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Professional Development Analytics: A Smart Model for Industry 5.0

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Abstract: This paper presents a novel AI-driven conceptual smart model designed to help organizations enhance workforce professional development by upskilling and reskilling employees while fostering job satisfaction and staying competitive in their markets; this novel model is called Professional Development Analytics (PDA). The model's main focus is to provide a new design model that concentrates on how artificial intelligence (AI) can optimize personalized training and how it can improve employees' technical and soft skills, enabling companies to create their talent map at the same time. By compiling personnel data and their roles within the company, AI is able to create detailed and personalized profiles. In the next stage, this information is classified, analyzed, and used to enhance current skills while also predicting future training needs. These processes result in the creation of personalized learning paths, where AI recommends customized courses tailored to each employee's unique needs. The system will be automatically fed and adjusted by means of the gathered data and continuous feedback from the employees and their supervisors. The proposed AI tools are powered by machine learning, deep learning, natural language processing, generative AI and data analytics. Our model aims to support learning and development departments by delivering precise, personalized training solutions that address employees' unique needs, enabling skill development and professional growth through an automated and customized process.

Keywords: professional development; artificial intelligence; learning and development; corporate education; Industry 5.0

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1. Introduction

The Fourth Industrial Revolution, often referred to as Industry 4.0, is characterized by the digitization of industries. This era involves the automation of complex tasks and the integration of advanced digital technologies, which connect physical systems, digital platforms, and individuals within a highly intelligent and automated ecosystem [1]. Its main features are the application of technologies such as the Internet of Things (IoT), big data and analytics, artificial intelligence (AI), machine learning (ML), cyber–physical systems (CPSs), automation and robotics, as well as augmented and virtual reality across various industrial processes [2,3]. Industry 4.0 was first introduced in 2011 as part of a high-tech strategy by the German government [4]. Since then, it has transformed into a hallmark of the 21st century, which emphasizes the integration of digital technologies with manufacturing processes to boost productivity, efficiency, and economic growth worldwide [5,6].

Industry 5.0 builds on the principles of Industry 4.0; it addresses its limitations and enhances its strengths. It was promoted by the European Commission in 2021 [7] and it

represents a vision for the future of industry that aligns technological innovation with societal needs and environmental sustainability, fostering a more inclusive and responsible industrial framework [8,9]. This revolution represents a shift from an industry centered on automation and efficiency to a model that emphasizes human–machine collaboration, fosters innovation and promotes alignment with environmental sustainability [10]. It is defined by three fundamental characteristics: human-centric, sustainable and resilient [11].

In this context, human-centricity is focused on the employees' well-being and on guaranteeing that technologies are designed to complement human capabilities instead of replacing them. This approach is closely aligned with the responsible and trustworthy use of AI [12]. Human-centric AI is an approach that places people at the center of the design and implementation of AI systems. It prioritizes security, ethics, privacy, and transparency, while aiming to reduce biases, to create a more inclusive and dynamic industrial environment that benefits both people and society in general [13]. Thanks to AI taking over repetitive and time-consuming tasks, employees can focus on more innovative valuable and strategic work that leverages their unique skills and abilities, fostering a more inclusive and supportive work environment [14].

Placing humans at the center of this new paradigm highlights the importance of professional development (PD) within companies. PD is known as the process by which individuals improve their knowledge and skills or gain new competencies through a variety of learning and development activities and programs, these include formal education, but also job experiences and professional relationships. Its main goal is to help employees advance in their careers, adapt to new working environments, and become more skilled and capable professionals [15]. Personnel are provided training opportunities by learning and development (L&D) professionals who are usually located within human resources (HR) departments. L&D and HR functions and responsibilities become key in this new Industrial Revolution; they are in charge of providing and designing corporate training programs that should include "career development systems, coaching and performance management, management development solutions, organizational development interventions, and job enrichment programs" [16] (p. 95). This results in having more skilled personnel with upgraded knowledge and skills, which translates into a lower rate of attrition and increased job satisfaction [17]. Providing personalized training and customized learning paths integrating technology, where immediate feedback is provided and content is adapted to the workers' skills and needs, is crucial to reaching the goals of this revolution where lifelong learning becomes highly important to face the challenges Industry 5.0 presents [18]. Lifelong learning is a continuous and personal process that extends across all stages of life, encompassing both personal growth and PD. It extends beyond formal education, incorporating a wide range of experiences, including those in the workplace. Engaging in everyday work activities provides valuable learning opportunities that are often more relevant and immediate than traditional educational settings. Many adults develop new skills and enhance their employability through interactions and challenges in their jobs, making workplace learning a crucial component of lifelong learning [19].

Current research in this field highlights the growing integration of AI into PD across healthcare, education, and industry, demonstrating its potential to enhance learning and skill acquisition. In healthcare, research highlights AI's role in surgical education and lifelong learning through dynamic web platforms that facilitate document management, personalized learning recommendations and remote learning. AI also enables healthcare professionals to efficiently access the latest research and best practices [20,21]. In education, AI-powered Continuous Professional Development (CPD) programs offer tailored training for teachers, improving AI literacy and preparing them for AI-integrated classrooms [22]. Additionally, blockchain technology is being explored to enhance the transparency and

efficiency of teacher PD, ensuring secure and decentralized documentation of professional growth [23]. Furthermore, AI-focused PD programs, such as those based on the Technological Pedagogical Content Knowledge (TPACK) framework, have been shown to improve novice EFL teachers' ability to integrate AI in their teaching [24]. According to a systematic literature review on teachers' use of AI technology in teaching and PD [25], only 35% of the studies explored AI's role in enhancing teacher PD. While existing research extensively discusses the application of AI in education, most studies primarily focus on its direct impact on teaching processes, with significantly less emphasis on the teachers' PD needs.

