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Artificial intelligence for informal workplace learning: a problem-solving perspective

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Rapid technological advances are constantly changing our workplaces and the organization of work. Formerly established workflows and role descriptions give way to short-term, skills-based project structures. The resulting skill shift heightens the importance of sustained informal workplace learning—ranging from unconscious, small-scale, everyday adaptation processes to intentional self-regulated learning activities. This concept paper explores informal workplace learning through the lens of problem solving, categorizing informal learning activities into reasoning, experimenting, researching, and observing, linked to personal, representative, social, and retrievable resources. It further examines how AI technologies can support these informal workplace learning activities. It is argued that AI's capacity for contextualized assistance within collaboration platforms, simulation environments and electronic performance support systems (EPSS) can support problem-solving and learning—if users maintain “process ownership” rather than delegating tasks entirely to AI. The concept of nudging (subtle prompts to foster reflection and learning) is proposed to ensure active engagement and prevent an “AI ghost-learner effect” (i.e., performing successfully through AI assistance without perceiving oneself as competent and as developing). Future research should focus on the empirical evaluation of these interventions and consider employees' utilization of AI to exploit the full potential for fostering informal workplace learning.

KEYWORDS

informal learning, workplace learning, learning activities, problem solving, artificial intelligence (AI), electronic performance support systems (EPSS), nudging

1 Introduction

Characteristics and requirements of work have always been shaped by applied technologies (Allvin and Movitz, 2017). In recent years, rapid technological advancements have dramatically reshaped modern workplaces. Automation and digitalization have streamlined routine tasks and changed work practices, while—above all—recent developments in artificial intelligence (AI) have continued these transformations and fostered the emergence of novel job roles and industries (Frey and Osborne, 2017; Harteis et al., 2022). These developments have changed the nature of many workplaces and the respective competencies required of employees (Billett, 2021; Korunka and Vartiainen, 2017; Kubicek et al., 2015). These changes in requirements are often labeled “skill shift” (Bughin et al., 2018; Lund et al., 2021). Following the European Commission's DigiComp framework, these competences include information and data literacy, communication and collaboration, digital content creation, safety, and problem solving (Vuorikari et al., 2022). Problem solving as a component of digital competence refers to identifying and resolving problems in digital environments, using digital tools to innovate processes and products, and keeping up to date with the digital technologies (Vuorikari et al., 2022) and points to fundamental changes in the organization of work. According to the management

consultancy sector, recent developments affect not only the types of skills required but also how skill requirements and individual capabilities shape the way work is orchestrated in what is referred to as “skills-based organizations” (Cantrell et al., 2022). Instead of long-term definitions of jobs, roles, and processes, work is evermore organized around ever-changing work tasks and agile project teams (Junker et al., 2023; Meier and Seufert, 2022). In skills-based organizations, as is enthusiastically described by accounting and consulting firms, “... people can be freed from being defined by their jobs and instead be seen as whole individuals with skills and capabilities that can be fluidly deployed to work matching their interests.” (Cantrell et al., 2022, p. 2). In their meta-analysis, Kim et al. (2018) confirmed that these kinds of empowering leadership indeed provide motivating work conditions, autonomy, and participation in decision-making and foster continuous learning within resourceful work environments. On the flipside, the vanishing of secure organizational roles not only allows for but also necessitates lifelong learning and a proactive engagement with new technologies to remain productive and competitive (Bughin et al., 2018; Kubicek et al., 2015; Parker and Grote, 2022). As a result, workplace learning has become even more critical (Billett, 2021; Harteis et al., 2022; Watkins and Marsick, 2023) and the concept of “new learning” as a response to the similarly enigmatic “new work” (Bergmann, 2019) describes an ideal of highly motivated and self-regulated learning in the workplace (Decius et al., 2022).

Workplace learning is understood here to include all learning processes—formal or informal, intentional or unintentional, conscious or unconscious—that result in changes to one’s professional competences, with competence defined broadly as the combination of domain-specific knowledge, skills, attitudes, and other characteristics that enable work performance (Kanfer and Ackerman, 2005; Noe, 2017; OECD, 2005). The formality of workplace learning refers to the organizational context in which learning takes place. Formal learning is typically characterized by scheduled start and end points; it is usually based on predefined learning goals and designed or guided from an educational perspective (Doornbos et al., 2004; Tannenbaum et al., 2010). By contrast, the concept of informal learning, which goes back to Dewey’s (1938, p. 48) “collateral learning,” basically refers to the absence of the above-mentioned structuredness of formal learning (Cerasoli et al., 2018). Work environments can, of course, be highly structured regarding the organization of work, but this structuredness then refers to the work processes, not to the potential learning within these work processes (Eraut, 2004; Harteis, 2002). Following Eraut (2004), informal and formal learning are defined here not as dichotomous categories but located rather on a continuum. Non-formal learning is often located between the ends of this continuum, “as it may be planned, but it is not provided by an educational institution” (Jacobs and Park, 2009, p. 142). Billett (2002), Jarvis (1987), and Malcolm et al. (2003) criticized the use of formality to distinguish learning processes because formality refers to the environment and not to types of learning. Nevertheless, the distinction between informal, non-formal, and formal learning points to substantial differences between these environments. Cerasoli et al. (2018) distinguished between formal and informal learning *behaviors*, thereby emphasizing that the difference lies not in the learning

but in the activities that lead to it, while Jarvis (1987) considered *situations* the distinguishing feature. Informal learning activities are usually triggered by a work-related problem situation, which is defined by a lack of knowledge on how to achieve a current work goal (Dörner, 1997; Duncker, 1945). Any problem-solving activity that aims to close a current (or an anticipated) knowledge gap concerning work goal achievement is hereinafter referred to as an informal workplace learning activity, regardless of whether actual learning takes place or is sustainable. Oftentimes this learning is not even perceived as such because, for many people, learning is associated with formal learning environments only. The primary goal of these problem-solving activities is preventing anticipated or solving existing problems (Jacobs and Park, 2009), harking back to Dewey. Considering knowledge gaps as triggers for activities, problem-solving research provides a very fruitful basis for analyzing informal learning in the workplace. Therefore, this article builds on a theoretical framework based on action regulation and problem-solving research to categorize informal workplace learning activities. This framework is then used to discuss the impact of recent applications of AI on the various workplace learning activities.

