Indicators of the Learning Context for Supporting Personalized and Adaptive Learning Environments

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***Abstract*—Personalized and adaptive learning environments (PALE) offer benefits for workplace learning because they can account for individual needs and constantly changing work requirements. Yet, the identification of reliable indicators for supporting trusted PALE remains a major challenge. This systematic review provides an overview of empirically investigated indicators of the learning context. Out of an initial set of 28,782 publications, a final sample of 273 key publications was identified, according to predefined inclusion criteria. The synthesis yielded 208 indicators of the learning context that were clustered into 26 dimensions. The findings show that the learning context has been associated with learning processes and outcomes in numerous included studies and should therefore be considered when designing PALE. Future research shall detect the most relevant indicators as well as design and evaluate specific learning interventions based on these indicators.**

Keywords—personalized and adaptive learning environments, workplace learning, learning context, systematic review

I. Introduction

Advancing digitalization and globalization are making workplace learning increasingly important as employees are constantly required to develop new skills and to adapt to new work requirements [1]. However, one major challenge in designing training programs for workplace learning is to design offerings that are appropriate for learners from various backgrounds and with different abilities and preferences [2]. Current research focusing on educational technologies and artificial intelligence suggests that this challenge may be overcome through the support of personalized and adaptive learning environments (PALE). PALE are defined as digital learning systems that continuously analyze and leverage education-related data to adapt the learning environment to individual needs and constantly changing requirements [3].

Yet, one challenge in designing trusted PALE for workplace learning remains the identification of reliable indicators. Indicators are variables (e.g., interests, motivation, daytime) that reveal useful information about learning behavior and that are processed by specific algorithms to personalize and adapt the learning environment. Reliable indicators are crucial for PALE as accurate and comprehensive information about learners and their contexts is needed to design effective interventions to support learning processes and outcomes [4, 5].

Several research efforts have attempted to identify indicators for supporting learning processes and study success in higher education. However, these research efforts have mainly concentrated on data-driven analytics rather than pedagogical theories [4, 5]. Pedagogical theories and rigorous findings from empirical-pedagogical studies are crucial for designing trusted PALE as they explain fundamental mechanisms of learning and help to derive pedagogically meaningful and comprehensible recommendations from education-related data [4]. Therefore, the aim of this systematic review was to identify theory-driven and pedagogically relevant indicators from previous research. Referring to Winne and Hadwin's theory of self-regulated learning [6], we focused on indicators of the learning context.

II. Theoretical Background

A. Learning Analytics and Personalized and Adaptive Learning Environments

The research area around data analytics and algorithms for education has been referred to as learning analytics for more than a decade [7]. Learning analytics refer to the collection and analysis of static and dynamic data from learners and learning environments, for real-time modeling, prediction, and optimization of learning processes, learning environments, as well as educational decision-making [8]. Learning analytics make use of a variety of methods that can be either descriptive, predictive, or prescriptive. Descriptive analytics collect data from learners and learning environments primarily for reporting purposes. Predictive analytics analyze similar data for making predictions about onward learning processes and outcomes. Prescriptive analytics go beyond predictive analytics by additionally providing recommendations for interventions to optimize learning processes and outcomes [5]. According to the above mentioned definition of PALE, PALE can be classified as learning analytics applications focusing on prescriptive analytics [3].

Previous research on learning analytics has largely concentrated on higher education, whereas research on learning analytics for workplace learning is scarce [3]. Thus, previous attempts to identify indicators for PALE and other learning

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analytics applications are located in the area of higher education. For example, clickstream data and retrieval of learning materials have been used as indicators to predict study success. However, these research efforts have been primarily guided by readily available data and the integration of learning analytics into pedagogical theories is still lacking [4, 5]

