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in Information and Enterprise Systems

The Use of Artificial Intelligence in Onboarding Processes

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Dissertation supervised by Professor Doutor Arnaldo Manuel Pinto dos Santos

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STATEMENT OF INTEGRITY

I hereby declare that I have conducted my thesis with integrity. I confirm that I have not engaged in plagiarism or any form of falsification of results in the process of elaborating this thesis. I further declare that I have fully acknowledged the Disciplinary Regulations of the Universidade Aberta (regulation published in the official Diário da República, 2ª série, Nº 215, de 6 de novembro de 2013).

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All AI-supported outputs were critically assessed, edited, and verified throughout the writing process. The author remains fully responsible for the accuracy, originality, interpretation, and final content of this dissertation. No Artificial Intelligence system was used to generate research results, conduct the data analysis, or formulate the scientific conclusions of this work.

Abstract

This study explores the role of e-learning in organizational training, focusing on onboarding processes and the integration of Artificial Intelligence (AI).

E-learning, supported by Learning Management Systems (LMS), is widely used to enhance skill development and reduce costs. In the Physical Activity, Leisure, and Health sector, particularly in gyms, high staff turnover presents onboarding challenges.

AI may support these processes by personalizing schedules, providing support, and collecting feedback, although human intervention remains essential.

Using a Systematic Literature Review (SLR), a survey-based empirical phase, and an implementation-oriented perspective, this study analyzes e-learning models and AI implementation in onboarding.

The questionnaire was administered through LimeSurvey between March 9, 2026, and April 13, 2026, made available in English, French, and German, and the extracted data were analyzed using Microsoft Excel.

A total of 49 responses were initially recorded, of which 27 fully completed questionnaires were considered valid for statistical analysis.

The findings offer practical insights into AI's potential applicability to onboarding and internal training processes and support the proposal of a hybrid AI-supported LMS onboarding model.

***Keywords**:*

Learning Management Systems, Artificial Intelligence, Onboarding, e-Learning

Table of Contents

Abstract ... 5
List of Tables ... 8
List of Figures ... 9
List of Acronyms ... 10
Chapter 1 – Introduction ... 10
Chapter 2 – Systematic Literature Review ... 16
2.1 Context and Purpose of the Review ... 16
2.2 Planning ... 17
2.3 Research Protocol ... 19
2.4 Inclusion and Exclusion Criteria ... 20
2.5 Conducting the Review ... 21
2.6 Data Extraction and Analysis ... 22
2.7 Reporting the Review ... 24
2.8 Synthesis of the SLR Findings ... 32
Chapter 3 – Survey Methodology ... 34
3.1 Purpose of the Survey ... 34
3.2 Survey Design and Administration ... 35
3.3 Questionnaire Design and Research Alignment ... 35
3.4 Alignment Between Questionnaire Sections and Research Questions ... 42
3.5 Ethical Considerations ... 43
3.6 Data Extraction and Analytical Preparation ... 44
3.7 Chapter Summary ... 44
Chapter 4 – Data Analysis and Extraction ... 46
4.1 Introduction ... 46
4.2 Profile of Respondents ... 46
4.3 Analysis of Current Onboarding Process ... 49
4.4 Internal Training, LMS, and E-learning ... 51
4.5 Perceptions of Artificial Intelligence ... 54
4.6 Preferred Applications of Artificial Intelligence ... 55
4.7 Barriers to AI Implementation ... 56
4.8 Human Role in Onboarding ... 58
4.9 Spearman Correlation Analysis ... 59
4.10 Discussion by Research Question ... 61
4.11 Conclusion ... 62
Chapter 5 – Implementation Proposal and Orientation Guidelines ... 63
5.1 Purpose and Scope of the Proposal ... 63
5.2 Empirical Basis for the Proposal ... 63
5.3 Proposed AI-Supported LMS Onboarding Model ... 65
5.4 Orientation Guidelines for Implementation ... 67

5.5 Implementation Roadmap 68
5.6 Governance, Human Oversight, and Ethical Safeguards 70
5.7 Risks and Mitigation Measures 71
5.8 Alignment Between Findings and Proposed Guidelines 72
5.9 Expected Organizational Contributions 73
5.10 Chapter Summary 74
Chapter 6 – Final Conclusions 75
6.1 Closing the Research Path 75
6.2 Main Conclusions 76
6.3 Contribution of the Study 77
6.4 Research Limitations 79
6.5 Future Work 81
6.6 Final Reflection 83
References 85
Appendix A – Questionnaire 88

