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Your AI Trainer: Generative AI Dashboards for Vocational Education and Training



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Your AI Trainer: Generative AI Dashboards for Vocational Education and Training¹

1 Skills Shortages, Apprenticeship Training, and New Opportunities for AI-assisted Learning

Germany faces substantial labour shortages (cf. GROISS/SONDERMANN 2025), which is largely driven by demographic change, in particular workforce ageing and the retirement of large cohorts.² As the share of young people gaining a vocational education and training (VET) certificate decreases while the share of people gaining higher school level certificates and academic education increases, these labour shortages are particularly pronounced in the medium skills level (cf. VANDEPLAS/THUM-THYSEN 2019). During times of labour shortages, firms rely more heavily on their existing workforce. Training apprentices is one potential strategy for meeting future skills needs (cf. LANGEN 2025). However, evidence from Germany indicates that both the number and the share of firms offering apprenticeships has been declining in recent years (cf. MOHR 2025b), which complicates relying on apprenticeship training alone to close gaps in future skills. This decrease differs especially by firm size and is strongest in small firms with up to nine employees. At the same time, small firms face the biggest problems when filling VET positions: 55% of the firms with up to 9 employees do not succeed in finding suitable applicants for VET positions (cf. MOHR 2025a). In consequence, they lower their hiring standards and recruit applicants with lower school-leaving certificates (cf. FRIEDRICH 2025). However, almost 30% of all VET training contracts end prematurely (cf. UHLY 2025). A crucial risk factor for permanent dropout is apprentices lacking important competencies, such as low mathematical ability (cf. HOLTMANN/SOLGA 2023).

Generative AI offers the potential to mitigate skills shortages by enabling learning solutions tailored to individual needs (cf. AYENI et al. 2024; EZZAIM et al. 2025; FRANCESCHELLI/MUSOLESI 2024). Heterogeneous skill levels among applicants are particularly relevant in VET, where some entrants lack competencies required to start and successfully complete an apprenticeship. Individualised learning approaches can help address these differences and reduce dropout risks. AI-assisted learning dashboards provide one promising approach. By continuously analysing learners' progress and interaction patterns, such systems can adapt learning content, difficulty levels, and pacing to the individual apprentice. For example, an apprentice struggling with basic technical calculations could receive additional practice tasks

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2 We acknowledge the use of ChatGPT (OpenAI) and Claude (Anthropic) in January 2026 for language editing and refinement.

and step-by-step explanations, while more advanced learners could be offered more complex problem-solving exercises or realistic workplace simulations. To sustain motivation and engagement, gamification elements can be integrated into AI-assisted learning dashboards. For instance, apprentices may earn achievement badges for mastering specific skills, collect points for completing learning modules, or track their progress through visual competence maps (cf. BENNANI/MAALEL/BEN GHEZALA 2022). Such features can encourage continuous learning while making progress more visible to both apprentices and trainers.

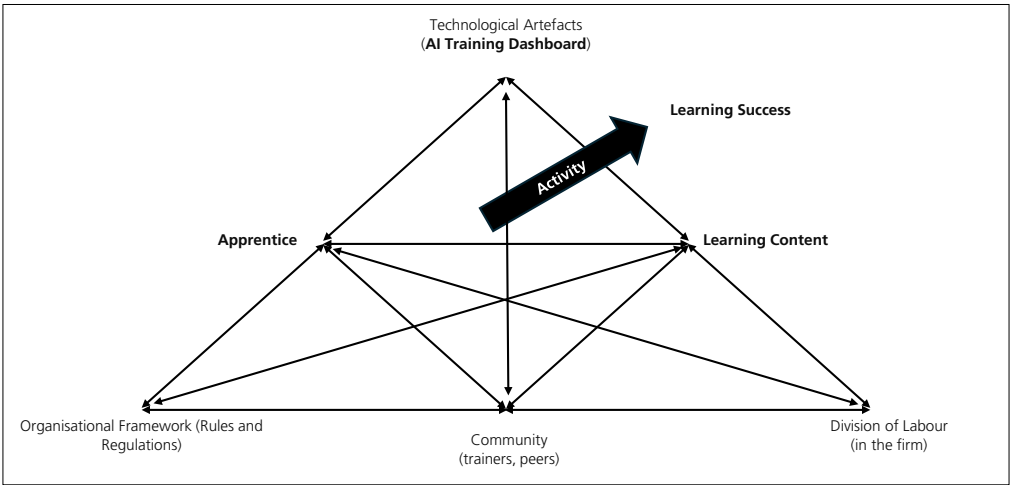
This article makes two key contributions to the ongoing discourse on the use of generative AI in vocational education and training (VET). First, it applies and adapts activity theory to the context of firm-based learning, highlighting the embeddedness of learning processes within a multi-actor socio-technical system. Second, it translates this theoretical perspective on human-computer interaction into practice by developing a prototype of an AI-assisted training dashboard for apprentices, thereby demonstrating how generative AI can be leveraged to enhance workplace learning outcomes.