B. Learning Context

According to Winne and Hadwin's theory of self-regulated learning [6], learning is inherently affected by the learning context. The learning context refers to a learner's resources and conditions, and can be divided into internal and external learning context. The internal learning context refers to personal and subjectively perceived variables (e.g., demographics, interests, motivation). It encompasses a learner's personal and emotional world as well as cognitive and motivational conditions. In contrast, the external learning context refers to objective and predefined variables (e.g., spatial context, daytime, course characteristics) of a learner's environment [4, 9]. According to [6], different characteristics of the learning context determine how learners engage on different tasks and operate on information resources. For example, if learners lack of interest for a specific task, they might engage in the task only superficially or even stop learning [10]. Further, if a course is graded, learners might participate more actively and invest more effort compared to ungraded courses [11]. Winne [9] suggests that the learning context is essential for understanding learning processes and outcomes, and data can adequately represent learning only if it contains information about the internal and external learning context. Therefore, indicators of the learning context should be considered when designing PALE.

The learning context has been researched in a wide range of empirical-pedagogical studies [10-12]. Nevertheless, the use of indicators of the learning context for supporting PALE and other learning analytics applications is scarce. In a recent systematic review, [5] analyzed indicators investigated in $N = 46$ previous publications studying learning analytics applications for predicting and supporting study success in higher education. Most of the reviewed publications followed a data-driven approach and concentrated on trace data recorded by the learning management systems, whereas the learning context has largely been ignored. Some publications considered indicators of the internal learning context such as demographics or prior academic performances [13, 14]. However, the consideration of latent psychological constructs such as motivation and emotions as well as indicators of the external learning context was scarce [5]. To be precise, only four out of the 46 publications considered indicators of the external learning context such as course or university characteristics [13, 15-17]. A comparable review for workplace learning does not exist so far.

The aim of the present paper was to investigate the importance of the learning context for PALE in more detail and to provide an overview of indicators of the learning context associated with learning processes and outcomes. Moreover, we wanted to extend previous research on PALE and learning analytics in the area of higher education to workplace learning. Thus, our paper is guided by the following research question: *Which indicators related to the learning context have been associated with learning processes and outcomes in empirical-pedagogical studies and shall therefore be considered when designing PALE for workplace learning?*

III. Methods

We conducted a systematic review following the guidelines proposed by [18]. To identify empirical-pedagogical studies that investigated indicators of the learning context, we searched the following databases: Google Scholar, Web of Science, ACM Digital Library, psycINFO (via EBSCO), Science Direct, Education Resources Information Center, DBLP Computer Science Bibliography, and Springer Link. We decided to search for publications published since January 2007 to ensure that there were enough publications to capture different research trends since the rise of digital learning [2, 3]. The search in databases was conducted between April 21 and April 25, 2021. We searched for the following terms in titles, keywords, abstracts, and full texts: *indicator* or *predictor* or *disposition* or *motivation* or *emotion* or *affect* or *"learning strategy"* or *"learning strategies"* in combination with (and) *"learning analytics"* or *"educational data mining"* or *"learning process"* or *"learning success"* or *"learning outcome"* or *"competence acquisition"* or *"workplace learning"* or *MOOC* or *"competence assessment"* or *(feedback and competence)*.

The search yielded a total number of $N = 28{,}782$ publications. After exporting the publications from the databases, we decided to start the screening process with the most recent publications from 2021 and then go back in years until saturation was reached, that is, until additional publications did not provide new information anymore. We developed a research protocol describing the inclusion and exclusion criteria, and all members of the research team were familiarized with the research protocol. The publications were screened for the following inclusion criteria: The study (1) presented empirical findings, (2) examined indicators of the learning context in relation to learning processes or outcomes, (3) was located in the field of adult education, (4) was written in English or German, and (5) was published in a scientific journal.

We excluded studies focusing on samples with mental disorders as well as studies related to physical education, learning with virtual reality, and clinical simulations with dolls or mannequins. Fig. 1 provides an overview of the different steps of the screening process. We first conducted an automatic search in Microsoft Excel to identify terms related to irrelevant topics (e.g., *child*, *primary school*, *disorder*; method adapted from [19]). Then, the remaining titles, abstracts, and full texts were screened for inclusion and exclusion criteria. After screening all publications back to January 2019, saturation was reached and $N = 249$ publications were retained. To cross-validate our findings with earlier publications, we then selected two random publications from each of the years 2007 to 2018 that met the inclusion criteria. Thus, a total number of $N = 273$ key publications were included in the systematic review.