List of Tables

Table 2.1. Search protocol used in the SLR 20
Table 2.2. Inclusion and exclusion criteria 20
Table 2.3. Filtering process of the SLR 22
Table 2.4. Contribution of selected articles to the research questions 23
Table 2.5. AI applications in LMS-supported onboarding identified in the SLR 25
Table 2.6. Main challenges in implementing AI in LMS-supported onboarding 26
Table 2.7. Potential impacts of AI implementation in onboarding and internal training 27
Table 3.1. Alignment between questionnaire sections and research questions 42
Table 4.1. Distribution by Department 47
Table 4.2. Professional Profile of Respondents 48
Table 4.3. Descriptive Statistics: Onboarding Experience and Internal Training Needs 49
Table 4.4. Predominant Training Format 51
Table 4.5. LMS Usage in the Organization 52
Table 4.6. Functional Use of LMS Platforms 52
Table 4.7. Perception of E-learning 53
Table 4.8. AI Perception Indicators 54
Table 4.9. Useful Applications of AI 55
Table 4.10. Perception of Barriers to AI Implementation 56
Table 4.11. Main Barriers Identified 56
Table 4.12. Human Intervention in Onboarding 58
Table 4.13. Spearman correlation analysis 59
Table 5.1. Orientation guidelines for an AI-supported LMS onboarding model 67
Table 5.2. Implementation roadmap for the AI-supported LMS onboarding model 69
Table 5.3. Risks and mitigation measures 71
Table 5.4. Alignment between empirical findings and proposed guidelines 72

List of Figures

Figure 2.1. Phases of the SLR, adapted from Kitchenham and Charters (2007) 17
Figure 2.2. Filtering process from the initial 322 records to the final 29 selected studies 22
Figure 3.1. Informed consent section of the questionnaire 36
Figure 3.2. Section I – Respondent profile 36
Figure 3.3. Section II – Onboarding experience 37
Figure 3.4. Section III – Internal training, LMS, and e-learning 38
Figure 3.5. Section IV – Perceptions of Artificial Intelligence 39
Figure 3.6. Section V – Barriers and challenges 40
Figure 3.7. Section VI – Final assessment and recommendations 41
Figure 4.1. Distribution by Department 47
Figure 4.2. Years of Professional Experience 48
Figure 4.3. Participation in Onboarding Processes 48
Figure 4.4. Predominant Training Format 51
Figure 4.5. LMS Usage in the Organization 52
Figure 4.6. Functional Use of LMS Platforms 53
Figure 4.7. Preferred Applications of AI 55
Figure 4.8. Barriers to AI Adoption 57
Figure 5.1. Components of the AI-supported LMS onboarding model 66

List of Acronyms

AI	Artificial Intelligence
GDPR	General Data Protection Regulation
GenAI	Generative Artificial Intelligence
HR	Human Resources
ITS	Intelligent Tutoring System(s)
LMS	Learning Management System(s)
LLM	Large Language Models
M	Mean
ML	Machine Learning
NLP	Natural Language Processing
RQ	Research Question
SD	Standard Deviation
SLR	Systematic Literature Review

Chapter 1 – Introduction

Training in organizations has become an essential strategic factor for developing and retaining talent, especially in dynamic sectors characterized by operational complexity, continuous service delivery, and frequent employee turnover. In recent decades, technological advances have transformed the way organizations design, deliver, and monitor training processes. Among these developments, e-learning has become one of the most widely adopted solutions because it allows training content to be accessed with greater flexibility, reduces operational costs, and supports the standardization of learning experiences across different locations and professional profiles.

Learning Management Systems (LMS) play a central role in this transformation. These platforms support the organization, distribution, monitoring, and evaluation of training activities, allowing companies to centralize learning resources and provide employees with structured access to information. LMS platforms are particularly relevant in organizational contexts where employees have different schedules, responsibilities, levels of experience, and training needs. By enabling asynchronous learning and structured monitoring, LMS can support both administrative and pedagogical dimensions of training.

At the same time, onboarding is a critical phase in integrating new employees. It contributes to role clarity, early engagement, socialization, retention, and a sense of belonging. A well-structured onboarding process can help employees understand their responsibilities, internal procedures, organizational culture, and expected performance standards. However, traditional onboarding methods, particularly those based primarily on face-to-face sessions, may require significant time, resources, and logistical coordination. These requirements can create operational constraints for both organizations and employees, especially when training must be delivered to different professional groups, locations, or schedules.

In the Physical Activity, Leisure, and Health sector, these challenges are particularly relevant. Organizations in this area often work with heterogeneous teams, flexible schedules, geographically dispersed staff, and frequent training needs. In this sector, onboarding must be structured enough to ensure consistency and compliance with organizational standards, yet flexible enough to accommodate different roles, backgrounds, availability constraints, and levels of prior experience. These characteristics make onboarding a complex organizational process that requires both standardization and adaptability.

Artificial Intelligence (AI) has emerged as a promising tool for supporting and personalizing learning and onboarding processes. AI can assist in scheduling, guidance, content recommendation, feedback collection, skills assessment, and the creation of adaptive training paths. When integrated into LMS platforms, AI can enhance personalized, responsive onboarding by identifying user needs, recommending relevant content, supporting autonomous learning, and providing managers with decision-making information. However, the use of AI in onboarding also raises important challenges related to privacy, data protection, transparency, digital skills, resistance to change, and ethical governance.

Therefore, the integration of AI into onboarding should not be understood as a purely technological decision. The literature and the empirical results of this study both indicate that human intervention remains essential. AI should support onboarding processes, not replace the relational and human dimensions of employee integration. Mentoring, social interaction, emotional support, organizational culture, and human judgment remain fundamental components of onboarding. For this reason, the present study adopts a hybrid perspective, in which AI is analyzed as a support mechanism within LMS-based onboarding. At the same time, human actors remain central to the integration process.