Apparently, new technologies such as AI not only require new competences but may also provide powerful resources of informal workplace learning (Bell, 2017; Kim et al., 2018; Karhapää et al., 2023; Littlejohn and Margaryan, 2014; Littlejohn and Pammer-Schindler, 2022; Za et al., 2014). While Holmes and Littlejohn (2024) rightly point out that “... currently there are few innovative or targeted examples of the application of AI to support workplace learning” (p. 200) many recent technologies aim at performance improvements by supporting problem solving in the workplace. For instance, collaboration platforms make it easier to ask colleagues for advice and to solve problems in distributed teams, AI-based chatbots make it easier to search through and process information, and performance monitoring can foster the awareness of and the reflection on aspects of one’s work performance that would otherwise remain unrecognized. Following the above line of argument, this problem-solving support represents an informal workplace learning support and therefore is a vital area of human resources development. Technology-based nudges (i.e. subtle interventions that guide individuals’ behaviors) can further trigger opportunities to learn and awareness of learning. However, AI also runs the risk of reduced skill requirements and skill acquisition in the workplace. This is the case, if it is used merely to provide orders to humans and restrict job autonomy, instead of providing humans with information resources for problem solving within high-performance work practices (Holm and Lorenz, 2022). Moreover, if AI “... takes over complex tasks and leaves workers with unstimulating ones, [the result will be] fewer learning opportunities and less autonomy.” (Lane and Williams, 2023, p. 19). From a perspective of problem solving, in this case, there are no more knowledge gaps in goal achievement to learn from, since the respective tasks are completely assigned to an AI. These ambivalent roles of recent technologies have been under-conceptualized and under-analyzed from the perspective of informal workplace learning.

To fill this gap, this conceptual paper builds on the concept of problem solving to combine approaches to informal

workplace learning activities and AI support in the workplace. Problem solving mediates between work requirements and informal learning, and AI tools are considered problem-solving resources. The two streams of research have distinct backgrounds, but elements of each can be complementary to developing a more holistic understanding of digital workplace learning support. Hence, this paper aims to categorize informal workplace learning activities, discuss the benefits and pitfalls of selected AI technologies, provide recommendations for fostering informal workplace learning, and identify research gaps in the field. Section 2 provides theoretical foundations of informal workplace learning activities and a framework for informal workplace learning activities from the perspective of problem solving. Section 3 delves into each of the areas of this framework to illustrate the effects of AI technologies on informal workplace learning. The contribution concludes with a discussion of the central findings, possible lines of development, and research requirements.

2 Informal workplace learning from a problem-solving perspective

2.1 A taxonomy of informal workplace learning processes

Building on [Eraut \(2004, 2011\)](#), in this paper, informal workplace learning is understood as an umbrella term to include a range of learning processes from unconscious everyday adaptation processes to self-regulated learning activities in the workplace. Informal workplace learning activities are often classified by intentionality, that is by the degree to which learning "... occurs purely by accident (unintentionally or incidentally) or through conscious deliberation (intentionally)." ([Cerasoli et al., 2018, p. 205](#)). This distinction builds on [Watkins and Marsick's \(1992, 2023\)](#) definition of incidental learning as the unintentional and unconscious by-product of some other activity. In the workplace, this other activity is usually a work activity that is, of course, also intentional, however, the intention refers to the completion of work tasks, not to learning while completing it. [Marsick and Watkins \(1990\)](#) used the term informal learning as the intentional and conscious counterpart to incidental learning ([Watkins and Marsick, 2023](#)). However, this definition of informal learning conflicts with the mainstream literature, because learning processes that are unintended and unrecognized by the learner are usually core characteristics of the definition of informal learning ([Johnson and Majewska, 2022](#)). In line with a systematic overview provided by [Wolfson et al. \(2018\)](#), informal learning comprises both, incidental and intentional learning. It also includes self-regulated learning which can take place in both, formal as well as informal settings. In his seminal publications on informal learning in the workplace, [Eraut \(2004, 2011\)](#) distinguished between implicit, reactive, and deliberative learning, which he understands as being located on a continuum.

Implicit learning refers to routine activities in which learning goals, learning processes, and learning outcomes are secondary and where the actor is unconscious of learning. It includes all the small-scale, day-to-day adjustments in an individual's knowledge,

skills, attitudes, or other characteristics based on subtle feedback from the task environment. These processes are usually not perceived as learning by employees and workers ([Eraut, 2004; Simons, 2005; Tynjälä, 2008](#)). Referring to a "non-educational perspective," [Doornbos et al. \(2004, p. 256\)](#) considered implicit learning to be "... part of belonging to and participating in a real-life context." These everyday adaptation processes that happen in the background result in broad socialization outcomes (e.g., the gradual adoption of corporate culture; also promoted by "vicarious learning"; [Manz and Sims, 1981; Tannenbaum and Wolfson, 2022](#)) and long-term personality developments (e.g., developing confidence in client interactions or greater conscientiousness in bookkeeping) ([Hodkinson and Hodkinson, 2004](#)). Implicit learning also enables ongoing routinization of already well-known work procedures (e.g., efficiency gains in wall leveling or greater spontaneity in customer discussions). As [Hatano and Inagaki \(1984, p. 31\)](#), put it, sometimes, "people merely learn to perform a skill faster and more accurately, without constructing/enriching their conceptual knowledge." In many domains, these individual routines mirror organizational routines. Organizational routines are day-to-day, repetitive patterns of interdependent organizational actions based on a shared understanding of how tasks are to be completed. Organizational core routines "... are specific to the firm, most vital to value creation, and represent the key components of the business model." ([Parmigiani and Howard-Grenville, 2011, p. 419](#)). Therefore, individual routine skills that improve actions within these organizational routines are an essential element of one's professional competence ([Gruber and Harteis, 2018; Kim, 2021](#)). These skills are also referred to as "routine expertise" ([Gruber and Harteis, 2018; Hatano and Inagaki, 1984](#)). Routine expertise results from proceduralization ([Gruber and Harteis, 2018](#)), and expertise, in general, is characterized, among other things, by having "available lots of routines and automatised procedures." (p. 5). Furthermore, routine expertise can also be developed through closely monitored practice, as opposed to "mindless, routine performance" ([Gruber and Harteis, 2018, p. 96](#)) but this planned learning and rehearsing refers to deliberative learning (see below).

Reactive learning is intentional and activated when problems arise, that is when routines are not available, or the available routines are not effective in achieving a current work goal. According to [Eraut \(2004, 2011\)](#), reactive learning includes the awareness of short-term situational learning needs, learning activities, and learning outcomes in terms of competence gains. Reactive learning can be illustrated very well using [Kolb's \(2015\)](#) concept of experiential learning as continuous, cyclical processes of adaptation to the world based on concrete experience, reflective observation, abstract conceptualization, and active experimentation. This concept of experiential learning is very prominent in theories of workplace learning (e.g., [Tannenbaum et al., 2010; Decius et al., 2019](#)). Triggers for reactive learning are, for instance, unknown variations in otherwise familiar work tasks or changes in well-established workflows (e.g., updated software tools with a slightly changed interface or new product versions in the sales portfolio with unfamiliar features). These changes might lead to errors and often go along with emotional states such as confusion or surprise ([Rausch et al., 2017](#)). These incidents