Following our research question, we extracted the indicators of the learning context that were investigated in the key publications and assigned them to the internal or external learning context. Then, similar indicators were synthesized based on the description of their operationalization in the respective publications and inductively clustered into different dimensions.

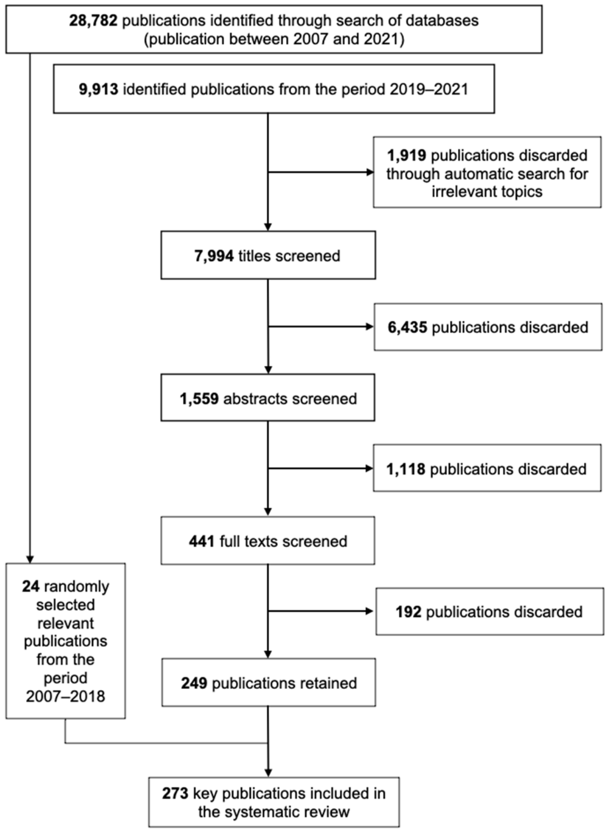

Fig. 1. Flow diagram of the publication screening process.

IV. RESULTS

An overview of all publications included in the systematic review is available online (https://t1p.de/ICALT22). A majority of publications (n = 227) focused on samples including higher education students, n = 19 publications were situated in the area of workplace learning, and n = 27 publications focused on learners in MOOCs (Massive Open Online Courses) or other areas.

A total number of 208 indicators were identified and clustered into 26 dimensions (see Table 1 and Table 2). Out of the 26 dimensions, 17 dimensions relate to the internal learning context, eight dimensions relate to the external learning context, and one dimension relates to both the internal and external learning context. The indicators were associated with different learning processes and outcomes such as use of learning materials [11], motivation [12], or grades [20]. As can be seen in Table 1 and Table 2, most dimensions have been studied across multiple areas (higher education, workplace learning, MOOCs). However, several dimensions have not been considered by publications in the areas of workplace learning and MOOCs. For workplace learning, especially dimensions of the external learning context such as teaching method or characteristics of the learning materials were underrepresented.

V. DISCUSSION

In today's rapidly changing labor market, where employees are constantly required to develop new skills and to adapt to new work requirements, PALE are considered to be a promising invention for workplace learning [1, 2]. This systematic review provides an overview of empirically investigated indicators of the learning context for supporting PALE. We identified 208 indicators of the learning context (e.g., age, daytime) that have been associated with learning processes and outcomes in empirical-pedagogical studies.