In industry, research highlights the need for lifelong learning and CPD to adapt to the evolving digital landscape, particularly in fostering human capital development [26]. However, the integration of AI into teams remains limited, often prioritizing productivity over employee development [27]. Recent studies explore the use of generative AI (GenAI), such as ChatGPT, to create personalized cybersecurity learning plans, addressing skill gaps through tailored training resources and career-oriented learning pathways [28]. While this approach requires user input and lacks automation, it provides valuable support for individualized learning. Moreover, research shows that employees are interested in developing AI-related competencies, though concerns about job reduction persist [29]. Additionally, studies in Pakistan's manufacturing sector highlight positive correlations between AI, potential development (PD), and high-performance work systems (HPWSs), emphasizing the need for comprehensive AI-driven training programs to enhance employee growth and operational efficiency [30]. These efforts collectively highlight AI's transformative role in PD, fostering continuous learning, skill enhancement, and workforce adaptability across various sectors.

Nevertheless, a comprehensive model specifically dedicated to PD—one that integrates performance evaluation, potential assessment, and a human-centered approach to empower employees in advancing their careers and expanding their knowledge—has yet to be identified in existing research. This paper explores the potential of the Professional Development Analytics (PDA) model to transform PD in the context of Industry 5.0. The objective of this study is to present a conceptual AI-driven model aimed at understanding how AI-powered tools can optimize learning paths, predict the benefits its use could bring to organizations, and align with human-centric industrial principles. The following sections examine the conceptual foundations of the PDA model, its alignment with Industry 5.0 and its implications for future research and practice.

2. Methodology

In order to create a new conceptual model, it is essential to follow a suitable research methodology to guarantee the credibility, reliability and reproducibility of the research results [31]. In this case, the methodology followed to create the model is the Educational Conceptual Model Design (ECMD) research methodology [32]. It was selected as it is a systematic method for developing conceptual models, systems and artifacts that involve the use of educational technology. In our case, the model will be used in corporate education and it will be powered by AI tools that will be defined in the model development section; therefore, the selected methodology will help to effectively produce this new model.

This methodology is grounded on and integrates elements from Conceptual Modeling, Conceptual Design, Design Science Research and Design-Based Research methodologies. It concentrates on the design phase of the model and helps to transform ideas into models that can be implemented in the future. The ECDM research methodology is composed of four steps: problem definition, conceptual foundation, model development and knowledge contribution. Therefore, the steps that will be followed in this research can be seen in Figure 1.

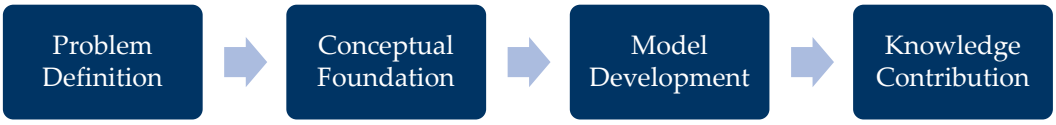

Figure 1. Phases of the Educational Conceptual Model Design (ECMD) methodology [32].

In the first step, the problem will be defined and the existing gap in current practices will be highlighted, along with the analysis of the context and the influential factors. In the second stage, the theoretical framework upon which the model will be based will be built, selecting the key concepts that will be used to address the problem. In the model development step, the key elements will be identified and a diagram to describe the process will be created. Finally, in the knowledge contribution step, how the model can contribute to the specific context of PD, the benefits it can bring to companies and how it aligns with Industry 5.0 principles will be analyzed, and a discussion of its limitations and future research directions will be presented. This last step will be developed in the Section 4.

3. Professional Development Analytics Model

3.1. Problem Definition

In the context of Industry 5.0, PD faces several challenges that will make it more difficult to train the workforce to cope with the ongoing changes in the market and the industry. The rapid evolution of technology has led to a significant gap between the skills employees have and the skills needed to effectively perform in their current and future positions. These skill gaps can be found both in technical and in soft skills. Regarding the former, after the rise in robotics, AI and automation, employees must adapt and acquire new knowledge about new technologies that were previously not part of their responsibilities. On the other hand, the latter, soft skills, which are extremely necessary to lead, collaborate, communicate, etc., are very often not included in corporate training programs. Both soft and technical skills are key to Industry 5.0, and they should be developed equally and in a well-balanced manner to ensure holistic workforce development. Businesses consider skill gaps as the primary obstacle to industry transformation, and they see learning and development as the most effective workforce strategy to invest in to be able to reach company goals. It is crucial to develop robust reskilling and upskilling strategies over the next five years to optimize workers and businesses' performance [33].

On the other hand, despite the significant advancements in AI and automated learning, many companies have yet to incorporate this technology into their training programs or are only in the initial stages of adoption. To improve PD and deliver more accurate and effective training, allowing for better upskilling and reskilling of employees in response to changes in the business environment, personalizing learning paths has become a priority for organizations [34]. AI-powered systems have the capacity to learn from and adapt to specific individual needs, as well as to streamline follow-up and automate assessments. Currently, these processes are overall handled manually, which limits the capacity to quickly and efficiently tailor learning experiences [35,36].

Talent mapping is used to assess skills and evaluate workers' performance in companies. It is necessary to detect highly skilled people with the potential to cope with future industry and company changes as well as with new skill requirements. This strategic process needs to draw information from employee data and provide the appropriate individual development programs to employees to manage the required skills to meet business needs. It supports organizations in fulfilling their objectives and managing succession planning. Therefore, collecting and analyzing employee data as well as offering personalized training are key to business success and PD [37].

These issues highlight the need for an innovative human-centered approach that takes advantage of advanced technologies to create a professional and personalized training model. The proposed model should be capable of minimizing the skill gaps, integrating both the development of soft and technical skills, aligning with the companies' strategic goals while at the same time adapting to the employees' needs. This model seeks to provide an integral solution to these challenges.

3.2. Conceptual Foundation

Our smart model is drawn on principles from data analytics, big data, people analytics, learning analytics, employee development and PD.