trigger reflections that lead to the questioning of previously acquired routines (Nieuwenhuis and Van Woerkom, 2007) once these routines have become ineffectual (e.g., cumbersome, error-prone, unethical, or simply wrong). The increasing flexibility to deal with changing situations and contexts is referred to as “adaptive expertise” (Gruber and Harteis, 2018). “Plausibly, in the acquisition of expertise, the development of routine expertise occurs before professional adaptive expertise is being developed.” (Gruber and Harteis, 2018, p. 44). *Deliberative learning*, as defined by Eraut (2004, 2011), refers to conscious, intentional, self-monitored problem-solving and decision-making activities in which learning goals emerge that are critical for achieving current or future work goals. Eraut (2004) admitted that reactive and deliberative learning are similar but explained that he used “... the term ‘reactive learning’ because, although it is intentional, it occurs in the middle of the action, when there is little time to think” (p. 250) and no time set aside for intentional learning. Hilkenmeier et al. (2021), describe these learning activities as being “... driven by employees’ needs to tackle unfolding and pressing tasks or problems at work.” (p. 413). Hence, the shorter the time set aside for learning, the more the episode falls into problem solving and decision making in the workplace. The longer the (anticipated) time lag between learning (i.e., pursuing learning goals) and performance (i.e., pursuing work goals), the more deliberative learning resembles participation in designated learning opportunities as defined by Hilkenmeier et al. (2021) and corresponds to autonomous learning (Kyndt and Beausaert, 2017; Noe and Ellingson, 2017) to self-directed workplace learning (Bell, 2017; Lemmetty and Collin, 2020), to informal field-based learning (Decius et al., 2024; Tannenbaum and Wolfson, 2022; Wolfson et al., 2019), and, in particular, to self-regulated workplace learning (Cuyvers et al., 2020; Decius et al., 2024; Endedijk and Cuyvers, 2022; Holmes and Littlejohn, 2024; Kittel et al., 2021; Margaryan et al., 2013). Based on a literature review and meta-analysis of self-regulated learning, Sitzmann and Ely (2011) conclude that self-regulation might be even more important in the context of informal learning than in formal learning settings, since “... employees must independently identify knowledge gaps, determine where they can access relevant and accurate information, monitor the accuracy of information obtained, and control their emotions if relevant information is difficult to obtain.” (Sitzmann and Ely, 2011, p. 437) or in Eraut’s words: “planning learning opportunities.” (Eraut, 2004, p. 250). Hence, deliberative learning includes the utilization of formal learning resources, such as textbooks or learning videos, and formal structures, such as mentoring relationships—outside formalized learning environments, however. Furthermore, deliberative learning also includes “rehearsing for future events” (Eraut, 2004, p. 250). This resembles “deliberate practice” which refers to the focused and supervised practice of designed (part-task) exercises conducted apart from (but in service of) actual performance (Ericsson et al., 1993). Deliberate practice is considered a key factor in developing outstanding expertise, at least in well-structured (sub-)domains (e.g., chess, sports, music), indicated by the relevance of the above-described organizational routines. Deliberate practice is a complex intervention composed of rehearsal, experimentation, and reflection with advice and feedback from others. Hence, it is self-regulated and, similar to coaching,

shares many characteristics with formal training settings: pursuing learning goals, being guided, following a curriculum, and practicing apart from the productive work activity. However, Goller (2017) as well as Köhler and Rausch (2022) have argued that deliberate practice does not usually apply well to the ill-structured domains of most workplaces. In ill-structured domains, “adaptive expertise” (Hatano and Inagaki, 1984) or “horizontal expertise” (Gegenfurtner et al., 2024) for flexible problem solving and recurring adaptation to dynamic demands seem to be more important than “routine expertise.” Table 1 provides an overview of key characteristics of implicit, reactive and deliberative learning according to Eraut (2004, 2011) and references to related concepts by other authors.

Implicit, reactive, and deliberative learning form a taxonomy, since “most learning from experience has some implicit aspects, and [...] awareness of explicit learning does not mean that implicit learning is not also taking place.” (Eraut, 2004, p. 250). Hence, deliberative learning is likely to also include processes of implicit and reactive learning; reactive learning is likely to also include processes of implicit learning. This taxonomy corresponds to the levels of mental regulation of activities as conceived by the long-standing line of research on “action regulation theory” within German work psychology (Frese and Zapf, 1994; Hacker, 2003, 2005). This view is that automated routine action can be part of knowledge-/rule-based action that, in turn, can be part of problem solving with the development of plans based on an intellectual analysis of the situation. Deliberative, reactive, and implicit learning describe levels of mental processing but not the actual activities that trigger, accompany, or follow these processes.

2.2 A review of informal workplace learning activities

Based on the above definitions, workplace learning activities refer to all kinds of intentional behaviors that result in reactive or deliberative learning processes (that may also include implicit learning processes). Definitions of workplace learning activities must be based on reactive and deliberative learning, since implicit learning can take place in any work activity and, hence, is not triggered exclusively by workplace learning activities. Nevertheless, following the above line of argument, implicit learning may also be part of reactive and deliberative learning. These informal workplace learning activities are voluntary and self-paced (Bednall et al., 2014). Stressing the awareness of the learning processes, Van Woerkom et al. (2002, p. 376) considered reflection to be the umbrella term and referred to these activities as “critical reflective behaviors at work.” In the case of deliberative learning (i.e., intentional learning), these activities are also referred to as workplace learning strategies (Crouse et al., 2011; Lee and Tan, 2023).

Lists of informal workplace learning activities and strategies have been provided by many authors, based on a variety of theoretical foundations (or sometimes not based on theory). However, to the best of this author’s knowledge, there is no comprehensive compilation and analysis of these lists, apart from

TABLE 1 Key characteristics of implicit, reactive and deliberative learning and related concepts.

Learning type (Eraut, 2004, 2011)	Key characteristics	Typical triggers	Typical outcomes	Related concepts
Implicit learning	• Unintentional and unconscious • Not recognized as learning • Integral part of belonging to and participating in work contexts	• Routine work • Subtle feedback from work environment	• Routinization • Small-scale adaptations • Long-term socialization and personality development	• Incidental learning (Watkins and Marsick, 1992) • Vicarious learning (Manz and Sims, 1981; Tannenbaum and Wolfson, 2022) • Routine expertise (Gruber and Harteis, 2018)
Reactive learning	• Awareness of situational learning needs • Short-term learning activities • Embedded in ongoing work	• Deviations from routines (e.g., problems) • Performance feedback (e.g., errors) • Workflow changes (e.g., novelty)	• Questioning of previously acquired routines or naïve concepts • Adapting competences	• Experiential learning (Kolb, 2015) • Reflection-in-action (Schön) • Adaptive expertise (Gruber and Harteis, 2018)
Deliberative learning	• Awareness of critical learning needs • Conscious, intentional, and self-monitored learning activities • Time and resources are intentionally used for learning	• Critical problem-solving and decision-making • Anticipated performance deficits • Anticipated changes in business processes • Deliberate practice	• Development of previously unknown solutions • Extending competences	• Self-regulated workplace learning (Cuyvers et al., 2020) • Self-directed workplace learning (Bell, 2017) • Informal field-based learning (Tannenbaum and Wolfson, 2022) • Autonomous learning (Noe and Ellingson, 2017)