The article is structured as follows: it first outlines the theoretical framework of AI-supported learning, then presents the prototype dashboard as an illustrative application, and finally discusses key considerations for the implementation and evaluation of AI-assisted training systems in organisational contexts.

2 Perspectives from Activity Theory and Human Computer Interaction

According to activity theory (cf. ENGSTRÖM 1987; 2014), learning is a collective activity embedded in socio-technical contexts in which technological artefacts affect learning processes. Figure 1 depicts an activity system, with arrows indicating the interrelations between its constituent elements.

Figure 1: Activity Theory in a training firm context

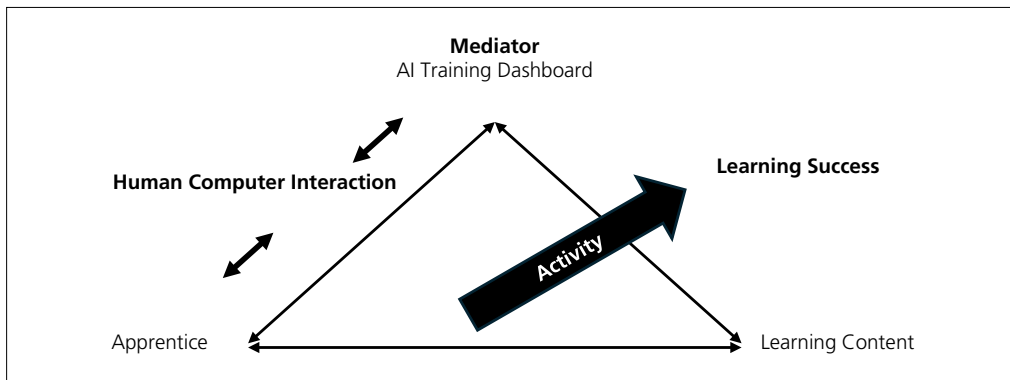


Source: own representation based on ENGSTRÖM 1987

Following this theoretical approach, learning activity is not a single action carried out by an individual but a joint activity involving multiple actors. In this constellation, the apprentice is embedded in an institutional setting shaped by the organisational framework of the training firm, including its rules, norms, and regulations. Learning is facilitated through the provision of learning materials, structured tasks, and practical examples, as well as through opportunities for questions, feedback, and discussion. VET trainers play a central role in organising and supporting these learning processes and fulfil an important intermediary function by balancing management interests (e.g. productivity requirements and standardisation pressures) with expectations of apprentices (cf. NICKLICH/BLANK/PFEIFFER 2025; BAHL 2019). Yet, viewing training as the responsibility of an individual trainer alone overlooks the collective and organisational nature of apprenticeship training. In practice, multiple employees are involved, and institutional arrangements on the level of the firm substantially shape learning experiences (cf. BAHL 2019). Also, peer effects may play a role in learning and VET success, as effects of the reference-group with respect to occupational status and achievement influence satisfaction and motivation of the apprentices (cf. THEUER 2025). Within the internal division of labour, the allocation of tasks links work activities to learning content and skills development, and empirical evidence suggests that training processes emphasising task variety and problem-solving are associated with improved training outcomes, particularly in terms of skills development and successful completion of training (cf. BURÉN/SCHWERI 2024).