This study investigates the use of Artificial Intelligence in onboarding processes supported by Learning Management Systems. It seeks to understand how AI can be applied to LMS-supported onboarding, the challenges that may affect its implementation, and the impact AI may have on onboarding and continuous internal training processes. The empirical component of this study was developed within an organization in the Physical Activity, Leisure, and Health sector with more than 4,300 employees globally, allowing the research problem to be examined in a real organizational context.

The research adopts a combined methodological approach. First, a Systematic Literature Review was conducted to identify and synthesize existing knowledge on Artificial Intelligence, Learning Management Systems, e-learning, and onboarding. Second, a survey was administered through LimeSurvey to collect empirical data from professionals in the organizational context under analysis.

The Systematic Literature Review was developed according to the methodological guidance proposed by Kitchenham and Charters (2007). Their protocol provides a clear structure for organizing the literature review, from the definition of the research questions to the selection, analysis, and reporting of the studies considered relevant to the topic. In this study, the SLR was used to establish the theoretical foundation of the research, identify existing applications of AI in LMS-supported learning environments, recognize implementation challenges, and understand the possible impact of AI on onboarding and continuous training processes.

Following Kitchenham and Charters' protocol, the SLR was organized into the main phases of planning, conducting, and reporting. In the planning phase, the research questions were defined, and the search protocol was established. In the conducting phase, the literature search was performed, and the results were filtered according to predefined criteria. In the reporting phase, the selected studies were analyzed and organized according to the research questions. This process enabled moving from a broad set of initial results to a final set of articles deemed relevant to the study's scope.

The literature search was conducted using search strings related to LMS, Artificial Intelligence, multimedia content, and learning management systems. The search process initially produced 322 records. These records were then screened through a filtering process based on relevance to the research questions, availability of full text, academic quality, and connection to the topic under study. Articles that did not contribute to answering the research questions or to understanding the research context were excluded. After this process, 30 articles were selected. Following full-text reading, one article was removed because it was not accessible without a paid subscription. Therefore, 29 articles were considered for the final analysis. The detailed filtering scheme, including inclusion and exclusion criteria, is presented in Chapter 2.

The empirical component of the study used survey methodology. The survey was designed to validate and contextualize the theoretical findings identified in the SLR within the organizational reality under analysis. The questionnaire was administered through LimeSurvey and made available in English, French, and German. English was used because it is the dissertation's language, while French and German were included because they are spoken within the organization. The valid questionnaire responses were collected between March 9, 2026, and April 13, 2026. A total of 49 responses were initially recorded, of which 27 fully completed questionnaires were considered valid for statistical analysis. The data were extracted from LimeSurvey and analyzed using Microsoft Excel.

The questionnaire was structured to collect information on respondents' professional profiles, onboarding experiences, internal training practices, LMS usage, perceptions of AI, perceived barriers to implementation, and expectations regarding AI-supported onboarding. The survey design was directly tied to the research questions. Each questionnaire section was designed to collect data relevant to understanding either the potential application of AI in LMS-supported onboarding, the challenges of AI implementation, or the expected impact of AI on onboarding and internal training. This connection between the survey structure and the research questions is further developed in Chapter 3.

The main objective of this study is to analyze how AI can support onboarding processes through LMS platforms and to propose orientation guidelines for an AI-supported LMS onboarding model in a real organizational context. This objective is both theoretical and practical. From a theoretical perspective, the study contributes to the discussion on AI, e-learning, LMS, and onboarding by connecting these domains through a structured literature review and empirical analysis. From a practical perspective, it proposes guidelines that may help organizations design more flexible, personalized, and human-centered onboarding processes.

Three research questions guide the research. The first research question examines how Artificial Intelligence can be applied to Learning Management Systems for onboarding. The second research question identifies the main challenges in implementing AI in LMS-supported onboarding processes. The third research question analyzes the potential impact of AI on onboarding and continuous internal training processes in organizations. Together, these research questions structure the study from the literature review to the empirical analysis and the final implementation proposal.

This dissertation is organized into six main chapters, followed by references and appendices. **Chapter 1** introduces the research context, problem, objectives, methodological approach, and the study's structure. **Chapter 2** presents the Systematic Literature Review, following Kitchenham and Charters' protocol and detailing the planning, conducting, and reporting phases, including the search strings, inclusion and exclusion criteria, filtering process, and analysis of the selected articles. **Chapter 3** presents the Survey Methodology, explaining the scientific construction of the questionnaire, the objective of each section, and the relationship between the survey items and the research questions. **Chapter 4** presents the Data Analysis and Extraction, based on the questionnaire results and the statistical analysis conducted in Microsoft Excel.

Chapter 5 develops the implementation proposal and orientation guidelines for an AI-supported LMS onboarding model in a real organizational context**. Chapter 6** presents the conclusions, including the study's global conclusions, its contributions, limitations, and future research directions.

Chapter 2 – Systematic Literature Review

2.1 Context and Purpose of the Review

A Systematic Literature Review (SLR) was conducted to identify, organize, and analyze existing academic knowledge on the use of Artificial Intelligence (AI) in Learning Management Systems (LMS), with particular attention to onboarding and continuous internal training processes. Since this dissertation examines the possible integration of AI into LMS-supported onboarding, it was necessary to understand what has already been studied, the applications proposed, the challenges identified, and the potential impact AI may have on organizational learning environments.