a shorter and less focused compilation by Moore and Klein (2020) and a compilation of operationalizations by Decius et al. (2023). The compilation in Table 2 focuses on informal workplace learning activities to illustrate similarities and differences between the various approaches. Less focused lists of learning activities are not included. For instance, Beier et al. (2017, p. 184), in their “examples of autonomous learning activities,” also included hobbies, training programs, career development services, and other activities that are rather detached from concrete workplace activities. Goller et al. (2020) list “avoidance of learning” (e.g., denying errors), which is left out of Table 2 because it is not a learning activity. In the original table, Eraut (2011) also lists “work processes with learning as a by-product” that may trigger implicit learning, and “learning processes at or near the workplace” that comprise more formal approaches, such as being coached or attending crash courses. Maintaining the focus on informal workplace learning activities, only the middle column on “learning activities located within work or learning processes” has been included in Table 2. Crouse et al. (2011) also listed “taking courses and programmes” and Lee and Tan (2023) listed “enrolling in formal studies,” “participating in on-site training,” and “participating in e-learning courses,” which were left out here because they refer to formal learning. Decius et al.’s (2019) octagon model of informal workplace learning (an extension of Tannenbaum et al.’s, 2010 model) included extrinsic and intrinsic intents to learn, which are not activities in the narrow sense but are still listed in Table 2 for the completeness of the model. Most of the lists were derived from theoretical reasoning or narrative literature reviews; meanwhile, Kyndt et al. (2016) did conduct a systematic review, which was limited in focus to teachers’ informal learning activities, however.

The informal workplace learning activities listed in Table 2 share a common focus on experiential and self-directed learning. Many of the lists cited here involve social interactions, such

as talking to others, collaborating, and sharing knowledge or feedback, emphasizing the role of relationships in workplace learning. Activities like reflection and learning from errors or experimentation highlight processes of personal insight. Furthermore, some activities are more passive, such as observing or receiving feedback, while others involve more active engagement, like seeking feedback or experimenting. Some lists are unstructured, while others provide categorizations of activities. Some categorizations differentiate learning by regulatory processes, while other categorizations differentiate learning by social context. In the following section, informal workplace learning activities are categorized by a framework of problem-solving approaches.

2.3 A model of informal workplace learning as problem solving

Any trigger for an informal workplace learning activity in the above sense can be considered a problem situation, where “problem” signifies that an individual “... wants to transform a problem situation from the given state to the goal state but lacks an obvious method for accomplishing the transformation.” (Mayer and Wittrock, 2006, p. 288). Every work task that cannot be completed on a routine basis therefore represents a minor or major problem and, hence, requires reasoning (Duncker, 1945). In their book *Innovative Performance Support: Strategies and Practices for Learning in the Workflow*, which is very popular in the consulting industry, Gottfredson and Mosher (2011) identify five moments of need: Workers need support when they (1) learn something completely new, (2) learn more to expand in breadth and depth, (3) face difficulties when applying their knowledge to work situations, (4) solve problems because things

TABLE 2 Compilations of informal workplace learning activities.

Authors	Informal workplace learning activities
Van Woerkom et al. (2002)	• Reflection • Vision sharing • Asking for feedback • Challenging group think • Learning from mistakes • Sharing knowledge • Experimentation • Awareness of employability (reflecting on whether to adapt to the changes or change career direction)
Lohman (2005)	• Talk with others • Collaborate with others • Observe others • Share materials and resources with others • Search the Internet • Scan professional magazines and journals • Trial and error • Reflect on your actions
Korpelainen and Kira (2010)	• Alone: trying things out, reading manuals • From others: asking for help from other people • With others: trying out things with others, assisting each other while working
Crouse et al. (2011)	• Doing work/new tasks • Working with others • E-learning • Observing others • Trial and error • Reading/researching • Reflection on action • Feedback
Eraut (2011)	• Asking questions • Getting information • Locating resource people • Listening and observing • Reflecting • Learning from mistakes • Giving and receiving feedback • Use of mediating artifacts
Noe et al. (2013)	• Learning from oneself: reflecting on past experiences and experimenting with new approaches to improve performance • Learning from others: seeking feedback and exchanging ideas with peers or supervisors to enhance work strategies • Learning from non-interpersonal sources: consulting written or digital materials to gain relevant knowledge or solve problems
Bednall et al. (2014)	• Reflection on daily work activities • Knowledge sharing with colleagues • Innovative behavior (seeking new methods and creating ideas)
Gijbels et al. (2014)	• External regulation of knowledge construction (e.g. asking for feedback) • Self-regulated knowledge construction through self-regulated information-seeking and reflection • Shared regulation of knowledge construction of workplace experiences through contacting and being involved in discussions with peers
Kyndt et al. (2016)	• Reading professional literature • Observation • Collaboration with colleagues • Reflection • Learning by doing/through experience • Browsing the Internet and social media • Experimenting • Trial and error • Talk with others • Sharing materials and resources • Storytelling
Sanders et al. (2017)	• Individual informal learning activities: reflection on daily activities, keeping up-to-date • Collaborative informal learning activities: seeking feedback from supervisors, knowledge sharing • Innovative behaviors: identifying potentials for doing things differently, implementing innovations
Rintala et al. (2019)	• Learning from oneself: reflection, experimentation • Learning from others: learning from colleagues, learning from supervisors, observation, collaboration • Learning from non-personal sources: searching and scanning information (e.g., Internet, journals), learning from errors, conflicts etc.

(Continued)

TABLE 2 (Continued)

Authors	Informal workplace learning activities
Decius et al. (2019); building on Tannenbaum et al., (2010)	• Experience/action: trying and applying own ideas, model learning • Feedback: direct feedback, vicarious feedback • Reflection: anticipatory reflection, subsequent reflection • Intent to learn: extrinsic or intrinsic
Kortsch et al. (2019)	• Learning from oneself: reflecting, experimenting, trial and error • Learning from others: interacting with mentor (supporter), interacting with supervisors • Learning from non-personal sources: professional magazines, websites, books • Learning from new media: new utilities (e.g., smartphone apps), pictures, videos, social networking
Goller et al. (2020)	• External regulation of learning: interns actively approach their mentors as external sources for the regulation of their work or learning activities. • Shared regulation of learning: interns purposefully approach more experienced colleagues for practical suggestions and ask colleagues for feedback. • Self-regulation of learning: interns try to solve problem situations on their own, seek information from codified knowledge sources and apply experimentation and simple trial and error. • Actively relating theory to practice: intern actively apply theory to solve tasks and problems at work or try to understand work-related phenomena based on their theoretical background
Crans et al. (2021)	• Passive learning: receiving feedback, observing others, receiving advice, role modeling, imitating best practice, being guided, receiving feedback through monitoring, receiving information • Proactive learning: feedback seeking, information seeking, help seeking • Collaborative learning: discussing, sharing knowledge, debriefing, talking to others, exchanging feedback, collaborating with others
Tannenbaum and Wolfson (2022)	• Feedback and reflection • Vicarious learning (learning from role models) • Experimentation/new experiences
Lee and Tan (2023)	• Self-driven strategies: self-exploration, problem-solving, reflecting • Social-leveraged strategies: observing, modeling, asking, sharing, and discussing • Enterprise-oriented strategies: researching available training documents (i.e. manuals, reports, or standard operation protocol) • IT-enhanced strategies: searching online information

do not work as intended, and (5) when they face change and have to change deeply ingrained work practices (i.e., routines). In their framework, the first two moments of need should be addressed by formal training, while the latter three moments of need correspond well to what is meant by problem situations in this paper.