Drawing on an activity theory approach to human-computer interaction, technological artefacts are understood not merely as tools but as mediators that actively shape learning activities (cf. BERTELSEN/BØDKER 2003). Figure 2 conceptualises the AI-assisted training dashboard as a mediator between the subject (the apprentice) and the object (the learning content).

Figure 2: Human Computer Interaction within the activity theory framework



Source: own representation based on BERTELSEN/BØDKER 2003

Rather than merely delivering instructional material, the AI-assisted training dashboard structures how apprentices engage with learning content by dynamically adapting tasks, feedback, and explanations to individual learning trajectories. Embedded within collective training arrangements involving multiple actors, the organisational framework and a firm's

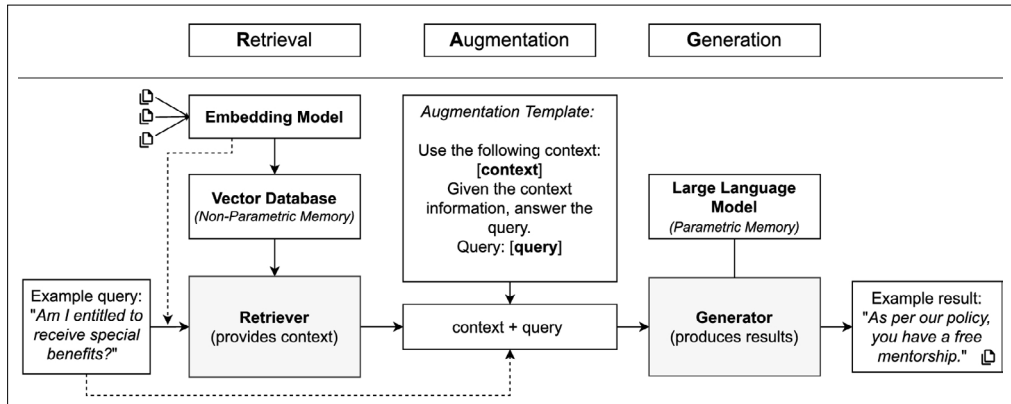
division of labour, the dashboard functions as a mediating artefact within ongoing learning activities rather than as an isolated instructional tool. In this role, it becomes an integral part of the learning activity itself, shaping apprentices' learning processes within the firm-based training context. For example, imagine a manufacturing firm where apprentices rotate between different departments such as assembly, quality control, and logistics as part of their vocational training. The AI-assisted dashboard can track the apprentice's progress in each area and identify specific competencies that need improvement, such as mathematical skills in quality control or technical vocabulary in assembly. Trainers from each department can input feedback and set targeted tasks, while the dashboard adapts learning materials and tests to the current needs of the apprentice. Moreover, the apprentice can use the dashboard to ask questions and receive instant, context-sensitive explanations, and even compare their progress with peers in other departments. In this way, the dashboard does not simply deliver content but actively mediates the collective learning process by facilitating communication between trainers, providing tailored resources, and fostering peer learning within the firm's organisational structure.

3 Your AI Trainer – An Interactive, AI-assisted Training Dashboard

3.1 Overview of Technical Features

We developed a prototype of an AI-assisted training dashboard based on Large Language Models (LLMs) to demonstrate how firms may use such systems to enhance apprenticeship training. The dashboard allows firms to upload their own training materials. These materials form a curated knowledge base for learning activities. Apprentices can adjust the preparation of learning content; for example, they can select the language style, modify the level of detail, or change the presentation format. The dashboard's aim is to create tailored knowledge dissemination, particularly by avoiding external, unverified sources to consistently reduce hallucinations – false or invented information generated by AI. Technically, the dashboard is based on a multi-layered architecture. First, the uploaded documents undergo thorough data preprocessing, which includes text normalisation, segmentation into meaningful sections, and semantic annotation. These steps are essential to optimally prepare the content for automated processing. Subsequently, the text segments are transformed into high-dimensional vector representations using modern embedding methods. These vectors are stored in a specialised vector database that enables fast and precise similarity searches.

