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THE ROLE OF ARTIFICIAL INTELLIGENCE IN THE PERSONALIZATION OF TRAINING PROCESSES IN THE CONTEXT OF SOCIETY 5.0

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Purpose: The article aims to concisely present the role of artificial intelligence in personalizing training processes in the light of the Society 5.0 paradigm.
Methodology: A method of analysis and critique of the literature was applied. Searches were conducted using predefined queries in scholarly databases: Google Scholar, Scopus, and Science Direct. The academic sources were supplemented with industry literature and verified online sources relevant to the topic.
Findings: Artificial intelligence is a key mechanism for the personalization of training processes, enabling the design of flexible, adaptive, and inclusive learning systems aligned with the concept of Society 5.0. Integrating AI into training systems makes it possible to develop knowledge and skills–and thus professional competencies. At the same time, ethical and technological challenges indicate the need for further research and responsible implementation practices.
Practical implications: Organizations should build interoperable ecosystems of data on learning and employee training in order to monitor progress in real time, audit personalization decisions, and iterate training and development programs more quickly.
Social implications: Personalizing the training process with the use of AI lowers educational, geographic, and architectural barriers, supporting diverse employee groups, including those at risk of exclusion (inclusiveness). At the same time, transparent data–governance rules, continuous human oversight, and regular audits of learning algorithms are necessary. From an organizational perspective, this fosters a learning culture and occupational mobility.
Originality: The article's originality stems from combining the personalization of training processes with the Society 5.0 model and an interoperable data infrastructure. Drawing on international literature, it enriches the existing body of knowledge on human capital in enterprises, signaling the author's contribution to the development of the field of management and quality sciences. The article is addressed primarily to researchers and scholars working in management. In addition, it is valuable for managers and HR professionals directly concerned with implementing AI–based technologies in training processes.
Keywords: Society 5.0, employee training, artificial intelligence.
Category of the paper: General review.

1. Introduction

In Society 5.0, the physical and digital spheres are tightly interconnected, which is intended to enhance employee safety, well–being, and development (Nakanishi, Gonokami, Takahashi, 2020). This concept envisages a transformation not only of industry but also of living environments and societal habits (Deguchi et al., 2020). Human-centrism–placing the human being, rather than technology, at the center–emphasizes welfare, psychophysical safety, needs, and opportunities for individual development (Del Giudice, Scuotto, Papa, 2023; Grudowska, Zieliński, 2022; Khullar et al., 2024). In this perspective, artificial intelligence (AI) supports equalizing educational opportunities, reducing geographical barriers, and fostering lifelong learning (Hamid, Ab Wahid, 2024; Foresti et al., 2020). Personalized educational platforms based on big-data analytics make it possible to tailor curricula to changing labor-market demands and to individual development pathways (Chen, 2023; Maghsudi et al., 2021; Xiao, Yi, 2020).

Organizations transitioning to skills-based models use AI to identify competency gaps and recommend micro-development pathways, which–according to industry and policy reports–accelerates reskilling and shortens the “half-life of skills” (OECD Digital Education Outlook, 2023; Workplace Learning Report, 2024; Deloitte, 2025). In parallel, ethical (privacy, impartiality, data security) and technical (data interoperability) challenges arise (Uddin et al., 2025).

In Polish-language literature on AI-enabled personalization of employee training, English-language contributions still predominate and the number of peer-reviewed studies remains limited. In market practice, the level of AI adoption by firms in Poland is still low. According to the latest Eurostat data, in 2024 only about 5.9% of enterprises reported using AI solutions, placing Poland among the lowest in the European Union (Eurostat, 2025).

The aim of this article is to review research from 2020–2025 on the implementation of AI in the personalization of employee training and to provide concise answers to two questions:

1. What are the possibilities for using AI to personalize employee training systems?
2. What additional effects accompany the introduction of AI into the training process?

2. Methods

A qualitative, problem-oriented non-systematic literature review was employed. This approach is appropriate when the aim is to conceptually map the field and integrate dispersed mechanisms (LLM tutoring, Knowledge Tracing, Reinforcement Learning, VR) with the Society 5.0 framework and interoperability infrastructure (xAPI/Caliper/LTI), rather than to produce a quantitative synthesis of effects (cf. Snyder, 2019).

The review was limited to 2020-2025 and focused on scholarly articles, trade press, and industry reports. Because the first wave of mass remote learning occurred during the COVID-19 pandemic, publications from 2020-2022 serve primarily as theoretical background. The main horizon of the review covers 2023-2025, reflecting rapid advances in artificial intelligence and its cross-sector implementation. The 2020-2025 window captures the technological inflection that began in 2020, including the emergence of large language models and the application of reinforcement learning, virtual reality, and extended reality.