A. Theoretical and Practical Implications

From a theoretical point of view, our systematic review provides empirical support for Winne and Hadwin's theory of self-regulated learning [6]. Our results show that the learning context has an impact on how learners operate on learning materials and construct new knowledge in different areas of adult education (higher education, workplace learning, MOOCs). Therefore, indicators of the internal and external learning context need to be considered when making predictions about learning processes and outcomes, otherwise, predictions may be inaccurate [4, 21]

The list of indicators identified in our systematic review offers a comprehensive starting point when designing PALE. It provides an overview of potential indicators that need to be considered for making accurate predictions and designing effective interventions to support learning processes and outcomes. For example, self-regulated learning strategies such as time management or effort regulation have been positively associated with learning success in several included publications [12, 20]. Thus, collecting information about learners' self-regulated learning strategies may lead to more accurate predictions of learning success. Moreover, PALE could use this information to individually support learners' self-regulated learning strategies. For example, if a learner has poor time management, PALE could suggest suitable learning times and learning materials as well as provide recommendations on how to better reconcile family and professional commitments with (workplace) learning [22].

Moreover, our systematic review complements previous research on PALE and learning analytics which has mainly focused on higher education and data-driven approaches [5]. We focused on empirically and theoretically sound indicators rather than data-driven approaches to provide a basis for pedagogically meaningful and comprehensible interventions [4]. In addition, by enlarging the scope of research to other areas of adult education, our systematic review provides a more comprehensive overview of indicators while allowing to look at each area individually. When designing PALE for workplace learning, especially the dimensions considered in publications focusing on workplace learning may be interesting. Nevertheless, a simultaneous consideration of indicators identified in research focusing on higher education and MOOCs can be useful as well due to similarities (e.g., adult education, self-regulated) between the areas [1].

B. Limitations and Implications for Future Research

Our systematic review is subject to limitations that provide implications for future research. First, the list of indicators identified in the systematic review is very large and represents only a qualitative summary of key publications. When designing PALE, more indicators do not always make better indicators as not all indicators are equally relevant [8, 21].

Thus, a closer consideration of effect sizes and an in-depth assessment of the quality of the different publications is needed to identify the most relevant indicators. Moreover, future research shall investigate how privacy issues might limit the collection of certain indicators [23]. Second, the systematic review covers a limited time period. As we included publications focusing on higher education, saturation was reached after screening all publications back to January 2019. However, comparatively few studies focusing on workplace learning (n = 19) were included. On the one hand, indicators identified in higher education may also apply for workplace learning as similarities between both areas exist (e.g., adult education, self-regulated). On the other hand, workplace learning also differs from higher education which usually occurs in more formal settings [1]. Thus, future research shall cover a wider time period to consider more publications focusing on workplace learning. Third, even though the indicators identified in the systematic review are empirically and theoretically supported, this does not necessarily mean that PALE based on these indicators are effective in supporting learning processes and outcomes. Thus, future research shall design and evaluate specific learning interventions based on our list of indicators.

C. Conclusion

PALE offer benefits for workplace learning. Yet, the identification of reliable indicators for supporting trusted PALE remains a major challenge. The aim of this systematic review was to integrate pedagogical theory and findings from empirical-pedagogical research into the development of PALE. It provides an overview of indicators of the learning context associated with learning processes and outcomes in previous empirical studies. Future research shall detect the most relevant indicators and evaluate the effectiveness of specific learning interventions based on these indicators.