The dashboard uses a concept named Retrieval Augmented Generation (RAG) (Figure 3, cf. (KLESEL/WITTMANN 2025)). RAG is a hybrid framework that dynamically grounds generative AI outputs in external, domain-specific knowledge bases without requiring retraining the model.

Figure 3: Proposed RAG architecture

Source: KLESEL/WITTMANN 2025, p. 554, licensed under CC BY 4.0

The process follows a sequential three-step pipeline:

- 1. Retrieval:** The system executes a semantic search across a vectorised knowledge base to identify relevant textual chunks upon receiving a user query. It is like having a huge library of documents, all converted into a format the computer can easily search. When the apprentice asks a question, the system quickly scans this library to find the most relevant pieces of information, similar to looking for the right chapter in a book.
- 2. Augmentation:** The retrieved documents are integrated into the prompt context, effectively instructing the model to utilise this specific evidence rather than relying solely on its pre-trained parametric memory. The computer then takes the bits it found and places them in front of the AI, making sure it uses these specific pieces of information when forming an answer.
- 3. Generation:** The LLM synthesises a response derived strictly from the augmented context, ensuring that answers are factually accurate, traceable to specific sources, and aligned with organisational data.

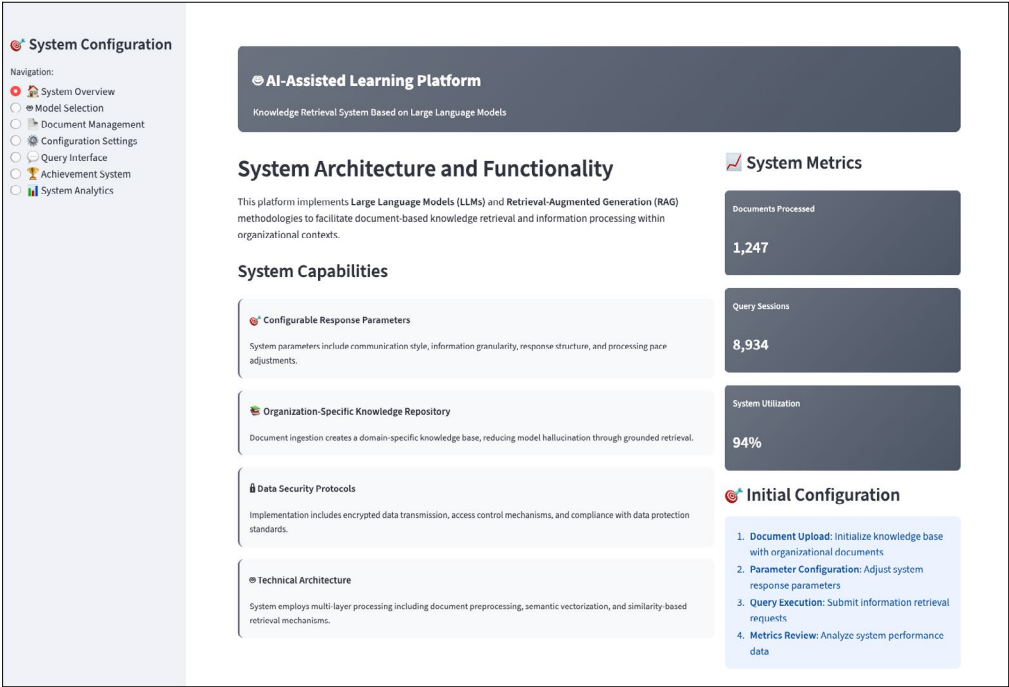
The model thus produces evidence-based outputs, minimising the risk of unsubstantiated or fabricated statements. Integrated mechanisms further exclude unverifiable information or flag it to indicate uncertainty. In short, this model always checks its facts and avoids making things up. If it cannot verify some information, it either leaves it out or marks it to indicate uncertainty.