The SLR was conducted according to the methodological guidance proposed by Kitchenham and Charters (2007), particularly the organization of the review into planning, conducting, and reporting phases.

This structure enabled defining the research questions, establishing search criteria, applying inclusion and exclusion filters, and reporting the results in a transparent and reproducible manner.

In this study, the SLR was not used solely as a descriptive literature review, but as a structured process to connect the dissertation's theoretical foundation with the empirical and practical phases developed in the following chapters.

As shown in Figure 2.1, the review was organized into three main phases: planning, conducting, and reporting.

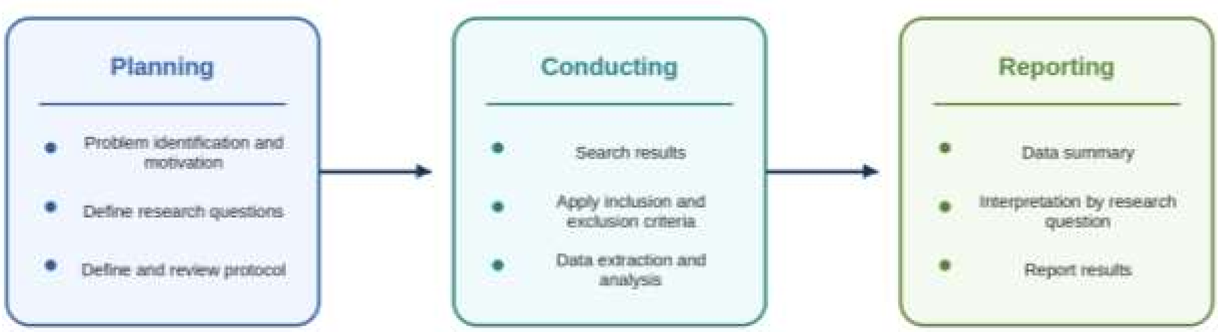


Figure 2.1. Phases of the SLR, adapted from Kitchenham and Charters (2007).

The *planning* phase defined motivation, research questions, and search protocol. The *conducting* phase involved searching, filtering, and selecting articles. The *reporting* phase organized and interpreted the findings in line with the research questions.

The purpose of this chapter is to present the full SLR process used in this dissertation. The chapter begins by explaining the planning phase, including the motivation and research questions. It then presents the research protocol, the EBSCO search process, the inclusion and exclusion criteria, and the filtering process used to reduce the initial 322 results to the final 29 articles included in the analysis. Finally, it presents the main findings in response to the three research questions.

2.2 Planning

The planning phase established the basis for the systematic review. In this stage, the motivation for the review was clarified, the research questions were defined, and the research protocol was prepared. This phase was important because it ensured that the literature search remained aligned with the dissertation's objective and the research problem, rather than being based on broad or disconnected searches.

The SLR was designed to support the study of AI in LMS-supported onboarding processes. More specifically, it aimed to identify how AI can be applied in LMS-supported onboarding, the challenges that may affect its implementation, and the impact AI may have on onboarding and continuous internal training.

2.2.1 Motivation

Organizations in the Physical Activity, Leisure, and Health sector increasingly need flexible and scalable training models. This need is reinforced by operational constraints, heterogeneous employee profiles, high turnover, geographically dispersed teams, and different levels of digital readiness. In this context, LMS platforms can support internal training by centralizing learning content, monitoring progress, and enabling asynchronous access to training resources.

However, the use of LMS for onboarding is not always fully developed. In many organizational contexts, onboarding still relies heavily on face-to-face sessions, the direct availability of trainers or managers, and informal information transmission. These practices may create difficulties when employees work with irregular schedules or when the organization needs to provide consistent onboarding across different teams and locations.

At the same time, Artificial Intelligence has become increasingly relevant in learning environments. AI can support personalization, content recommendation, adaptive learning paths, feedback collection, skills assessment, and predictive analysis. These possibilities suggest that AI may strengthen LMS-supported onboarding by making the process more flexible, personalized, and data-driven.

Nevertheless, implementing AI in LMS-supported onboarding also raises challenges. These include privacy and data protection, ethical concerns, resistance to change, lack of digital skills, algorithmic bias, transparency, and the continued need for human monitoring. For this reason, the SLR was necessary to understand both the opportunities and the risks associated with this type of technological integration.

2.2.2 Research Questions

The SLR was guided by the same research questions that structure the dissertation. These questions were used to organize the literature search, article selection, data extraction, and reporting of results.

> ***RQ1: How can Artificial Intelligence be applied to Learning Management Systems for onboarding?***
>
> *This first question focuses on the possible applications of AI within LMS-supported onboarding and internal training environments. It considers how AI may support personalization, content recommendation, adaptive learning paths, intelligent tutoring, feedback mechanisms, and performance prediction. In the context of this dissertation, RQ1 helps identify technological and pedagogical possibilities relevant to onboarding processes.*
>
> ***RQ2: What are the main challenges in implementing Artificial Intelligence in LMS-supported onboarding processes?***
>
> *The second question addresses the difficulties that may emerge when AI is introduced into LMS-supported onboarding. These challenges include technical limitations, privacy and data protection, ethical concerns, digital skills, resistance to change, transparency,*

and the need for human monitoring. This question is especially important because AI implementation depends not only on technological feasibility but also on organizational readiness and responsible use.