Data analytics is the systematic process of integrating different datasets from multiple sources, identifying relationships, trends, patterns and connections, and using predictive methods to extract valuable insights and guide decision-making processes [38]. An example of this is the information that can be gathered through the recruitment process in which the CV from an employee, the output of the interviews, the skills, the experience, etc., are a valuable source of information for further development and training within the company. With the advancement of technology, larger amounts of data of larger sizes are produced, gathered and processed; there has since been a need for faster data analysis methods as well as the capacity to extract useful information from the data, and from there, the term big data analytics was born [39]. Currently, it has emerged as a crucial tool for organizations to discover "hidden information", information that could not be analyzed with classical data analytics and become more competitive in their markets [40].

In the field of HR, data analytics applied to this area has been referred to as people analytics (PA), which can be defined as an "HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making" [41] (p. 15). PA is currently being widely used by HR departments and management in general, and has collected a large amount of useful information for companies. The data that can be extracted might be of different types, from typical surveys and business performance data to information obtained from electronic personal devices that can include and are not limited to health and location [42]. However, there are several trends and research lines in PA that face several challenges; one of them is the lack of specific research or new perspectives in employee development [43]. Our research seeks to offer a solution to this problem through a human-centric approach that enhances PD data collection by using AI-driven tools.

Learning analytics consists of gathering, measuring, analyzing and reporting data from trainees of any type to obtain insights of their learning experience as well as the learning environments with the goal of enhancing teaching and learning and helping to design new educational interventions. There are several methods and tools that can be used for this purpose, such as network and clustering analysis, text and process sequencing mining among others [44].

Employee development is focused on monitoring and improving the workers' knowledge, skills and competencies with the goal of having more high-skilled capable workers with higher performance rates. This is driven by companies and seeks to align individual goals with company goals, considering their personnel needs [45]. To effectively implement employee development, it is essential to conduct both an employee performance evaluation and an assessment of potential. The performance evaluation identifies current skills, achievements and areas for improvement [46], while the assessment of potential focuses on the employee's capacity for growth and readiness to take on new challenges [47]. Combined, these evaluations provide a foundation for creating personalized development

plans that align with both organizational goals and the employee's career aspirations. Additionally, organizations must embrace flexibility to adapt to ever-changing demands, ensuring that employees are equipped with the right tools and knowledge through upskilling and reskilling [48]. This approach not only addresses immediate skill gaps but also prepares employees for future roles, aligning their growth with organizational goals in a dynamic environment.

On the other hand, PD has a more individual focus and it is driven by individuals with the aim of growing in their careers and improving their skills to stay competitive in their current and future jobs [49]. PD concentrates on the long-term, whereas employee development focuses more on the short-term employees' growth for the current or future positions within companies. Many companies have decided to implement both elements for better performance and to offer more opportunities to their workers, resulting in a more satisfied workforce [50]. HR and, more specifically, L&D departments are key in facilitating the training and tools needed for workers' personal and professional growth [51]. Our model integrates both concepts and aims at providing new skills tailored to the employees' individual needs for both the short and long term that can be used within the company for a better performance of their current position, as well as to advance in their careers in future roles in the company but also to acquire knowledge for new job opportunities, and therefore putting their well-being and their needs at the center of the process following the human-centric principle of Industry 5.0.

3.3. Model Development

The model to address the problem identified in this study is developed during this phase. The initial step involves identifying its fundamental components, which are employees, AI applications, employees' supervisors and companies.

Workers are at the center of the model, in which their PD is the core and main goal. This human-centric approach ensures that the model is personalized to meet their individual needs as well as their career goals. Advanced artificial intelligence software is used to analyze data and generate personalized training recommendations based on the worker's profile and progress. Along the same lines, ML algorithms play a key role in adapting the system, continuously improving its recommendations by learning from the interactions between workers and the system.

The employees' supervisors will also play a role; they will act as guides throughout the training process, providing mentorship and regular feedback to workers. Their involvement makes sure that the training remains aligned with practical workplace needs that might not have been detected by AI systems. On the other hand, L&D departments are responsible for implementing the model within the company; they also gather feedback from stakeholders to refine and optimize the model over time. Finally, companies are also part of the model as they set overarching goals and the training is designed to be aligned with them, guaranteeing that individual development contributes to broader corporate objectives and success.

The model has been depicted as a diagram to make it more comprehensible (Figure 2); it shows how the different elements interact, as well as how data flow through the system, linking employee inputs with AI data processing and feedback loops to generate personalized outcomes. The objective of the model is twofold: the maximum PD of the employee and the creation of a talent map, thereby addressing the challenges of upskilling and reskilling, which are part of a company's everyday operations.

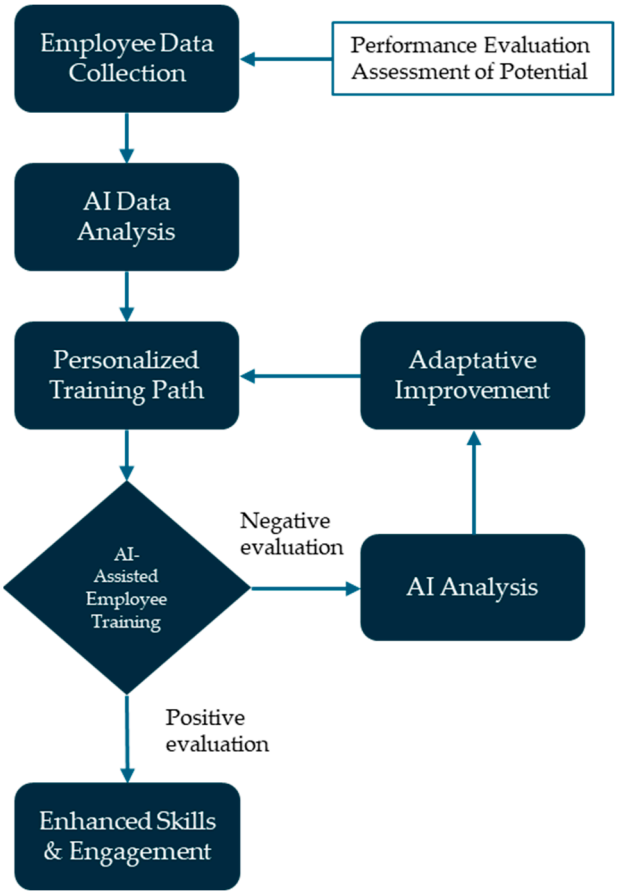

Figure 2. Professional Development Analytics model diagram.