3.2 Visual Representation of Features

The dashboard's objective is to offer an interface that allows apprentices to directly input their preferences and thereby adjust the prompt parameters for the LLM. For instance, the style of addressing the user, the desired level of detail of the learning material, or the format (explanation, bullet points, examples) can be configured using sliders. This dynamic control may increase user satisfaction and promotes an individualised learning experience.

The dashboard integrates a central management interface that operationalises the RAG pipeline through three distinct functional layers (Figure 4), which can be interpreted as elements of a socio-technical activity system. Within this system, VET trainers assume a key mediating role by configuring, monitoring, and adapting the system in line with both organisational requirements (e.g. data security, norms and standards) and pedagogical objectives. The System Capabilities module (left) governs the core processing logic, enabling trainers to define response parameters (e.g. style, granularity) and curate the organisation-specific knowledge repository, thereby shaping the mediating artefacts through which apprentices engage with learning content. The System Metrics panel (right) supports operational stability by providing real-time telemetry on knowledge base scale (“Documents Processed”) and computational load (“System Utilization”), enabling trainers to oversee system performance and align technical functioning with training processes.

Figure 4: AI-assisted Learning Dashboard – System Overview Pane



Source: own representation

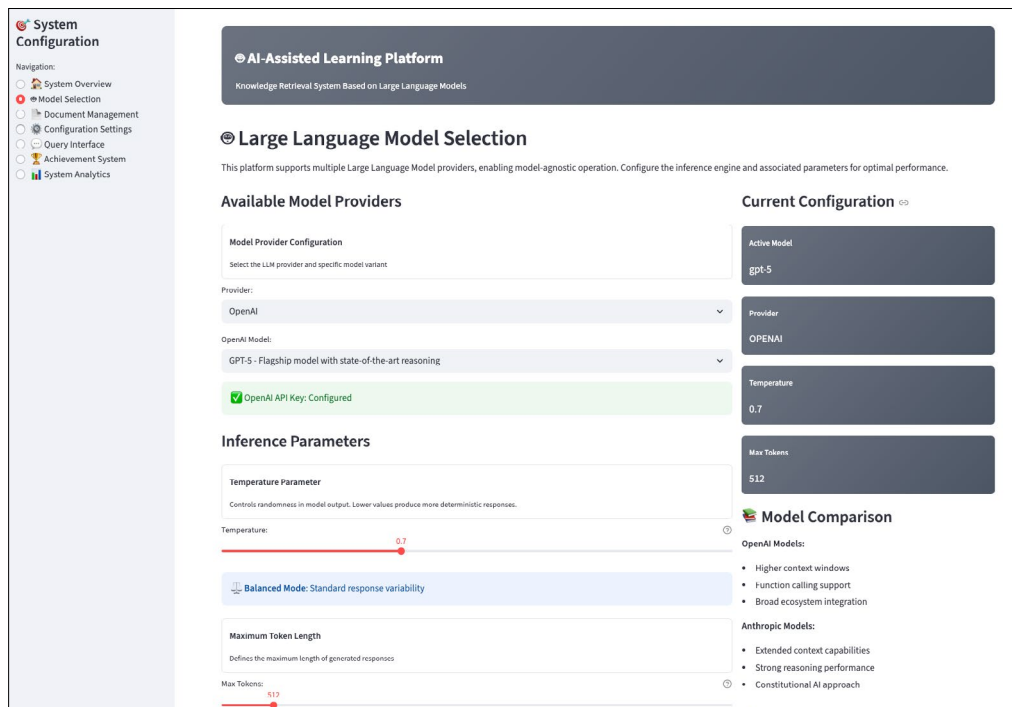
The dashboard is designed to be flexible. It enables VET trainers to choose between different AI systems according to their training needs (model-agnostic inference layer; LLM providers such as OpenAI, Anthropic, or Mistral AI). For example, trainers may select a suitable model to explain basic concepts or to support more complex problem-solving tasks. The Provider Configuration panel (top left) is used to set up and manage access to these systems (API authentication and model versioning), while the settings below allow trainers to adjust how the

AI responds – for instance, whether answers should be more precise or more exploratory, and how detailed they should be (inference parameters such as temperature and maximum token length).