RQ3: What impact could the implementation of Artificial Intelligence have on onboarding and continuous internal training processes in organizations?

The third question examines the potential effects of AI on onboarding and continuous internal training. It examines whether AI can improve flexibility, accessibility, personalization, learning effectiveness, feedback collection, and decision-making. At the same time, it considers the limits of these possible impacts, particularly the importance of maintaining human intervention in the onboarding process.

2.3 Research Protocol

The research protocol defined the source, search strategy, search strings, and filters applied during the SLR. The search was conducted on the EBSCO platform. EBSCO was selected because it provides access to academic publications and allows filtering by peer-reviewed status and full-text availability.

The search was performed using Advanced Search, focusing on the Abstract field. The Abstract field was selected to ensure that the retrieved articles were directly connected to the topic of the review, rather than merely containing isolated keywords elsewhere in the text.

Two filters were applied from the beginning of the search process: Full Text and Peer Reviewed.

These filters supported the academic quality of the results and ensured that the selected articles could be accessed and analyzed.

The search strings were defined based on the dissertation's key concepts: LMS, Artificial Intelligence, multimedia content, and learning management systems.

Table 2.1. Search protocol used in the SLR

Search Source	Search Mode	Search Field	Filters Applied	Search Strings
EBSCO	Advanced Search	Abstract	Full Text; Peer Reviewed	LMS AND AI
EBSCO	Advanced Search	Abstract	Full Text; Peer Reviewed	(multimedia contents) AND (Artificial Intelligence)
EBSCO	Advanced Search	Abstract	Full Text; Peer Reviewed	(learning management systems) AND (Artificial Intelligence)

Using three search strings enabled the review to capture different dimensions of the topic.

The first string was broad and directly connected to LMS and AI. The second string included multimedia content because AI-supported learning environments often involve content generation, adaptive multimedia resources, and digital learning materials. The third string expanded the LMS concept by using the full expression "learning management systems" in combination with Artificial Intelligence.

2.4 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were defined to ensure that the selected articles were relevant to the research questions and suitable for academic analysis. These criteria were used during the abstract screening and full-text reading stages.

Table 2.2. Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
Full-text articles available through EBSCO	Articles without full-text access
Peer-reviewed academic articles	Non-peer-reviewed documents
Articles related to AI, LMS, e-learning, onboarding, internal training, adaptive learning, or HR-related learning processes	Articles unrelated to the topic of AI, LMS, e-learning, onboarding, or internal training
Articles that contributed to at least one research question	Articles that did not contribute to RQ1, RQ2, or RQ3
Articles with abstracts providing enough information to assess relevance	Articles with abstracts that were too vague or unrelated to the research context
Articles with conceptual, methodological, or practical relevance to the study	Articles with insufficient academic or practical connection to the dissertation topic
Articles accessible for analysis after selection	Articles requiring paid access after initial selection when the abstract did not indicate a sufficiently relevant contribution

The main selection principle was relevance to the research questions. Therefore, an article was included when it helped answer at least one research question or contributed to understanding the broader context of AI in LMS-supported learning and onboarding. Articles were excluded when their abstract did not provide a meaningful contribution to the topic, when they were unrelated to the research problem, or when they could not be accessed for full-text reading.

This review did not apply a separate numerical quality scoring system. Instead, quality was controlled through the initial use of peer-reviewed and full-text filters, followed by abstract screening, relevance analysis, and full-text reading.

This approach was considered appropriate because the main purpose of the SLR was to support the dissertation's theoretical and conceptual foundation and to identify evidence relevant to the research questions.

2.5 Conducting the Review

The conducting phase consisted of applying the search protocol, screening the results, filtering the selected articles, and preparing the final set of studies for analysis. The search process initially returned 322 results in EBSCO.

The first filtering stage was based on reading the abstracts. During this stage, each abstract was analyzed to determine whether the article was related to AI, LMS, e-learning, onboarding, internal training, or related organizational learning processes.

Articles were retained when they answered at least one research question or contributed to understanding the research context. Articles were discarded when their abstract did not contribute to answering the research questions or when the topic was too distant from the scope of the dissertation.

After this abstract-based filtering process, 30 articles were selected. These articles were then saved and prepared for full-text reading. During the second filtering stage, one article was excluded because it required paid access.

As the abstract did not provide enough evidence that its contribution would be essential or sufficiently relevant to the research questions, the article was not included in the final analysis. As a result, 29 articles were included in the final analysis.

Figure 2.2 illustrates the filtering process from the initial 322 records to the final 29 selected studies.