Searches were conducted using predefined queries across three academic databases: Google Scholar, Scopus, and ScienceDirect. A non-systematic review was then performed based on the keywords *Society 5.0*, *employee training*, and *artificial intelligence* in various combinations, with Boolean operators (AND, OR, NOT) and special characters. Google Scholar initially returned 90 records containing combinations of these terms. Scopus yielded 629 items, which were reduced to 138 after restricting to the *Business, Management & Accounting* subject area. ScienceDirect produced 914 sources, narrowed to 162 under the same subject constraint. In the next stage, the content of shortlisted materials was screened for topical relevance, followed by an in-depth analysis of the retained literature; principal findings are reported in the results section. The scholarly corpus was complemented by trade literature and vetted online sources.

This method enabled the collection and critical synthesis of the latest evidence on the effectiveness of AI for personalizing training processes, and its alignment with the Society 5.0 framework and interoperability standards.

3. Results

Studies show that applying artificial intelligence to employee training is associated with a higher level of personalization and better learning outcomes compared with traditional training approaches (Alasfour, Alsmaeel, 2025; Kestin et al., 2025; Hrytsenko et al., 2024).

Findings from the literature review indicate that AI enables the personalization of corporate training by continuously identifying training gaps (Chen, 2023), tailoring the sequence of tasks, the difficulty level, and the type of support to the learner's profile, and dynamically adjusting training content and pacing (Rane, Choudhary, Rane, 2023; Pandya, 2024; Alasfour, Alsmaeel, 2025). This is based on analyses of learning behaviors, preferences, progress, individual aspirations and career goals, as well as current competence levels (Tusquellas, Santiago, Palau, 2025; Sha Ri Na, 2023).

Knowledge Tracing models (including Bayesian Knowledge Tracing, Deep Knowledge Tracing, and Self–Attentive Knowledge Tracing) estimate a worker's current knowledge or skill state and predict the probability of a correct response at the next step in learning.

Newer approaches–explainable Knowledge Tracing (xKT)–also clarify why the model assesses mastery of a given skill at a particular level, which leads to a more appropriate selection of content and its level of advancement (Abdelrahman, Wang, Nunes, 2023; Sarsa, Leinonen, Hellas, 2022; Bai et al., 2024; Su et al., 2023).

Reinforcement Learning helps the system accurately select the next learning step (e.g., which module or exercise to launch), thereby accelerating and improving training progress (Lan, Baraniuk, 2016; Cai et al., 2021; Memarian, Doleck, 2024; Mon et al., 2023). Contextual Bandit algorithms–methods that choose the best next activity based on the user profile and current context–support personalized selection of learning actions and increase the relevance of recommendations (Lan, Baraniuk, 2016; Cai et al., 2021; Memarian, Doleck, 2024; Mon et al., 2023).

Large Language Models (LLMs) act as co–tutors: they ask guiding questions, offer hints and clear explanations, and structure the flow of learning. Studies show that, compared with traditional approaches, this leads to better outcomes and higher engagement (Kestin et al., 2025; Vanzo, Chowdhury, Sachan, 2025; Labadze, Grigolia, Machaidze, 2023). In addition, these systems can forecast future skill needs and build personalized development pathways accordingly (Madhumithaa et al., 2025).

In virtual reality (VR), training is adaptive–the system continuously adjusts difficulty and support, controls learning pace, and monitors specific behaviors. This reduces errors and facilitates transfer of skills to real workplaces (Tashev et al., 2023; Hrytsenko et al., 2024).

At the organizational level, AI implementations are associated with cost reductions (travel, trainer time, materials, etc.) and with the automation of content development and formative assessment, which shortens delivery and scaling time for training (Masrek, Anuar, Mazlan, 2025; Smith, Taylor, Underwood, 2024; Pesovski et al., 2024). Continuous progress monitoring and immediate feedback further increase learning productivity and make it easier to adjust development pathways during the program (Hrytsenko et al., 2024; Chen, 2023). Consequently, this shortens the time required to reach the target competence level and boosts employee engagement, motivation, and on-the-job effectiveness (Shvardak, Popovych, 2025; Hrytsenko et al., 2024; Aldyandra, 2024; Barrera Castro et al., 2024; Tapalova, Zhiyenbayeva, 2022; Chen, 2023).