Solving a problem means overcoming the knowledge gap by achieving an understanding of the situation, finding alternative solutions, deciding on and executing a solution, and evaluating goal achievement, which, hence, results in acquiring knowledge on how (not) to handle the given work task (Hung et al., 2008). This task-related learning can typically foster the acquisition of new competences or an adaptation of previously acquired competences (Wielenga-Meijer et al., 2010). Following the concept of progressive problem solving by Bereiter and Scardamalia (1993), learning in the workplace results from solving and reflecting on increasingly complex work tasks (Bereiter, 2002). However, to be able to learn from problem solving, Rausch et al. (2015) stressed that, to ensure learning opportunities, it is important for the problem solver to not delegate the problem but instead remain the “process owner.” This is the case, for instance, if the problem solver receives assistance in planning, but still implements the plan by himself/herself; if the problem solver receives assistance in implementing the plan, but still follows and reconstructs the implementation; or if the problem solver implements the plan unaided and is only provided feedback. These kinds of cooperative and collaborative problem solving are considered to support informal workplace learning, whereas delegating and free riding does not (Rausch et al., 2015). Similarly, Holmes and Littlejohn (2024) discuss the

detrimental effects of AI-based intelligent tutoring system (ITS) on learner agency.

According to the German tradition of action regulation theory (Hacker, 2003, 2005; Hacker and Skell, 1993), every action starts with the perception of a discrepancy between a desired target and an undesired actual situation and includes the development and evaluation of different action plans based on prior knowledge and experience (“action-guiding mental models”). Problem solving is considered a special type of situation in which these mental models are not sufficient to develop an effective action plan. Problem solving corresponds to expanding these mental models to fill the gaps in an action plan (Dörner, 1997, 2001). To fill these gaps, Dörner (2001) lists reasoning (i.e. combining available parts of action plans), exploring (i.e. testing hypotheses), observing others, and communicating with others, and researching codified action plans (e.g., manuals). Regarding similar problem-solving approaches, Hacker and Skell (1993) differentiate between learning based on one’s own actions and learning from the mentally reconstructed actions of others. In several revisions, Rausch (2011), Rausch et al. (2015), and Leiß et al. (2022) have classified approaches to problem solving in the workplace by whether the approach is based on an indirect experience (i.e., mental models of the world) or a direct real-world experience, and by whether the approach is self-developed (i.e., based on personal or representative resources) or whether it is a third-party approach that can be adapted (i.e., based on social or retrievable resources). The framework presented in Table 3 builds on these contributions and further develops them.

TABLE 3 Problem-solving approaches.

Source of problem-solving approach	Activated resources	Approaches based on indirect experience	Approaches based on direct experience
Self-developed approaches	Personal resources	<i>Reasoning</i> based on mental representations	<i>Experimenting</i> in a real-world situation
	Representative resources	<i>Reasoning</i> based on externalized representations	<i>Experimenting</i> in a simulation of a real-world situation
Third-party approaches	Social resources	<i>Researching</i> by consulting others	<i>Observing</i> live demonstrations
	Retrievable resources	<i>Researching</i> by consulting codified information	<i>Observing</i> recorded demonstrations

The classification of problem-solving approaches in the matrix in Table 3 is considered exhaustive: every problem-solving approach can be categorized according to these two dimensions, though, in practice, problem-solving processes will often involve several approaches and combinations of them. Revisiting the manifold workplace learning activities in Table 2, exhaustiveness means that all these activities can be assigned to one or more cells in the matrix of Table 3 and all of them relate to one or more of the resources listed there. Here is a brief explanation of the four problem-solving approaches, their variations, and resources:

- *Reasoning* refers to all kinds of operations on one's own mental model of the problem situation (i.e. personal resources). It includes awareness, reflection, mental simulation, interpolation, abstraction, reduction, analogies, and so forth. It is usually also the starting point of every problem-solving episode and has a central position for planning, monitoring, and evaluating the utilization of further resources and drawing conclusions. Reasoning can be supported by externalized representations (i.e., representative resources such as notepads, etc.) to model complex situations and reduce cognitive load.
- *Experimenting* refers to all kinds of hypothesis testing (i.e., testing well-considered solution attempts) and trial-and-error behavior (i.e., trying out several, rather arbitrary solutions quickly). Hypothesis testing is based on prior reasoning, while trial-and-error behavior is more spontaneous and therefore only advisable in safe, error-friendly, maybe simulated environments. Experimenting can result in the successful implementation of the ultimate solution. However, experimenting can also take place in simulations of the corresponding real-world problem (i.e., representative resources). For instance, transferring the quantitative information of a financial problem situation into a spreadsheet results in an externalized representation (see above) that can be used to simulate various future scenarios (e.g., based on varying interest rates).
- *Researching* refers to consulting others (i.e., social resources providing assistance, guidance, instruction, etc.) and consulting codified information (i.e., retrievable resources such as guidelines, manuals, checklists, etc.). In both cases, it refers to indirect, mediated experience and provides solution approaches from others that can be adopted by the problem solver.
- *Observing*, like experimenting, provides problem-solving approaches based on direct experience; however, unlike

experimenting, these approaches are not self-developed but can be adopted. As with researching, the observation can relate directly to other individuals who are demonstrating their problem-solving approach (i.e., social resources) or be technologically mediated as with video tutorials (i.e., retrievable resources). The adoption of the observed problem-solving approaches, in turn, requires at least a minimum of reasoning.

In the following section, these problem-solving approaches are used to structure the discussion on technological trends that support informal workplace learning.