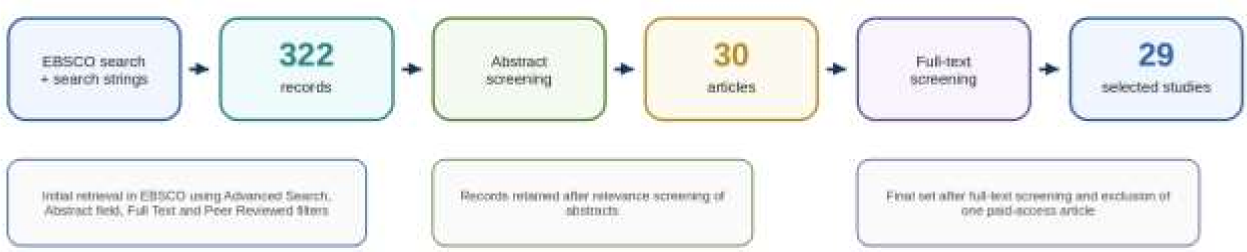


Figure 2.2. Filtering process from the initial 322 records to the final 29 selected studies. 22

Table 2.3. Filtering process of the SLR

Stage	Description	Number of Records
Initial EBSCO search	Search using the three defined strings in the Advanced Search, Abstract field, with Full Text and Peer Reviewed filters	322
Abstract screening	Removal of articles not related to the topic or not contributing to the research questions	30
Full-text screening	Removal of one article requiring paid access, whose abstract did not provide sufficient evidence of an essential contribution	29
Final articles included	Articles used for data extraction and reporting	29

This process made the selection more transparent and enabled the literature review to shift from a broad initial search to a focused set of articles directly related to the research questions.

2.6 Data Extraction and Analysis

After the selection process, the research results were exported to Mendeley in .ris format. This allowed the selected references to be organized and managed during the analysis phase.

The data extraction process involved reading abstracts, followed by a full-text review of the selected studies. The information extracted from the articles was organized according to the three research questions. For each article, the analysis considered whether the study contributed to understanding the possible applications of AI in LMS-supported onboarding or learning environments, the challenges related to AI implementation, and the potential impacts of AI on onboarding, internal training, and organizational learning.

The extracted information was then grouped into thematic categories. These categories included personalization, content recommendation, content creation, predictive analysis, adaptive learning, automation, data privacy, ethical concerns, human monitoring, digital skills, and organizational challenges. To make the articles' contributions more visible, Table 2.4 presents the relationship between the selected references and the research questions.

Table 2.4. Contribution of selected articles to the research questions

Ref.	Main Topic	RQ1	RQ2	RQ3
[1]	AI-enabled personalized recommendations	X		X
[2]	AI-enhanced digital learning and sustainability		X	X
[3]	Ontology-based recommender systems in e-learning	X		
[4]	AI assistants integrated into LMS	X		X

[5]	LMS evaluation using AI fuzzy logic			X
[6]	Educational datasets and AI requirements		X	
[7]	Student performance prediction using machine learning	X		X
[8]	Intelligent immersive learning environments			X
[9]	Virtual HR development and online learning		X	
[10]	AI in employee onboarding programs	X		X
[11]	AI-based intelligent content creation platform	X		X
[12]	Cross-modality and image understanding			X
[13]	AI and fuzzy logic in learning management evaluation	X		
[14]	AI and educational technology visualization	X	X	X
[15]	Natural language processing and peer feedback		X	X
[16]	Agents in e-learning and skills management			X
[17]	AI-based online teaching management platform	X		
[18]	Student modeling for intelligent tutoring systems	X		X
[19]	Multimedia Intelligence and AI	X		
[20]	Multimedia and deep reinforcement learning		X	
[21]	Blockchain-based LMS and self-regulated learning			X
[22]	Educational technology and AI society		X	
[23]	AI, e-learning technology, and learner experience	X	X	
[24]	Moodle flexibility and research support		X	
[25]	Digital skills in open distance learning		X	
[26]	AI and HRM systematic review		X	X
[27]	Big data analytics for predicting success factors	X		X
[28]	Sociodemographic factors and AI-generated content	X	X	
[29]	AI-based adaptive e-learning decision framework	X		X

This table shows that the selected studies contributed differently to the research questions. Some articles were directly connected to AI applications in LMS and e-learning environments, while others were more relevant for understanding challenges or potential impacts. This reflects the interdisciplinary nature of the topic and supports the need to analyze the literature through thematic categories rather than through a single narrow perspective.

2.7 Reporting the Review

The reporting phase presents the findings of the SLR according to the three research questions. The purpose of this section is not only to summarize the articles, but also to identify the main patterns emerging from the literature and connect them to the research problem of this dissertation.

2.7.1 RQ1 – Applications of AI in LMS-Supported Onboarding

The first research question examined how Artificial Intelligence can be applied to Learning Management Systems for onboarding. The selected literature indicates that AI can support LMS-based learning environments through personalization, recommendation systems, adaptive learning paths, content creation, performance forecasting, intelligent tutoring, and analytical comparison. AI-supported personalization is one of the most relevant applications identified in the literature. Personalized learning enables the system to adapt training content, learning paths, and recommendations based on user needs, performance, background, and progress. This is particularly relevant for onboarding because new employees may have varying levels of prior knowledge, different roles, and distinct learning needs [1], [4], [10], [13], [17], [18], [23], [28].

Recommendation systems are also highly relevant. In LMS environments, AI can recommend learning content, activities, or resources based on an employee's profile and progress. This can help reduce information overload and support a more efficient onboarding experience [3], [4], [11], [13], [14].

The literature also identifies content creation and adaptive multimedia resources as relevant AI applications. AI-based tools can support the creation and organization of training content, including multimedia learning materials. This is important in onboarding contexts where information must be presented in a clear, accessible, and engaging way [11], [23], [29].

