with organizational learning managers to examine open issues, including ethical and privacy concerns, and integration into organizational learning academies. Moreover, research should elaborate how personalized learning paths can respond to learner's individual needs and contribute to tackling the re-&upskilling demands of organizations in the 21st century.

6. Conflict of Interest and Acknowledgements

We thank Innosuisse for funding parts of this research (Flagship PFFS-21-29).

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