3 The role of AI tools in informal workplace learning

3.1 Generative and analytical AI tools

At the time of writing this paper, the most obvious opportunities for workplace learning in organizations have arisen from technological advancements in the fields of artificial intelligence (AI), immersive simulation environments, including extended reality, and digital communication and collaboration platforms, in general. First and foremost, in the public mind, AI is particularly associated with the fast development and increasing availability of tools providing generative artificial intelligence (genAI) based on large language models (LLM), initially boosted by OpenAI's ChatGPT (Alhusban et al., 2024; Budhwar et al., 2023). Referring to the role of genAI in human learning in general, Yan et al. (2024, p. 1) argued for advantages in "... scaling personalised support, diversifying learning materials, enabling timely feedback, and innovating assessment methods." Regarding workplace learning, GenAI is particularly relevant in office work (Krishnasamy and Lee, 2024), provides a valuable resource for "... seeking immediate answers, guidance, or support in ... work-related tasks," (Fahad et al., 2024, p. 267) and thus enhances employees' performance and satisfaction (Brynjolfsson et al., 2025; Jo and Park, 2024). Xu et al. (2023) found that, in turn, informal workplace learning mediated the relation between AI opportunity perception and workplace wellbeing. GenAI applications are powerful problem-solving tools. Applied as an externalized representation, these tools process comprehensive and complex information and, thus, enhance reasoning by providing summaries, abstractions, analogies, analyses, and syntheses based on given information. Even more obvious, in researching further

information, AI tools are very helpful, especially if they are fine-tuned and customized based on corporate knowledge corpora. However, not only is genAI developing rapidly, but analytical AI is also enabling ever better analyses of large amounts of multimodal data in real time (Bankins et al., 2023; Jagatheesaperumal et al., 2022). This enables advanced electronic performance monitoring (Kalischko and Riedl, 2021) which is a basis for feedback and thus, an important source of learning within work environments (Sitzmann and Ely, 2011; Wang et al., 2025). Meaningful and timely performance feedback also enables the acquisition of routine expertise by means of deliberate practice.

In the following sections, I discuss possible implementations of selected technologies to support informal learning in the workplace, concerning the categorization of problem-solving approaches and resources presented above. Some of the scenarios are already more or less widespread in practice; others are more forward-looking. In any case, the selection is to be considered subjective.

3.2 AI implementations in collaboration and simulation platforms

An already widespread, but important technological trend lies in the use of digital communication and collaboration platforms. These platforms are particularly important in the context of international teams and increasing remote work and can also facilitate informal workplace learning (Karhapää et al., 2023). These platforms are subject to the latest AI developments like no other technology in companies, as the extensive content is analyzed using analytical AI, and genAI contributes its own content in the form of AI agents (e.g., Microsoft's CoPilot; depending on the definition of an AI agent). Communication plays an important role in workplace learning activities when, for instance, seeking help, receiving feedback, observing others, sharing knowledge, and so forth (Crans et al., 2021; Hilkenmeier et al., 2021; Rausch et al., 2015). Collaboration platforms such as Microsoft Teams combine many basic features, such as collaborative office software for document editing, several channels for synchronous and asynchronous communication, and shared file management as well as numerous third-party plug-ins. Altogether, these platforms realize what Littlejohn et al. (2012, p. 229) outlined as "charting environments" for self-regulated informal workplace learning by allowing "... experts and novices to create and share knowledge by connecting with each other and the broader collective." Increasingly enriched with AI functionalities, these platforms can actively recommend retrievable resources (i.e., codified information or recorded performance). If linked to an organization's skills management system, they can also recommend social resources for consulting more experienced others based on the context.

Further developed into so-called metaverses, future collaboration platforms promise an immersive experience based on the simulation of a work environment. Simulation-based learning environments have a long tradition in various domains (Hallinger and Wang, 2020), but new technological advancements offer even more immersive environments, comprising augmented reality

(AR), virtual realities (VR), and virtual worlds within so-called metaverses (Damaševičius and Sidekierskiene, 2024). Metaverses are virtual shared spaces with the synergistic combination of the real world with the virtual world (Damaševičius and Sidekierskiene, 2024; Umbelino et al., 2024). They allow for experimenting in a simulation of the real-world situation to find problem solutions. In metaverses, users "... can engage with complex ecological systems [...] in a risk-free setting, allowing for experimentation and exploration that would be impractical or impossible in the real world." (Damaševičius and Sidekierskiene, 2024). Metaverses are not yet widely used in companies, but from a laboratory study, Hendriks et al. (2024) reported "... higher levels of immersion, social presence, and collaboration among team members in the metaverse," (p. 686) as compared to groups collaborating via video conference. Digitally mediated presence rather restricts learning (Karhapää et al., 2024), while reduced social distance, in turn, facilitates advice-seeking (Korpelainen and Kira, 2010). Besides its use in immersive formal training, these simulations of work environments offer a virtual space for creating, sharing, and managing knowledge. Based on the Japanese concept of "ba" (= place), introduced in Nonaka and Takeuchi's (2019) circular knowledge management model SECI (socialization, externalization, combination, internalization), Umbelino et al. (2024) referred to simulated work environments as a "virtual ba." Developing, maintaining, and updating such simulation environments is still very time-consuming. However, there are already AI applications that enable the creation of a simulation environment via text prompts (e.g., "Xara—XR Dialog Trainer" by afca AG).

3.3 The "AI ghost learner effect"

AI applications offer manifold resources for informal learning in the workplace but it may also result in what I call the "AI ghost learner effect". To learn by the help of AI tools, it is important that employees remain "process owners" (see Section 2.3) and do not just delegate tasks to AI tools without reflecting on the results. This would resemble the "AI ghostwriter effect" found when using AI in text production (Draxler et al., 2024). Based on studies on academic writing, the authors defined the "AI ghostwriter effect" when students "... do not consider themselves the owners and authors of AI-generated text but refrain from publicly declaring AI authorship" (p. 1). Translated to the context of workplace learning, an "AI ghost learner effect" could occur when employees use AI-generated solutions or problem-solving strategies without engaging in deeper cognitive processing and reflection, thereby neglecting opportunities to learn. In such cases, employees may actually learn that "AI can handle that" but this learning remains superficial, as employees adopt AI outputs passively rather than actively integrating the resulting information into their own mental model. Similarly to the phenomenon reported by Draxler et al. (2024), employees may not perceive the implemented solution as their own, yet remain responsible for it. This, too, may create tensions similar to those described in academic contexts, as employees may "refrain from publicly declaring AI authorship." At the same time, they

may misinterpret their increased performance as an indicator of increased competence or even as evidence that further learning is no longer necessary. I label these phenomena as the “AI ghost learner effect.” One way to counteract this detachment is nudging, where AI can also play a supportive role.