The diagram provides a comprehensive overview of the entire operational process of the model, illustrating each step and component involved in its functionality. The first step of the process consists of collecting employees' job-related data. AI needs to access and gather all these data to be able to create detailed and personalized profiles. This data-driven approach not only enhances the accuracy of the profiles but also helps organizations to make informed decisions regarding talent management, employee development and recruitment strategies. For this purpose, AI Resume Parsing powered by natural language processing (NLP) and ML will be used to extract information on experience, education, skills and other CV data. NLP algorithms will also analyze job descriptions and match employees with relevant training programs by aligning past experience with future career goals [52].

A crucial part of this phase is collecting performance evaluation and potential assessment results. These evaluations serve as the foundation for creating personalized development paths and enable organizations to create their talent map effectively. Performance evaluation emphasizes the importance of assessing employees' competencies and the level of supervision they will require to effectively fulfill their job responsibilities. It will identify their current skills as well as detect their skill gaps. This evaluation is crucial for assessing and enhancing employee performance, which at the same time supports employee development and motivation, aligning with organizational strategy and goal achievement [53]. On the other hand, the assessment of potential identifies talented employees and their capacity to embrace new challenges as well as to grow and develop in the future. Identifying this talent is key for companies since they need talented workers to be in strategic positions that will help to achieve organizational goals [54]. Additionally, training history data will be compiled, consisting of a record of the courses, certifications,

workshops or other PD programs that the employee has successfully completed, showing their acquired knowledge and skills relevant to their role or potential career advancement. These data will be examined by AI Predictive Analytics based on ML algorithms that will analyze historical data, make future predictions, track employee performance and predict leadership potential [55].

Another critical component of the data collection stage is the assessment of technical and soft skills. Technical skills are specific and job-related abilities and knowledge that will vary depending on the industry. For instance, in a biopharmaceutical company, they could be as follows: laboratory techniques, equipment handling, molecular biology, etc. Soft skills will be identified and gathered; they are essential interpersonal and professional skills that can include, among others, strong communication skills for clear and constructive interactions, teamwork in order to collaborate efficiently with others, leadership to guide and inspire teams to meet shared goals, and time management skills to be able to prioritize tasks and meet deadlines efficiently. To effectively evaluate cognitive abilities, personality traits and psychological characteristics that contribute to identifying individual learning styles, AI Psychometric Testing will be integrated at this stage. This process incorporates advanced technologies such as ML, NLP and data analytics to ensure a comprehensive and data-driven assessment [56]. Language proficiency also needs to be taken into consideration, particularly for roles that require communication with international clients, companies or stakeholders from diverse countries. Although it is true that with the help of AI-tools language is no longer a barrier, employees should be capable of communicating effectively in other languages at a proficient level for in-person communication.

After having collected and analyzed the relevant data, this analytical process will allow for the identification of trends and patterns. A competency analysis will be performed by using ML techniques to classify the skills that are required for each position and compare them with employees' profiles; this will also identify the possible skill gaps, i.e., areas where the employee requires additional training; this will be based on comparisons between current and required competencies. Finally, the prediction of future needs will take place: AI-driven Predictive Analytics will anticipate future skill requirements based on industry trends, technological advancements and regulatory changes. By analyzing historical workforce data, AI can identify potential career paths and emerging skills, allowing companies to proactively invest in talent development and succession planning.

After analyzing employee data, in the following phase, AI will generate personalized training paths using GenAI within an AI-powered learning management system—specialized platforms designed to manage, deliver and track educational and training programs [57] enabled by ML, NLP and data analytics that will tailor learning experiences, recommend content, automate assessment and track learner progress. Additionally, the use of AI-powered adaptive learning systems will adjust training content in real time based on individual learning styles and engagement patterns, ensuring a personalized learning experience by providing multi-format learning options. ML is used to analyze the learners' engagement and adjust the content to the learning style, for instance, by changing the format (text, video, quizzes, etc.) [58]. This process will include technical training, where AI would recommend courses or certifications needed to develop technical skills based on their role in the company; for example, for soft skills, using employee performance data and working style, AI would suggest areas for improvement in soft skills (e.g., communication, project management, etc.), and likewise for language learning, where the data would be based on the worker's role and the level of communication needed with internal and external collaborators. The training plan will be structured into progressive modules, with suggestions for training levels based on the employee's experience and skill development.

Training sessions will be AI-assisted, and workers will receive immediate feedback throughout the process. This ensures that the training will be tailored to every worker's unique needs and skill gaps. During the training, employees will receive real-time feedback and AI tutor support from chatbots powered by ML, NLP and deep learning (DL), which will immediately identify areas for improvement and will also apply corrective measures. Moreover, AI-powered motion tracking and computer vision offer an advanced solution for improving technical skill training: they analyze employees' movements in real time, compare them to optimal models and provide instant corrective feedback [59]. The model will be trained on high-quality, domain-specific datasets that will include video recording and expert annotations, workflows, historical performance data and training manuals. This immediate feedback will result in a more interactive, effective and personalized learning experience. In addition to AI-generated feedback, input from supervisors will also be integrated. Supervisors will give personalized guidance and provide contextual insight, ensuring a wide perspective and a more balanced approach to skill development; they will provide feedback to the employees on what they consider needs to be improved, as well as positive feedback to increase the employees' motivation. The dual support system of AI and supervisor guidance fosters an environment for ongoing development and learning.