Predictive analysis is another important application. AI can be used to analyze learning data, identify knowledge gaps, detect users at risk of poor performance, and support managers in monitoring training progress. In onboarding, this may help organizations identify employees who need additional support at an early stage [7], [18], [27].

Table 2.5. AI applications in LMS-supported onboarding identified in the SLR

Method	Description	References
Personalization	Engagement and performance, intelligent tutoring, content suggestion, and adaptation of pedagogy	[1], [4], [10], [13], [17], [18], [23], [28]
Visualization efficiency	Learning algorithms and visual support for educational processes	[3], [4], [11], [13], [14]
Content creation	Adaptability and increased positive impact on onboarding and training resources.	[11], [23], [29]
Forecasting results	Analysis of knowledge levels and identification of users at risk of failure	[7], [18], [27]
Analytical comparison	Analysis of current situations, design of models, experimental testing, and evaluation of results	[7], [19], [27]

In relation to onboarding, these findings suggest that AI can be integrated into LMS platforms not as an isolated technology, but as a functional layer that supports personalization, recommendation, monitoring, and feedback. This is relevant for the Physical Activity, Leisure, and Health sectors because the workforce may include employees with different schedules, roles, experience levels, and degrees of professional investment. AI-supported LMS onboarding may therefore help organizations create more flexible and adaptive training paths.

2.7.2 RQ2 – Challenges in Implementing AI in LMS-Supported Onboarding

The second research question focused on the main challenges in implementing AI in LMS-supported onboarding processes. The literature shows that these challenges are not only technical. They also involve ethical, organizational, human, and regulatory dimensions.

One of the most significant challenges is data privacy and security. AI-supported LMS platforms depend on the collection and analysis of user data. In onboarding, this may include training progress, assessment results, feedback, interaction history, and user profiles. This data can be useful for personalization, but they also require clear governance, transparency, and compliance with data protection principles [2], [9].

Ethical concerns are also central. AI systems may reproduce biases, generate unequal recommendations, or make decisions that are difficult to explain. In learning and onboarding contexts, this raises concerns about fairness, accountability, transparency, and the role of human judgment [22].

Another challenge relates to digital skills. Employees, trainers, and managers may not have the same level of familiarity with AI-supported systems. If users do not understand how the system works or why certain recommendations are made, they may resist using it or mistrust the process [25].

Human monitoring also appears as a recurring challenge. The literature suggests that AI should not be implemented without supervision. In onboarding, human intervention remains essential because integration into an organization involves socialization, emotional support, mentoring, cultural transmission, and contextual interpretation [14], [15], [20], [23].

Table 2.6. Main challenges in implementing AI in LMS-supported onboarding

Challenge	Description	References
Technical and ethical requirements	Weak technological and moral neutrality, difficulty in training complex models with multimedia data, and constant technological evolution	[6], [24], [25]
Automating decision-making processes	There is a need for human monitoring and further research to improve information extraction.	[15], [20], [23]
Data privacy and security	Technical and ethical requirements related to the use and protection of learning data	[2], [9]
Insufficient research into intercultural and organizational management	Gaps in the literature, including limited research on intercultural management, industrial relations, and cross-sectoral collaboration	[26], [28]
Monitoring	There is a need for effective evaluation systems and human supervision to orchestrate the technology.	[14]
Lack of moral neutrality	Concerns about fairness, accountability, bias, inclusion, and transparency in AI algorithms	[22]

These findings show that implementing AI in LMS-supported onboarding must be carefully planned. The main challenge is not simply whether AI can technically be integrated into an LMS. The central issue is whether the organization can implement it responsibly and transparently, while preserving the human dimension of onboarding.

2.7.3 RQ3 – Potential Impact of AI on Onboarding and Continuous Internal Training

The third research question examined the potential impact of AI on onboarding and continuous internal training processes. The selected studies suggest that AI may improve flexibility, personalization, accessibility, monitoring, content distribution, and decision-making in learning environments.

One of the most important impacts is adaptive learning. AI can support learning paths that adapt to an employee's progress, profile, or needs. In onboarding, this may help employees access the most relevant content without following a rigid, one-size-fits-all process [2], [8], [10], [11], [12], [14], [15], [16], [21], [26].

AI may also improve efficiency in training and human resources processes. Some studies indicate that AI can support recruitment, onboarding, training, performance analysis, talent acquisition, and retention. In this dissertation, the focus is specifically on onboarding and internal training, but the literature suggests that AI may also contribute to broader HR processes [10], [14], [16], [26].

Another potential impact is process automation. AI can automate repetitive elements of onboarding, such as answering common questions, recommending content, collecting feedback, or identifying training gaps. This may reduce the workload of trainers and managers, allowing them to focus on more complex human support tasks [10], [14], [26].

The literature also points to inclusion and accessibility. AI-supported systems may help create more accessible learning environments by adapting content formats, supporting different learning needs, and improving access to information [8].