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TABLE 1

INDICATORS OF THE INTERNAL LEARNING CONTEXT IDENTIFIED IN THE SYSTEMATIC REVIEW

Dimension	**Area**[a]	**Indicators**
Demographics	H, W, M	Gender, age, race, culture, origin/nationality, international status, marital status, socioeconomic status, parents' education, athlete
Past performances	H, W, M	Educational degrees, previous grades, rank, previous experiences with the course content, prior credits, delay index, course repetition, previous experiences with the course format
Values and life attitudes	H, W	Materialism, intrinsic life values, optimism, religious commitment, long-term/short-term orientation, tradition, achievement, hedonism
Attitudes towards (digital) education	H, W	Beliefs about mistakes, beliefs about assessments, attitudes towards digitalization and digital education, perceived responsibility for learning
Learning approaches	H, W	Deep/surface approach, learning style, self-regulated learning strategies (i.e., cognitive and metacognitive strategies, resource management strategies such as time management or effort regulation), adequacy of previously acquired study techniques, individual tendency to self-handicapping
Skills and abilities	H, W	Study ability, intelligence, language skills, prior knowledge, leadership abilities, self-profiling and career control
Personality	H, W, M	True colors personality, openness to experience, conscientiousness, extraversion, agreeableness, neuroticism, need for cognition, grit, resilience, perfectionism, risk affinity, trait mindfulness, trait anxiety
Needs	H, W, M	General need satisfaction, autonomy, relatedness, control, competence
Self-perception	H	Attributions regarding learning, self-concept
Motivation	H, W, M	Type of motivation, general motivation for the course, source of motivation, voluntariness of participation, intention to complete the course, learning goals and goal orientation, self-efficacy, task value
Emotions	H, W, M	Valence, arousal, anxiety, fear of missing out, fear of loosing face, annoyance, overburdening, discomfort, tension, shame, frustration, boredom, surprise, confidence, joy, satisfaction, curiosity, pride, excitement, hope
Mental/cognitive states	H, W, M	Cognitive load, ego depletion, attention, engagement, flow, trust, cognitive presence, mood
Physiological measures and physical condition	H	Electroencephalogram data, stress, burnout, depressive symptoms, fatigue, exhaustion, energy level
Perception of the course	H, W, M	Expected grade, preparedness, attitudes towards course content, authenticity, immersive experience, overall quality, compatibility, trialability, intention to (re)use the learning system, hedonic value, transactional distance, demonstrability, perceived difficulty, expectation disconfirmation, learning climate, sociability
Perception of the teacher	H, M	Teacher's engagement, discouraging teaching, transformational teaching, teacher's competence, teacher's goal orientation, sense of responsibility, meta-lay theories
Perceived social influence	H, W, M	Group identification, social support, subjective norm, native English-speaking friends, acquaintances and friends in the course, study ability of friends, coercive pressures, mimetic pressures
Duties outside the course	H, M	Leisure activities, family commitments, commitments in other courses, number of courses enrolled in, professional commitments
Job characteristics	H, W	Position, work experience, benevolent leadership, organizational culture of learning, bullying, job satisfaction, job challenges

[a.] H = higher education, W = workplace learning, M = MOOCs (Massive Open Online Courses).

TABLE 2

INDICATORS OF THE EXTERNAL LEARNING CONTEXT IDENTIFIED IN THE SYSTEMATIC REVIEW

Dimension	**Area**[a]	**Indicators**
Job characteristics	H, W	Hours of work, tenure with direct supervisor, working area
Course characteristics	H, W, M	Educational level, level of difficulty, course size, course length, knowledge type, homework, grading, pretest, time in course/course progress
Teaching method	H, M	Active/passive methods, collaborative learning, m-learning, self-regulated learning interventions, peer tutoring
Characteristics of the learning materials	H, M	Media type, communication channel, spatial contiguity, human agent, gamification, amount of motion in learning videos, seductive details, disfluency, deduction/induction, nonlinear learning/content flexibility, quizzes/tests, social media learning, type of discussion settings, number of discussion topics, type of learning management system, exam format, presence of eye movement modelling examples, learning pace regulation/time flexibility, prompts, social comparison
Characteristics of the learning group	H, M	Timing of group formation, number of active learners in the group, homogeneity, group size, average grade, prior knowledge of group members
Characteristics of the educational institution	H, M	Reputation, sponsorship, institution type, size, country
Feedback	H	Receiving feedback, type of feedback, source of feedback, valence
Physical and temporal learning environment	H, M	Spatial context, daytime, background music, presence of other people, distance from home to campus, type of living arrangement, technical and material resources
Multi-tasking	H	Distraction due to disruptive factors, simultaneous activities

[a.] H = higher education, W = workplace learning, M = MOOCs (Massive Open Online Courses).