The review indicates that effective and scalable personalization requires access to consistent "learning traces" and interoperability across tools used in the Learning & Development ecosystem. The sources examined identify the xAPI standards (IEEE 9274.1.1–2023/xAPI 2.0) and Caliper Analytics (1EdTech) as key technical mechanisms for normalizing event logging, as well as LTI 1.3 for secure integration of tools with Learning Management Systems (e.g., Moodle, Canvas, Blackboard) while maintaining data continuity. Applying these standards enables continuous outcome monitoring and the auditability of personalization decisions at the organizational level (Hernández-de-Menèndez et al., 2022; Experience API overview, 2024; 1EdTech/IMS–Caliper, LTI).

“Learning traces” are understood as digital records of employee activity generated during interactions with materials, tools, and people. Data sources include: learning platforms (e.g., module and quiz logs, simulators, mobile apps, MOOCs); immersive environments–virtual/augmented/mixed reality (e.g., hand trajectories, collision paths, controller pressure, reaction time); support tools (e.g., chatbots/LLMs: type of intervention, effectiveness after a hint); and devices/sensors (e.g., eye–tracking, haptic controllers, location beacons). Consistent recording of these data in interoperable standards (xAPI/IEEE 9274.1.1–2023, Caliper Analytics) enables real–time progress monitoring and powers personalization algorithms and “next–step” recommendations (Hernández-de-Menèndez et al., 2022; Experience API overview, 2024; 1EdTech/Caliper; da Silva Soares Jr. et al., 2023; Liu, Cui, 2025; Abdelrahman, Wang, Nunes, 2023; Ban, Qi, He, 2024).

4. Discussion

The findings of the literature review confirm that applications of AI in employee training lead to a higher level of personalization and better learning outcomes compared with traditional approaches. This aligns with the Society 5.0 paradigm, which emphasizes a human–centric fusion of the physical and digital spheres (Alasfour, Alsmaeel, 2025; Kestin et al., 2025; Hrytsenko et al., 2024; Uddin et al., 2025; Smith, Taylor, Underwood, 2024; Chigbu, Makapela, 2025). In this view, AI does not replace the human being; rather, it strengthens learners’ agency and autonomy, ensuring inclusion and transparency of system decisions. Addressing the first research question posed in the Introduction, the key mechanisms – Knowledge Tracing (including xKT), Reinforcement Learning, Contextual Bandits, LLM tutoring, and VR-operate by continuously estimating an employee’s proficiency, accurately selecting the “next step”, and providing real-time explanations and guidance. This configuration supports optimal cognitive load and faster mastery, which explains the observed advantages over traditional training conditions (Abdelrahman, Wang, Nunes, 2023; Sarsa, Leinonen, Hellas, 2022; Bai et al., 2024; Lan, Baraniuk, 2016; Cai et al., 2021; Memarian, Doleck, 2024; Mon et al., 2023; Kestin et al., 2025; Vanzo, Chowdhury, Sachan, 2025; Tashev et al., 2023; du Plooy, Casteleijn, Franzsen, 2024). Results from meta-analyses/reviews suggest that intelligent tutoring systems and adaptive platforms increase learning outcomes and employee engagement, while the latest randomized controlled trials with LLM tutors indicate significant knowledge gains relative to comparison conditions (Kestin et al., 2025; du Plooy, Casteleijn, Franzsen, 2024). We interpret this as the effect of better “next-step” selection and immediate feedback, consistent with the logic of personalization within the Society 5.0 paradigm.

With respect to the second research question, there are additional, concrete organizational benefits: cost reductions (materials, travel, trainer time), automation of content preparation and formative assessment, and shorter time needed to reach the required competence level. This occurs thanks to immediate feedback and continuous monitoring of progress (Masrek, Anuar, Mazlan, 2025; Smith, Taylor, Underwood, 2024; Pesovski et al., 2024; Hrytsenko et al., 2024; Chen, 2023). The scale of these effects, however, depends on human oversight, the quality and completeness of data, and system interoperability. In relation to the second question, AI systems–by aggregating data on the course of training–enable continuous program optimization: identifying skill gaps, evaluating the effectiveness of interventions, and forecasting development needs, which supports a closer alignment of competencies with job roles and the organization's dynamic requirements. A practical precondition for scale remains an interoperable data infrastructure (e.g., xAPI/Caliper/LTI) that enables combining evidence from multiple tools and auditing personalization decisions.