Apart from providing feedback, AI will also evaluate the employees' results obtained in each course or training program. Following this, there will be two possible results: positive and negative evaluation. If the evaluation is positive, this will indicate that the trainees have acquired and/or improved their skills, resulting in a higher level of engagement in their role and within the company. On the other hand, in some cases, an employee may not pass the evaluation even after completing the AI-assisted training. If this happens, AI will reanalyze all available data to adapt and refine the employee's learning path. This process might involve recommending additional foundational skills needed to succeed in the previous training, restructuring the course content with an alternative learning style, or tailoring the program further based on the employee's learning preferences.

The main advantage of this approach is the continuous improvement of the AI system. With each interaction and analysis, AI learns more about the employee's strengths, weaknesses, learning behavior and style; therefore, it will allow it to offer more personalized and precise course recommendations every time. This iterative process will not only help the employee but also improve AI's ability to support other employees effectively over time. In summary, the more the model is used, the better it will personalize training paths for employees' PD.

AI technology can support the implementation of the PDA model. However, no single software currently aligns fully with this conceptual model. Instead, various existing solutions can perform individual tasks or cover specific phases of the process. At this stage, a thorough evaluation of available software must be conducted within the company where the model would be implemented. The selected software will then need to be customized and trained to fulfill all the requirements of the PDA model.

4. Discussion

The PDA model contributes to the field of PD by providing a model to integrate AI in personalized training to holistically address soft and technical skills. From a practical perspective, it offers guidance to companies who seek to implement automated and personalized training programs and who are looking to invest in their L&D strategies to boost personnel development and plan to align it with the objectives of Industry 5.0 through the following aspects: inclusion, the model will adapt to every individual's needs and will not take into consideration traits such as race, gender or other personal characteristics that in the past may have been subject to bias from human trainers [60]; adaptability, training

will be tailored according to the learners' results and their interactions with the system; and sustainability, it will reduce training costs, minimize resource waste and lower the carbon footprint by optimizing learning delivery. Additionally, it will free L&D and HR personnel's time, enabling them to focus on more strategic projects that drive long-term organizational growth and workforce innovation.

The model offers significant potential benefits by delivering tailored training experiences to employees. This personalized approach enables them to develop new personal and professional skills that will make them feel more confident and prepared to perform their responsibilities [61]. Additionally, it would provide them with the qualifications and the expertise needed to opt for higher positions within the company, contributing to their career growth. This would result in a more motivated and job-satisfied workforce, consequently reducing attrition rates [62]. Beyond individual benefits, the model enhances organizational performance by addressing skills and digital gaps while fostering innovation across the company. Having a more highly skilled workforce not only strengthens competitiveness in the market but also positions organizations to be able to cope effectively with changes and challenges in the industry [63].

This paper serves as a foundation for future studies to evaluate the conceptual model's practicality and scalability. It is centered on the design process to guarantee that it has thoroughly been developed. However, it presents several limitations: it is based on the use of advanced technologies and this can represent a challenge for companies since not all of them will count on such technology to implement the model. Furthermore, the personnel from L&D departments, final users and other stakeholders who are part of the process will have to be trained in the use and administration of such tools.

Additionally, the implementation of the model can also represent an initial high cost, similarly to what happens when implementing new software in a company [64]. Although in the future this could be amortized and its posterior use in the following years could reduce training costs compared to previous years, companies will need to take it into account and consider if the investment will be worth it, especially in small companies.

Moreover, since the PDA is a conceptual model, it has not been tested yet in real-world situations and its effectiveness is yet to be measured. Additionally, the capacity of the model to work in different industrial sectors or cultural contexts has yet to be determined.

Furthermore, the model is based on employees' data collection that will be analyzed by AI; this raises important ethical considerations, particularly regarding the collection and use of personal data related to educational history, cognitive abilities and performance metrics. As the model relies on these data to personalize learning experiences, it is essential to prioritize privacy, fairness and transparency throughout the process. The misuse or mismanagement of such information could lead to privacy violations, biased outcomes and discriminatory practices; therefore, it is essential to guarantee that the data collected are private and protected against unauthorized access or third parties, that the model complies with the specific regulations on data protection from each country, such as the General Data Protection Regulation in Europe (GDPR) [65], and that mechanisms for algorithmic transparency and fairness are implemented.

Future work should focus on developing bias detection techniques and explainable AI frameworks to guarantee that the model's recommendations are both reliable and equitable. Additionally, fostering an ethical culture around AI in PD requires clear communication with employees regarding how their data will be used, as well as incorporating their feedback into ongoing model improvements. By addressing these ethical risks proactively, the model can maintain its commitment to human-centric principles while delivering personalized, effective and fair training experiences for all employees.

Furthermore, future research should also concentrate on implementing the model in pilot companies from different sectors and to perform a comparative analysis in order to compare the model against other more traditional training programs to identify its strengths and weaknesses. On the other hand, further exploration is needed to develop specialized software solutions tailored to the model's requirements, ensuring usability and smooth integration with existing systems. A special focus should be put on creating a user-friendly interface for workers, supervisors, managers and administrators. Future research should also focus on analyzing data privacy and transparency in the use of AI tools to avoid reticence from employees and to encourage adoption by stakeholders. Another important line of study is examining the model's adaptability across different cultural and regulatory contexts to ensure its global applicability.

Lastly, studies should analyze the future impact of the model in the long term at the organizational level, and measure key outcomes like return on investment (ROI) and its alignment with strategic corporate goals, as well as the capacity to react and adapt to rapid industry changes. These efforts will be crucial in refining the model and maximizing its potential to transform PD in the era of Industry 5.0.

5. Conclusions

This paper introduced a novel AI-powered model for personalized PD, adapted to the human-centric and adaptive principles of Industry 5.0. In addressing the limitations of traditional training programs, the model offers a path for organizations to improve their workforce skills while fostering satisfaction and engagement among their employees.