In practice, this enables trainers to adapt the system to different learning situations: more structured and concise responses can be used for standardised training content, while more open and detailed answers can support individual learning and reflection. The Current Configuration panel (right) provides an overview of the selected settings and helps trainers understand how different configurations may influence the quality and style of responses (real-time feedback on active model settings and comparison of model capabilities, e.g. context window and reasoning performance).

Overall, the dashboard supports trainers in their role as facilitators of learning by giving them control over how AI-generated content is tailored to learning needs of apprentices.

Figure 5: AI-assisted Learning Dashboard – Model Selection Pane



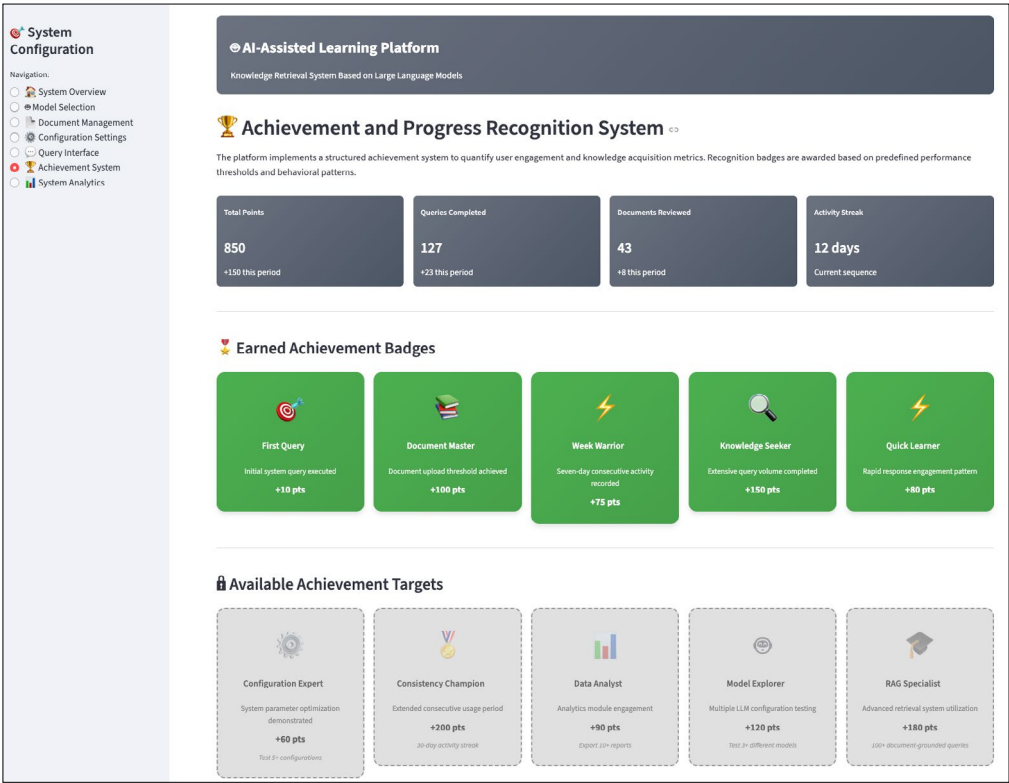
Source: own representation

The dashboard integrates a structured achievement and progress recognition subsystem (Figure 6) designed to support sustained engagement and continuous learning within the AI-assisted training environment. This module uses gamification elements to make learning progress visible and motivating, transforming passive information use into a more active and trackable process. It comprises two main components: Continuous Engagement Metrics,

which reflect ongoing learning activity, and Threshold-Based Achievement Markers, such as points or badges that signal the attainment of specific milestones.

In addition, the system enables comparison with peers, allowing apprentices to situate their progress relative to others. Such comparative feedback can foster motivation but also requires careful interpretation. VET trainers therefore play a crucial role in contextualising performance indicators, mitigating potential demotivation or unhealthy competition, and maintaining peer comparisons as a support for rather than a distortion of learning processes. By visualising progress and achievements, the system seeks to link external incentives (e.g. points and badges) to learning outcomes (e.g. knowledge acquisition and skills development). Trainers act as key mediators in this process. They integrate these indicators into pedagogical practice and align them with organisational training objectives as well as the individual learning needs of apprentices.