3.4 AI-based nudging of informal workplace learning

Nudging refers to subtle interventions that guide individuals’ behaviors in ways that are beneficial to themselves without restricting choices or significantly altering incentives (Thaler and Sunstein, 2008). Lim and Lee (2022) and Bell (2017) report findings on nudging learning in academic settings and Watkins and Marsick (2023) report a success story at IBM implementing nudging in more formal workplace learning. While there are studies on the effects of nudging engagement and performance in the workplace (Weintraub et al., 2021), there are hardly any empirical studies on nudging interventions to support informal workplace learning. Bell (2017) provides an overview of several “prompting strategies” that aim to trigger specific self-regulatory mechanisms (e.g., monitoring, metacognition) derived from research in formal learning environments. Arya and Hindolia (2024, p. 2) raise the prospect that “organizations can cultivate a culture of ongoing learning and adaptation by skillfully incorporating nudging tactics.”

Nudging learning when using AI tools: “AI-assisted systems ideally would support learner agency to actively plan, perform, self-regulate, and reflect on their learning.” (Holmes and Littlejohn, 2024, p. 203). To foster informal workplace learning, the AI tool could be designed to trigger reflection by posing follow-up questions to encourage metacognition (e.g., “How does this solution compare to your initial task understanding?”), to promote self-assessment (e.g., “Do you think, your solution is adequate, accurate, and complete?”), to suggest further learning resources (e.g., “If you would like to find out more about these topics, take a look at this content: ...”), and to support the transfer of learning (e.g., “Similar approaches could also help with the following workflows: ...”). These triggers are initiated by the concrete use of an AI tool; hence, occasion and context are provided already by the user, which makes these triggers quite simple to implement in the context of collaboration platforms.

Nudging learning when using business software: even smarter implementations of nudging can be based on employees’ behavior within productive business software like enterprise resource planning (ERP) systems. These *ad-hoc* help systems are referred to as electronic performance support systems (EPSS). An EPSS is defined as “... an electronic infrastructure that captures, stores, and distributes individual and corporate knowledge assets throughout an organization to enable individuals to achieve required levels of performance in the fastest possible time and with a minimum of support from other people.” (Noe and Ellingson, 2017, p. 368). An EPSS presents granular task-specific information to solve a problem at hand (Mao and Brown, 2007). To date, most implementation of EPSS has been rule-based, which means a limited number of predefined help texts are linked to predefined user behaviors based

on hard-coded rules. With AI, however, the *ad-hoc* assistance could be tailored “... based on specific employee preferences, needs, or historical interactions.” (Alavi et al., 2024, p. 10). Current EPSS platforms often recommend videos that have been created by colleagues or developers beforehand for observing recorded performances based on anticipated problems of the users. Future videos could be created *ad-hoc* by generative AI and, hence, provide an even greater adaptability. In a survey study, Leiß et al. (2022) found that ERP users highly valued the features of existing EPSS and intensively used the more developed EPSS. The authors concluded that EPSS will play an important role in future workplace learning. The assistance provided by an EPSS, in turn, can be supplemented by the more general nudges suggested above and, for instance, by encouraging users to take notes after difficult tasks and even by making suggestions for these notes.

A general advantage of AI-based assistance is its adaptability based on user interactions. Moreover, Weinmann et al. (2016) emphasized the role of user interface design in digital nudging, because user-interface design elements guide people’s behavior in digital choice environments such as business software. Hence, it is not just the functionality that makes digital nudging work but also the “look and feel” as perceived by the users.

3.5 AI tools as problem-solving resources

AI applications—based on analytical AI, generative AI or both—offer a multitude of affordances for informal workplace learning. However, to make sense of this diversity, it is helpful to analyze how these technologies can serve as a problem-solving resource, and in doing so, support distinct learning activities. Table 4 provides an overview of analytical and generative AI categorized by problem-solving resources as introduced above.

This perspective underscores that the learning potential of a technology does not lie in the technology itself, but results from its contextual use in the workplace. A single tool may support reasoning, experimenting, researching, observing or combinations of these—depending on how it is implemented. Therefore, workplace learning researchers and professionals should focus not only on the availability of particular technologies and tools but on the ways that these represent problem-solving resources, activate and support workplace learning activities and still ensure a human ownership of the problem-solving process.

4 Discussion

It is argued that informal workplace learning, due to ongoing technological advancements and changes in the organization of work, will become even more important in the future. This informal workplace learning ranges from unconscious, small-scale, everyday adaptation processes to intentional self-regulated learning activities. There are numerous lists focusing on informal workplace learning activities, but these lists often lack a systematic approach. Through the lens of problem solving, any work situation in which a routine solution is not immediately available is a problem situation that offers learning opportunities. Approaches to problem solving in the workplace can be classified by

TABLE 4 AI tools as problem-solving resources.

Problem-solving resources	Analytical AI	Generative AI
Personal resources	Identifying and highlighting individual user behavior (e.g., errors or delays)	Creating documentations, feedback, warning notices and prompts based on user behavior, proposing reflection logs or learning diaries (e.g., within collaboration platforms)
Representative resources	Identifying and highlighting critical areas and variables of the situation for further externalization	Externalizing critical areas and variables of the situation (e.g., creating summaries, causal maps, decision trees), creating simulations of critical situations that allow risk-free exploration
Social resources	Identifying experts based on task context, user behavior, and interaction history with experts and AI agents	Generating social presence and expert advice by AI agents based on fine-tuned LLMs
Retrievable resources	Identifying and delivering context-sensitive assistance (i.e. AI-based EPSS with predefined content; pre-existing tutorials and demonstrations)	Identifying and generating context-sensitive, multi-model assistance (i.e. AI-based EPSS with dynamic content; <i>ad-hoc</i> generated tutorials and demonstrations)

whether the approach is based on an indirect experience (i.e., mental models of the world) or a direct experience and by whether the approach is self-developed (i.e., based on personal or representative resources) or a third-party approach that can be adapted (i.e., based on social or retrievable resources). This scheme has resulted in four key informal workplace learning activities: reasoning, experimenting, researching (as consulting others or consulting codified information), and observing. These informal workplace activities are based on personal, representative, social, and retrievable resources. The conceptual benefit of this “lens of problem solving” lies in the fact that the matrix adapted from the problem-solving literature (1) is exhaustive, i.e. allows a categorization of all informal workplace learning activities (see Table 2), (2) thus allows a classification into self-developed vs. third-party approach based on indirect vs. direct experience and (3) names relevant resources in each case, which in turn facilitates the allocation and characterization of recent technological tools. By using the four resource types (personal, representative, social, retrievable) as analytical categories, the manifold opportunities that modern technologies afford for informal workplace learning support can be disentangled. At the same time as the conceptualization of informal learning presented here was being finalized, the article by Decius et al. (2024) was published, which models workplace learning from the perspective of theories of (meta-)cognition and memory and offers many interesting points of reference. Bringing these specific perspectives together offers great potential for enhancing our understanding and analysis of informal learning.