The proposed model enhances, rather than replaces, the role of human HR and L&D specialists by offering scalability, real-time adaptability and personalization that traditional training cannot achieve alone. Unlike HR specialists, who face time and resource constraints, AI can simultaneously track, assess and personalize training for thousands of employees, ensuring that each learner receives tailored training paths based on their skills, progress and career goals. It also provides instant feedback through AI-driven assessments, eliminating human bias and delays in performance evaluation. By automating repetitive tasks like training assignments and progress tracking, the model will free HR professionals to focus on more strategic functions, such as mentorship and organizational culture. With adaptive learning algorithms, the system evolves dynamically, keeping training relevant and engaging. The PDA model enhances efficiency, personalization and scalability, making PD more effective, cost-efficient and accessible compared to traditional learning and development.

The model offers a compelling human-centric vision for the future of workforce development; however, it is essential to validate its practicability through real-world testing. Additionally, the model must address ethical risks related to data privacy, bias and fairness by implementing robust governance, transparency and compliance with regulations like GDPR. Future studies should focus on assessing the model's effectiveness across different industries, measuring long-term learning outcomes, refining AI-driven training methodologies, detecting and preventing bias, making AI decisions more transparent, and communicating clearly with employees to build trust and ensure that the technology truly serves people. By addressing these challenges, the PDA model has the potential to transform PD, fostering a highly skilled, adaptable and more engaged workforce.

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References

1. Lu, Y. Industry 4.0: A Survey on Technologies, Applications and Open Research Issues. *J. Ind. Inf. Integr.* **2017**, *6*, 1–10. [CrossRef]
2. Javaid, M.; Haleem, A.; Singh, R.P.; Suman, R. An Integrated Outlook of Cyber–Physical Systems for Industry 4.0: Topical Practices, Architecture, and Applications. *Green Technol. Sustain.* **2023**, *1*, 100001. [CrossRef]
3. Folgado, F.J.; Calderón, D.; González, I.; Calderón, A.J. Review of Industry 4.0 from the Perspective of Automation and Supervision Systems: Definitions, Architectures and Recent Trends. *Electronics* **2024**, *13*, 782. [CrossRef]
4. Vogel-Heuser, B.; Hess, D. Guest Editorial Industry 4.0–Prerequisites and Visions. *IEEE Trans. Autom. Sci. Eng.* **2016**, *13*, 411–413. [CrossRef]
5. Bettiol, M.; Capestro, M.; Di Maria, E. Is This Time Different? How Industry 4.0 Affects Firms' Labor Productivity. *Small Bus. Econ.* **2024**, *62*, 1449–1467. [CrossRef]
6. Santhi, A.R.; Muthuswamy, P. Industry 5.0 or Industry 4.0S? Introduction to Industry 4.0 and a Peek into the Prospective Industry 5.0 Technologies. *Int. J. Interact. Des. Manuf.* **2023**, *17*, 947–979. [CrossRef]
7. Breque, M.; De Nul, L.; Petridis, A. *Industry 5.0: Towards a Sustainable, Human-Centric and Resilient European Industry*; Directorate-General for Research and Innovation; European Commission: Brussels, Belgium, 2021; p. 46.
8. Leng, J.; Sha, W.; Wang, B.; Zheng, P.; Zhuang, C.; Liu, Q.; Wuest, T.; Mourtzis, D.; Wang, L. Industry 5.0: Prospect and Retrospect. *J. Manuf. Syst.* **2022**, *65*, 279–295. [CrossRef]
9. Xu, X.; Lu, Y.; Vogel-Heuser, B.; Wang, L. Industry 4.0 and Industry 5.0—Inception, Conception and Perception. *J. Manuf. Syst.* **2021**, *61*, 530–535. [CrossRef]
10. Rame, R.; Purwanto, P.; Sudarno, S. Industry 5.0 and Sustainability: An Overview of Emerging Trends and Challenges for a Green Future. *Innov. Green Dev.* **2024**, *3*, 100173. [CrossRef]
11. Zeb, S.; Mahmood, A.; Khowaja, S.A.; Dev, K.; Hassan, S.A.; Gidlund, M.; Bellavista, P. Towards Defining Industry 5.0 Vision with Intelligent and Softwarized Wireless Network Architectures and Services: A Survey. *J. Netw. Comput. Appl.* **2024**, *223*, 103796. [CrossRef]
12. Pusztahelyi, R.; Stefán, I. Improving Industry 4. 0 to Human-Centric Industry 5.0 in Light of the Protection of Human Rights. In Proceedings of 25th International Carpathian Control Conference (ICCC), Krynica Zdrój, Poland, 22 May 2024.
13. Rane, N.L.; Kaya, O.; Rane, J. Human-Centric Artificial Intelligence in Industry 5.0: Enhancing Human Interaction and Collaborative Applications. *Artif. Intell. Mach. Learn. Deep. Learn. Sustain. Ind.* **2024**, *5*, 94–114.
14. Patil, K.P.; Kulkarni, M.S. Harmonising Human and Robotic Workforces in Industry 5.0: Creating a Resilient, Hu-Man-Centric, and Sustainable Organisational Ecosystem. In *Modern Technologies and Tools Supporting the Development of Industry 5.0*; CRC Press: Boca Raton, FL, USA, 2024; pp. 179–208.
15. Dachner, A.M.; Ellingson, J.E.; Noe, R.A.; Saxton, B.M. The Future of Employee Development. *Hum. Resour. Manag. Rev.* **2021**, *31*, 100732. [CrossRef]
16. Wash, G.L. Improving Employee Performance through Corp2orate Education. *J. Bus. Educ. Leadersh.* **2023**, *13*, 95–108.
17. Paigude, S.; Pangarkar, S.C.; Hundekari, S.; Mali, M.; Wanjale, K.; Dongre, Y. Potential of Artificial Intelligence in Boosting Employee Retention in the Human Resource Industry. *Int. J. Recent Innov. Trends Comput. Commun.* **2023**, *11*, 1–10. [CrossRef]
18. Rial-Gonzalez, P.; Sarceda-Gorgoso, C.; Santamaría Queiruga, O. Lifelong Learning as a Response to the Challenges of Industry 5.0 within the Context of Horizon 2030. *Educar* **2024**, *60*, 305–319. [CrossRef]
19. Billett, S. Distinguishing Lifelong Learning from Lifelong Education. *J. Adult Learn. Knowl. Innov.* **2018**, *2*, 1–7. [CrossRef]
20. Almansour, M.; Alfhaid, F.M. Generative Artificial Intelligence and the Personalization of Health Professional Education: A Narrative Review. *Medicine* **2024**, *103*, e38955. [CrossRef] [PubMed]
21. Hachoumi, N.; Eddabbah, M.; El Adib, A.R. Health Sciences Lifelong Learning and Professional Development in the Era of Artificial Intelligence. *Int. J. Med. Inform.* **2023**, *178*, 105171. [CrossRef]
22. Fakhar, H.; Lamrabet, M.; Echantoufi, N.; Ajana, L. Towards a New Artificial Intelligence-Based Framework for Teachers' Online Continuous Professional Development Programs: Systematic Review. *Int. J. Adv. Comput. Sci. Appl.* **2024**, *15*, 480. [CrossRef]
23. Sakhipov, A.; Baidildinov, T.; Yermaganbetova, M.; Ualiyev, N. Design of an Educational Platform for Professional Development of Teachers with Elements of Blockchain Technology. *Int. J. Adv. Comput. Sci. Appl.* **2023**, *14*, 519–527. [CrossRef]