Figure 6: AI-assisted Learning Dashboard – Gamification System



Source: own representation

3.3 Benefits of this Dashboard

The integration of proprietary firm knowledge with Large Language Model (LLM) technology provides the basis for a learning dashboard that can support apprenticeship training. From

the perspective of activity theory, the dashboard can be conceptualised as a mediating artefact that shapes how apprentices engage with learning tasks, workplace knowledge, and training objectives. It does not replace human instruction; rather, it structures the interaction between the apprentice, the learning task or occupational problem, and the broader activity system, including rules, division of labour, and the training environment. Within this framework, VET trainers remain central actors. They guide learning processes, interpret workplace requirements, contextualise AI-generated information, and ensure that the system is used in pedagogically appropriate ways. The dashboard can support trainers by structuring complex work-related problems into step-by-step explanations and by adjusting learning content to the apprentice's current level of understanding and pace.

Avoidance of AI Hallucinations

A central advantage of the proposed approach is the reduction of AI hallucinations, which pose a significant threat to learning accuracy when systems generate plausible but incorrect information. This risk can be reduced using controlled learning environments in which firms upload verified and authoritative training materials, guaranteeing the quality and reliability of the content provided and strengthening the credibility of the AI system.

By integrating the AI-assisted learning dashboard with a curated repository of firm-specific documents, the system minimises reliance on generic or publicly available data, which are more prone to inaccuracies. The dashboard's design mandates that only validated materials are used as the primary knowledge source, anchoring AI responses in factual, contextually-relevant content.

Furthermore, the system employs a real-time monitoring mechanism that detects when the knowledge base is not properly initialised, when e.g. the document repository is empty. In these cases, the dashboard automatically switches to a general knowledge mode, alerting users to potential limitations in the AI's grounding. This transparent approach allows users to distinguish between responses based on authoritative firm data and those generated from standard language model inference, thereby reducing the risk of unintentional misinformation.

The configuration validation module ensures consistent application of output parameters (e.g., granularity and structure), supporting accurate and reliable content. By reducing AI hallucinations, the dashboard safeguards learning outcomes, reinforces training integrity, and enables organisations to confidently deploy AI for skills development and knowledge transfer.

Data Confidentiality

Firm documents may contain confidential information; therefore, security and data protection are critical. Data flows are fully encrypted, access rights strictly controlled, and stored data managed in line with applicable standards. Authentication and role-based permissions limit access to authorised users, reducing the risk of data leaks. Audit trails and compliance checks further ensure accountability and traceability.

The dashboard can be deployed for offline or local operation when used with open-weight models, directly addressing data security concerns and guaranteeing that sensitive firm-spe-

cific knowledge remains protected within the organisation. By not relying on external or cloud-based servers, the dashboard effectively eliminates exposure to internet-based threats, making it especially suitable for firms with heightened confidentiality requirements or those operating under strict regulatory environments. This comprehensive security approach not only safeguards intellectual property but also builds trust among users and stakeholders by demonstrating commitment to data privacy and protection.

Model-agnosticism

The system is model-agnostic, allowing firms to choose among different large language models and to evaluate which model best suits their specific operational requirements and training needs. This flexibility enables organisations to adapt the dashboard to their preferred AI technology, whether it be open-source models, proprietary solutions, or those tailored for industry contexts. By not being tied to a single AI provider, firms can respond quickly to technological advancements, regulatory changes, or shifts in business priorities.

Moreover, model-agnosticism supports the integration of custom models, which ensures that training content remains closely aligned with organisational goals and learner profiles. While these design choices offer clear advantages, further research is required to assess their effectiveness in addressing the broader range of challenges associated with AI-enhanced learning systems, such as maintaining consistent quality across models, robust security standards, and guaranteeing seamless interoperability within diverse IT environments.