The magnitude of adaptive effects in VR depends on the fidelity of simulation and the quality of sensory channels: precise motion tracking (head, limbs, whole body), haptics that reproduce resistance and texture, eye tracking that allows monitoring of attention/procedures, and spatial audio synchronized with head movements all increase presence and make feedback more realistic, which helps reduce errors and improves transfer to the workplace. At the same time, richer sensing yields more accurate learning traces (trajectories, reaction times, gaze patterns) that power personalization models and effectiveness audits; without adequate signal quality, adaptation and evaluation may be distorted (see Cyrek, 2025). Proper calibration and hardware comfort condition data reliability; poor tracking or haptics can artificially increase cognitive load. Events from VR (trajectories, collisions) should be recorded in xAPI/Caliper to enable session comparison and personalization audits. Eye-tracking and facial expression data are sensitive and thus require data minimization, purpose limitation, and clear access rules (audit logs).

Masrek, Anuar, and Mazlan (2025) cite examples of platforms/tools that, in their view, offer cost-effective and innovative solutions. From an organizational standpoint, the greatest value of these tools is the shortened time needed to professionally prepare training materials and deploy them on appropriate platforms. Solutions that convert text (e.g., training scripts, blog posts, PDFs) into short video modules reduce time-to-content and facilitate iteration (Lumen5, 2024). Likewise, AI-supported translation and copy-editing enable rapid adaptation of courses to multiple languages and communication styles (DeepL Translator/Write, 2024), which is crucial for distributed teams. Video with synthetic narrators/avatars (Synthesia, 2024) scales the production of training clips without a recording studio, offering ready-made avatars and multilingual voice tracks. This increases accessibility and deployment speed, though it requires clear ethical and licensing rules. On e-earning platforms it is possible to create interactive and adaptive training courses that monitor learner progress (Articulate 360, 2024). Writing-assistance tools (QuillBot, 2024) support the creation and refinement of written training materials–assignments, quizzes, scripts, and summaries. These tools fit the Society 5.0 paradigm because they deliver individualized, multimedia, multilingual resources to trainees more quickly.

Analysis of learner behaviors and data exploration make it possible to quantify effects (e.g., time on task, rate of progress, share of correct responses) and dynamically adjust pathways and content based on feedback, thereby reinforcing personalization mechanisms (Sha Ri Na, 2023).

At the same time, AI implementation entails challenges: data protection, mitigation of algorithmic bias, and provision of adequate technological infrastructure (Rane, Choudhary, Rane, 2023; Pandya, 2024; Aldyandra, 2024; Madhumithaa et al., 2025). To keep the Society 5.0 vision human–centric, clear ethical principles are necessary–data privacy and security, system transparency, human oversight, and respect for learners' agency (Chigbu, Makapela, 2025; Smith, Taylor, Underwood, 2024). Authors emphasize the need to balance technological innovation with ethical requirements so that integrating AI into personalized and adaptive educational environments is both responsible and effective (Rane, Choudhary, Rane, 2023; García-López, Trujillo-Liñán, 2025). In practice, this means regular algorithm audits (monitoring for bias, side effects, and feedback quality) and the establishment of concrete ethical frameworks for learning analytics (García-López, Trujillo-Liñán, 2025).

5. Summary

This literature review covering 2020-2025 indicates that AI-based solutions raise the level of personalization in employee training and are associated with better outcomes than traditional approaches. Beyond the didactic effect, organizations see benefits such as cost reductions, automation of content development and assessment, and shorter timelines for delivering and scaling programs. The effectiveness and auditability of these solutions increase when an organization maintains an interoperable learning-data infrastructure (xAPI/Caliper) and applies human oversight to interactions with AI models. From the Society 5.0 perspective, AI-driven personalization supports inclusive competence development and accelerates reskilling, provided data governance and bias risks are managed responsibly.

This article has several limitations. First, the literature review relied on scholarly databases – Google Scholar, Scopus, and ScienceDirect–which may have constrained the number and quality of retrieved works. Second, the search used specific keyword combinations with Boolean operators, which may have led to the omission of relevant publications and, consequently, narrowed the spectrum of other authors' perspectives.

The article focuses on English-language literature published mainly between 2020 and 2025 and only to a limited extent engages earlier work. Narrowing the review to the pandemic and post-pandemic period increases comparability across AI model generations but may omit prior studies. There is also a risk of selection bias stemming from including only those publications the author considered most valuable.

The analysis presented is secondary (literature-based) and does not include primary data. Although it synthesizes findings from multiple studies, it does not provide new empirical evidence. Despite these limitations, the article can serve as a foundation for further practice-oriented research.

The literature points to the need for additional studies and long-term evaluations in real-world settings (i.e., workplace environments), further development of personalization models, and assessment of how data interoperability (xAPI/Caliper/LTI) affects the quality and auditability of personalization (Bai et al., 2024; Bhutoria, 2022).

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