24. Zulianti, H.; Hastuti, H.; Nurchurifiani, E.; Hastomo, T.; Maximilian, A.; Ajeng, G.D. Enhancing Novice EFL Teachers' Competency in AI-Powered Tools Through a TPACK-Based Professional Development Program. *World J. Engl. Lang.* **2024**, *15*, 117. [CrossRef]
25. Tan, X.; Cheng, G.; Ling, M.H. Artificial Intelligence in Teaching and Teacher Professional Development: A Sys-Tematic Review. *Comput. Educ. Artif. Intell.* **2024**, *8*, 100355. [CrossRef]
26. Balog, M.M.; Demidova, S.E. Human capital development in the context of the fourth industrial revolution. In Proceedings of the IOP Conference Series: Earth and Environmental Science, Vladivostok, Russian, 8–10 December 2020.
27. Evseeva, S.; Evseeva, O.; Burmistrov, A.; Siniavina, M. Application of artificial intelligence in human resource management in the agricultural sector. In Proceedings of the E3S Web of Conferences, Saint Petersburg, Russia, 20 May–6 June 2021.
28. Kallonas, C.; Piki, A.; Stavrou, E. Empowering professionals: A generative AI approach to personalized cybersecurity learning. In Proceedings of the 2024 IEEE Global Engineering Education Conference (EDUCON), Kos, Greece, 8–10 May 2024.
29. Popescu, I.M.; Zavatin, I.; Manea, D.I.; Pamfilie, R.; Jurconi, A. Adapting the Competences of the Employed Personnel in the Context of the Integration of Artificial Intelligence in Organisations. *Amfiteatru Econ.* **2024**, *26*, 817–831.
30. Zahoor, S.; Chaudhry, I.S.; Yang, S.; Ren, X. Artificial Intelligence Application and High-Performance Work Systems in the Manufacturing Sector: A Moderated-Mediating Model. *Artif. Intell. Rev.* **2025**, *58*, 11. [CrossRef]
31. Adeoye, M.A. Mastering the Basics: A Guide to Research Methodology for Effective Writing and Publication. *Chalim J. Teach. Learn.* **2024**, *4*, 30–41. [CrossRef]
32. Tusquellas, N.; López-Villanueva, D.; Palau, R.; Santiago, C. Educational Conceptual Model Design Research Methodology. *UTE Teach. Technol. Univ. Tarracon.* **2025**, *2*, e4103. [CrossRef]
33. The future of jobs report 2023. In Proceedings of the World Economic Forum, Davos, Switzerland, 30 April 2023.
34. Pavitra, K.H.; Agnihotri, A. Artificial Intelligence in Corporate Learning and Development: Current Trends and Future Possibilities. In Proceedings of the Second International Conference on Smart Technologies for Smart Nation (SmartTechCon), Singapore, 18–19 August 2023.
35. Ma, Y.; Wang, L.; Zhang, J.; Liu, F.; Jiang, Q. A Personalized Learning Path Recommendation Method Incorporating Multi-Algorithm. *Appl. Sci.* **2023**, *13*, 5946. [CrossRef]
36. Mansouri, N.; Soui, M.; Abed, M. Full Personalized Learning Path Recommendation: A Literature Review. In Proceedings of the International Conference on Advanced Intelligent Systems and Informatics, Port Said, Egypt, 18 May 2023.
37. Yasin, M. Talent Mapping/Assessment: Picturizing Talent in Organization. *Int. J. Bus. Appl. Soc. Sci.* **2017**, *3*.
38. Kumari, A.; Golyan, A.; Shah, R.; Raval, N. Introduction to Data Analytics. In *Recent Trends and Future Direction for Data Analytics*; IGI Global: Beijing, China, 2024; pp. 1–14.
39. Elgendy, N.; Elragal, A. Big Data Analytics: A Literature Review Paper. In Proceedings of the Advances in Data Mining. Applications and Theoretical Aspects: 14th Industrial Conference, ICDM 2014, St. Petersburg, Russia, 16–20 July 2014.
40. Chong, D.; Shi, H. Big Data Analytics: A Literature Review. *J. Manag. Anal.* **2015**, *2*, 175–201. [CrossRef]
41. Marler, J.H.; Boudreau, J.W. An Evidence-Based Review of HR Analytics. *Int. J. Hum. Resour. Manag.* **2017**, *28*, 3–26. [CrossRef]
42. Peeters, T.; Paauwe, J.; Van De Voorde, K. People Analytics Effectiveness: Developing a Framework. *J. Organ. Eff. People Perform.* **2020**, *7*, 203–219. [CrossRef]
43. Yoon, S.; Han, S.; Chae, C. People Analytics and Human Resource Development—Research Landscape and Future Needs Based on Bibliometrics and Scoping Review. *Hum. Resour. Dev. Rev.* **2024**, *23*, 30–57. [CrossRef]
44. Tsai, Y.; Rates, D.; Moreno-Marcos, P.; Muñoz-Merino, P.; Jivet, I.; Scheffel, M. Learning Analytics in European Higher Education—Trends and Barriers. *Comput. Educ.* **2020**, *155*, 103933. [CrossRef]
45. Pujianto, S. Effectiveness of Employee Training and Development in Increasing Productivity and Innovation in Multinational Companies. *Glob. Int. J. Innov. Res.* **2024**, *2*, 2245–2256. [CrossRef]
46. Guerra, J.I.G.; Buenaño, K.E.V.; Moreno, S.S.E.; Baldeón, N.B.R. Evaluación Del Desempeño Del Talento Humano Por Competencias, Estrategia Para Mejorar La Productividad Laboral. *Código Cient. Rev. Investig.* **2024**, *5*, 299–325. [CrossRef]
47. Kabalina, V.; Osipova, A. Identifying and Assessing Talent Potential for Future Needs of a Company. *J. Manag. Dev.* **2022**, *41*, 147–162. [CrossRef]
48. Lemańska-Majdzik, A.; Okręglicka, M. The Role of Knowledge-Based Resources in Building Organizational Flexibility. *Ann. Univ. Mariae Curie-Skłodowska Sect. H–Oeconomia* **2024**, *58*, 65–78. [CrossRef]
49. Kovács, Z.; Kálmán, C. Professional Learning in the Workplace. *J. Adult Learn. Knowl. Innov.* **2022**, *4*, 41–43. [CrossRef]
50. Sava, L.; Tirsu, V. Management of the Professional Training of the Personnel and the Process of Evaluating the Training Activity at the Level of the Economic Entities. *Bull. Transilv. Univ. Brasov Ser. V Econ. Sci.* **2023**, *16*, 89–98. [CrossRef]
51. Huq, M. Role of HR for Improving Employee Performance through Training in Development Organizations of Bangladesh. *Chetana's J. Manag. Res.* **2024**, *16*, 10–25.
52. Sharma, A.; Sharma, S. Machine Learning and Natural Language Processing for Intelligent Hiring with Resume Parser and Ranking. *Int. J. Adv. Technol. Eng. Res. IJATER* **2023**, *13*, 8–12.
53. Yapa, C.G. *The Concepts of Performance Evaluation*, 1st ed.; IGI Global: Beijing, China, 2024; pp. 91–122.