3.4 Limitations of AI-assisted Training Dashboards

Despite these benefits, significant challenges remain in maintaining the effectiveness of AI-assisted learning dashboards. From an activity-theory perspective, learning outcomes arise not from the mere provision of tools but from the interaction between subjects (apprentices), mediating artefacts (the dashboard), the organisational framework, the community, the division of labour, and the training content (object). A key limitation is sustaining apprentices' motivation over time, as AI systems struggle to replicate the emotional, social, and situational cues provided by human instructors and peers. Further concerns include inefficient learning practices, with learners tending to engage primarily with familiar content rather than extending their competencies.

Beyond these pedagogical challenges, significant implementation barriers must be considered. The development, integration, and maintenance of AI-assisted dashboards are associated with high financial and organisational costs, particularly when firm-specific knowledge bases, secure infrastructures, and customised interfaces are required. Moreover, the effective use of such systems presupposes substantial competence development among VET trainers who must acquire not only basic digital skills but also a deeper understanding of AI systems, their limitations, and their pedagogical integration. In terms of activity-theory, this implies a reconfiguration of the division of labour, as trainers take on new roles as facilitators, interpreters, and critical evaluators of AI-generated content. Without this expertise, there is a risk that the system is either underutilised or used in pedagogically suboptimal ways.

Importantly, the technical quality of an AI system alone does not guarantee learning success. Motivation and the active involvement of training personnel remain decisive factors.

Consequently, AI-assisted dashboards should not be treated as stand-alone solutions but must be deliberately embedded into the broader learning system – complemented by social interaction, professional guidance, and organisational integration – in order to unfold their full educational potential.

4 Implications and Future Directions of Research

This paper has demonstrated how an AI-assisted dashboard can enhance workplace learning, offering tangible opportunities for its integration within vocational education and training (VET) practice. By conceptualising the dashboard as a mediating artefact within an activity system – connecting apprentices, trainers, organisational rules, and the division of labour – it becomes evident that successful learning outcomes are the result of the dynamic interaction between technological, social, and institutional elements, rather than being solely dependent on technical solutions.

The dashboard presented here marks an initial exploratory step, establishing a solid basis for future empirical investigation. Implementation studies and randomised controlled trials (RCTs) are recommended to rigorously assess its impact on learning outcomes. Such studies could involve assigning apprentices to treatment and control groups, with learning achievements measured both before and after the intervention, thereby enabling causal inference regarding the effectiveness of specific dashboard designs. To uphold ethical standards and promote fairness in educational environments, it is crucial that, after the experimental phase, all apprentices are provided access to the same dashboard and its features.

Beyond its academic contribution, the dashboard is highly relevant from a training policy perspective, particularly in the context of ongoing debates on digitalisation, quality assurance, and innovation in VET. However, its broader diffusion – especially among small and medium-sized enterprises (SMEs) – is likely to depend on the establishment of inter-organisational training networks that enable firms to share implementation costs, infrastructure, and expertise. Such collaborative arrangements can lower entry barriers and facilitate the collective development and maintenance of AI-supported learning dashboards.

At the same time, maintaining control over sensitive firm data remains a central prerequisite for its adoption. This highlights the importance of data sovereignty and the development of European-based AI solutions and infrastructures that comply with strict data protection standards and reduce dependence on external providers. Ensuring that organisational knowledge remains securely embedded within the firm or trusted networks is critical for building trust and long-term usability.

From a policy perspective, targeted support measures are required to enable firms to effectively implement and use such dashboards. This includes funding schemes, shared platforms, and, crucially, programmes for training VET personnel, as trainers must develop the competencies needed to integrate AI tools pedagogically into learning processes at the workplace. In terms of activity theory, this entails a transformation of the division of labour and the strengthening of the roles of trainers as facilitators and mediators of AI-supported learning.

Finally, future research should explore the potential of fine-tuning AI models to further adapt training content to specific organisational contexts and learner needs, thereby enhan-

cing the flexibility and effectiveness of AI-assisted dashboards. Overall, the perspective of activity theory underscores that AI-based learning systems will only realise their full potential when embedded in collaborative, well-supported, and institutionally-aligned training ecosystems.

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