Contemporary technological trends offer manifold opportunities to support informal workplace learning. AI undoubtedly has a huge impact on problem solving in the workplace. However, limitations of AI-based tools include the generation of incorrect content due to “hallucinations” or already biased training data as well as risks such as overreliance and reduced transparency that may undermine critical thinking and hinder competence development. The extent and manner of the use of new technologies for workplace learning activities also depend on the extent to which corresponding work and learning practices are cultivated in the relevant communities (Karhapää et al., 2023). A paradox arises from the assumption of an “all-knowing” AI. If a workflow can completely be monitored and evaluated by AI, it is likely that this workflow can be completely

automated—and then there may indeed be no need to learn this workflow, or a greatly reduced need to do so. More generally, in the face of digitalized work, Harteis (2022) has distinguished an “automation scenario” and a “tooling scenario,” similarly to “AI automation vs. AI augmentation” (Nguyen and Elbanna, 2025). The present paper has addressed cases of “tooling,” while, of course, many future workflows will be completely automated, too. Harteis (2022) describes the “tooling scenario” as one in which digital technologies support employees by extending their capabilities rather than replacing them. However, the remaining work tasks will be complex and ever-changing. Informal workplace learning will be more relevant than ever, and the technological developments, above all AI, will offer plenty opportunities to support this learning. The framework developed here can also be used to systematize other future technological workplace learning support interventions. Within the “tooling scenario,” the importance of “process ownership” must be emphasized in order to take advantage of the learning opportunities offered by using these tools. Watkins and Marsick (2023, p. 44) described informal workplace learning as “... a way of putting control for learning in the hands of intrinsically motivated, purpose-driven employees who continuously learn.” Therefore, we need to prevent an “AI ghost-learner effect” (similar to the “AI ghostwriter effect”; Draxler et al., 2024), which leads to only superficial learning and occurs when employees adopt AI outputs passively without reflection.

Nudging—subtle interventions that guide individuals’ behaviors (Thaler and Sunstein, 2008) also referred to as prompting (Bell, 2017)—is considered a promising approach to ensure process ownership and learning opportunities during AI-supported problem solving. So far, nudging has remained detached from concrete workflows and implemented at predefined intervals (Bell, 2017), like experience sampling (Seifried and Rausch, 2022). However, AI enables contextualized and timely nudges (prompts). Different types of nudging can be implemented during AI use, within EPSS, and in smart collaboration platforms. However, since there is hardly any empirical research, it will be important for future research to focus on the effects of nudging (prompting) strategies in the context of informal workplace learning (Bell, 2017). A possible downside of nudging might be that, to some degree, it formalizes informal learning, a general paradox addressed by Rintala et al. (2019) and also discussed in

the context of cultivating communities of practice (Wenger et al., 2002).

The practical implications derived from this conceptual paper suggest that organizations should address all types of informal learning—ranging from implicit to deliberative learning—and should therefore intentionally design workflows and digital environments that support not just performance but also ensure informal opportunities to learn embedded in work processes. Different technologies can support different problem-solving resources. Practitioners should not ask “Which tool is best?” but “Which resource do we want to provide for which kind of work processes?” This more analytical perspective helps avoid technology-driven decisions and enables learning-driven designs of workflows and workflow support. Generative AI should be used to trigger and support learning, not to replace it. To avoid the “AI ghost-learner effect” (i.e., performing via AI without developing competence), organizations could implement nudging mechanisms that foster reflection. Simulated work environments (e.g., via metaverses) can function as representative resources, enabling experimentation with complex problems in situations where real-world trial and error would be too risky or costly. Collaboration platforms are already widely in use, but they are usually not intentionally designed to support informal workplace learning activities. Organizations can scaffold reflecting on, researching for, and the documentation of learning in these collaboration platforms. Creating social presence in collaboration platforms, encouraging a general learning orientation when collaborating in virtual teams or with AI agents, and using AI to connect these platform activities to skill profiles, skills ontologies, and context-sensitive learning materials will help further fostering reflection, researching, advice-seeking and knowledge sharing. In a similar vein, the integration of AI and real-time analytics within other software applications (e.g., enterprise resource planning systems; ERP) enables adaptive responses based on user behavior in the moment of need (e.g., tailored nudges, links to learning materials or experts). These developments, however, must be accompanied by clear ethical guidelines and compliance with data protection regulations, especially when user behavior is monitored or learning-related data is processed. Altogether, HRD should, of course, try to improve employees’ AI adoption (Khandelwal et al., 2024) but, at the same time, by providing an adequate digital infrastructure can also foster “digitally minded and agile organizational cultures, structures, and workforce practices.” (Thite, 2022, p. 10).

The research implications derived from this conceptual paper suggests a closer look at problem-solving and learning processes in the workplace. With regard to workplace learning activities and resources, it is worthwhile to examine the conditions under which specific activities and resources are favored. Field experiments (e.g., waitlist control group designs) could be conducted to evaluate the implementation of the technological tools discussed above. The introduced concept of the “AI ghost-learner effect” calls for research on how employees maintain or lose a sense of ownership when they use AI tools to solve work-related problems and how nudging helps to counteract this. In doing so, some of the above questions could be addressed via interviews. However,

to gain closer insights into everyday informal workplace learning, it seems advisable to use more fine-grained, *in situ* methods for data collection such as experience sampling or diaries (Rausch et al., 2022; Seifried and Rausch, 2022). Furthermore, many of the workplace learning activities discussed here generate digital traces, making the analysis of resulting log data a promising avenue for research. However, such analyses must be conducted with careful attention to ethical standards and data protection regulations, particularly when dealing with sensitive behavioral or performance-related information. In addition to these situational factors (within-person perspective), individual differences should also be taken into account (between-person perspective). A broad range of possible influencing factors at the personal level includes work experience, domain-specific competences, motivation, and technology acceptance including perceived usefulness and ease of use of digital tools. Finally, differences in organizational contexts such as the organization of work, the digital tool environment, team climate, psychological safety and so forth should also be considered as influencing factors (see 3-P model by Tynjälä, 2013). Multilevel analysis (i.e. hierarchical linear models, mixed models) enables researchers to disentangle within-person dynamics from between-person differences in intensive longitudinal designs.

5 Conclusion

In response to ongoing technological transformations and shifting work practices, this paper has emphasized the increasing importance of informal workplace learning as a key mechanism for adapting to changing demands. Building on a problem-solving perspective, a framework that categorizes informal learning activities is proposed that distinguishes reasoning, experimenting, researching, and observing and links these activities to various resources. This lens enables a systematic understanding of how emerging applications—based on analytical and generative AI—can support informal learning processes embedded in everyday work. These tools can foster learning through contextualized support and reflection prompts within specific business software or collaboration platforms. At the same time, if problem solving is overly delegated to AI, employees may lose learning opportunities—a risk that is termed the “AI ghost-learner effect.” To ensure that technology supports rather than replaces learning, intentional design of workflows and digital environments is needed. The framework developed here serves as a conceptual foundation for future empirical research on informal workplace learning in digitalized work contexts. It encourages analytical differentiation of learning activities and resources and invites investigations into the impact of specific technologies and corresponding implementation strategies.

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AR: Conceptualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

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