54. Haro, J.M.; García-Izquierdo, M.; Castaño, A.; García-Izquierdo, A.L. Predictive Competences of High-Potential Talent Employees. *Rev. Psicol. Trab. Y Organ.* **2023**, *39*, 121–130. [CrossRef]
55. Basnet, S. The Impact of AI-Driven Predictive Analytics on Employee Retention Strategies. *Int. J. Res. Rev.* **2024**, *11*, 50–65. [CrossRef]
56. Veldkamp, B.P. Trustworthy Artificial Intelligence in Psychometrics. In *Essays on Contemporary Psychometrics*; Springer International Publishing: Cham, Switzerland, 2023; pp. 69–78.
57. Anitha, J.; Pramod, S.; Rakesh, R. Learning Management System. *J. Emerg. Technol. Innov. Res.* **2021**, *8*, 208–213.
58. Joshi, M.A. Adaptive Learning through Artificial Intelligence. *Int. J. Integr. Educ.* **2024**, *7*, 41–43. [CrossRef]
59. Nandasena, N.A.S.N.; Vimukthi, W.A.A.; Herath, H.M.K.K.M.B.; Wijesinghe, R.; Yasakethu, S.L.P. Real-Time Upper Body Motion Tracking Using Computer Vision for Improved Human-Robot Interaction and Teleoperation. In Proceedings of the 2023 Moratuwa Engineering Research Conference, Moratuwa, Sri Lanka, 9–11 November 2023.
60. Owoyemi, O.A.; Oyelere, M.; Elegbede, T.; Gbajumo-Sheriff, M. Enhancing Employees' Commitment to Organisation through Training. *Int. J. Bus. Manag.* **2011**, *6*, 280–286.
61. Khan, M.; Sahu, K.K. Assessing the Effectiveness of Training and DEVELOPMENT Programmes on Employee Performance at Tata Steel Ltd. *Int. Sci. J. Eng. Manag.* **2024**, *3*, 1–9. [CrossRef]
62. Kasdorf, R.L.; Kayaalp, A. Employee Career Development and Turnover: A Moderated Mediation Model. *Int. J. Organ. Anal.* **2022**, *30*, 324–339. [CrossRef]
63. Oliinyk, A.; Tiutiunnyk, V. Theoretical and Methodological Basis of Employee Development in the System of Innovation Management of Modern Enterprises. *Actual Probl. Econ.* **2024**, *1*, 186–193. [CrossRef]
64. Oliveira, J.; Nunes, M.; Afonso, P. Managing Costs in Software Development. In Proceedings of the 2018 International Conference on Intelligent Systems (IS), Funchal, Portugal, 25–27 September 2018; pp. 365–370.
65. Tusquellas, N.; Palau, R.; Santiago, R. Analysis of the Potential of Artificial Intelligence for Professional Development and Talent Management: A Systematic Literature Review. *Int. J. Inf. Manag. Data Insights* **2024**, *4*, 100288. [CrossRef]