Table 2.7. Potential impacts of AI implementation in onboarding and internal training

Impact	Description	References
Adaptive learning	Simulation and immersion, engagement and collaboration, representation of abstract concepts, active project-based learning, inclusion, and accessibility	[2], [8], [10], [11], [12], [14], [15], [16], [21], [26]
Efficiency in recruitment and training	Improved efficiency of distance learning and support for AI use in HR processes, including onboarding, training, performance analysis, talent acquisition, and retention	[10], [14], [16]
Decision processes	Support for organizational and learning-related decision processes	[5], [26]
Process automation	Cost reduction and automation of repetitive training and HR-related processes	[10], [14], [26]
Multichannel distribution	Improved content distribution across different channels and formats	[11]
Flexibility and portability	Multi-agent systems and technological structures that improve content creation, redistribution, and learning accessibility	[8], [11], [16]
Predictive analysis	Web-based and data-driven decision support systems	[2]
Inclusion and accessibility	Development of social skills, empathy, and improved access to distance learning	[8]

The findings suggest that AI may positively influence onboarding and continuous internal training by making learning processes more flexible, personalized, and measurable. However, the impact of AI depends on how it is implemented.

If AI is introduced without ethical governance, user training, and human supervision, its benefits may be reduced or even transformed into organizational risks.

For this reason, the literature supports a hybrid model. In such a model, LMS provides the structure for organizing and delivering training, AI supports personalization and analysis, and human actors preserve the social, cultural, and relational dimensions of onboarding.

2.7.4 AI Technologies for LMS-Supported Onboarding

The literature reviewed in this dissertation shows that **Artificial Intelligence** can support LMS-based onboarding through different technological approaches. Although the selected studies do not focus exclusively on onboarding, they identify several AI technologies that can be adapted to organizational training contexts, particularly when digital learning platforms support onboarding.

Although these technologies are frequently grouped under the broader concept of Artificial Intelligence, they represent different technical approaches with distinct functionalities, levels of autonomy, and organizational implications.

These technologies include recommender systems, adaptive learning mechanisms, Intelligent Tutoring Systems (ITS), Machine Learning (ML), predictive analytics, Natural Language Processing (NLP), AI assistants, Generative Artificial Intelligence (GenAI), Large Language Models (LLMs), and learning analytics.

One of the most relevant technologies identified in the SLR is the use of recommender systems. In learning environments, recommender systems analyze user profiles, learning behavior, previous interactions, and progress indicators to suggest content, activities, or learning paths. In onboarding, this type of technology may help new employees access the most relevant training materials based on their role, prior experience, department, or learning needs.

Instead of offering the same sequence of content to all employees, the LMS can recommend specific modules, documents, videos, assessments, or practical resources. This is particularly relevant in organizations with heterogeneous professional profiles, where onboarding requirements may vary significantly between management, technical, operational, and instructional roles. The studies reviewed show that recommender systems can support learning engagement, content relevance, and individualized learning experiences [1], [3], [4], [13].

Adaptive learning is closely related to recommender systems but focuses more specifically on dynamically adjusting the learning path. In adaptive learning environments, the system adjusts the sequence, difficulty, or type of content based on the learner’s progress, performance, and interactions with the platform. In onboarding, this may allow the LMS to differentiate between employees who already understand certain procedures and those who need additional support.

For example, an employee who completes an initial assessment successfully may be directed to more advanced content, while another employee may receive additional explanations, practice activities, or support materials. This type of adaptation can make onboarding more efficient and less rigid, particularly when employees have different levels of prior knowledge or digital readiness. The SLR identified adaptive learning, ITS, and personalization as recurring AI-supported mechanisms in learning environments [17], [18], [23], [29].

ML and predictive analytics also emerge as important AI technologies in the literature. ML models can analyze data generated by LMS platforms, including completion rates, assessment results, access frequency, response patterns, and learning progression. These data can then be used to identify tendencies, detect difficulties, and support decision-making. In onboarding, predictive analytics may help identify employees at risk of not completing required modules, those who may need additional support, or those who are having difficulties in specific training areas.

This does not mean that AI should make decisions about employees independently. Rather, predictive analytics can provide HR teams, managers, and trainers with indicators that support earlier and more informed intervention. The selected studies on performance prediction and learning analytics show that AI can be used to anticipate learning difficulties and support more data-informed educational management [7], [18], [27].

NLP is another relevant technology for LMS-supported onboarding. NLP enables systems to process, interpret, and generate human language. In training contexts, this can support automated feedback, analysis of written responses, question-answering tools, and interaction with virtual assistants. In onboarding, NLP may enable new employees to ask questions in natural language and receive immediate guidance on procedures, training content, organizational rules, and frequently asked questions.

This can be particularly useful when employees work with different schedules or when managers and trainers are not immediately available. NLP can also support feedback analysis by helping identify recurring concerns, unclear procedures, and common difficulties employees encounter during the onboarding process. The literature reviewed includes NLP-based approaches to peer feedback and learning support, which can be adapted to employee training and onboarding contexts [15].

AI assistants and chatbots represent a more visible application of NLP and conversational AI. Integrated into an LMS, an AI assistant can guide employees through onboarding modules, explain where to find specific content, remind users of pending activities, answer common questions, and provide basic support outside regular working hours. In this sense, the assistant functions as a first layer of guidance, not as a substitute for managers or mentors. This is important because onboarding involves procedural, technical, and relational dimensions. While an AI assistant may support access to information and reduce repetitive questions, complex situations still require human interpretation and follow-up. Recent literature on AI assistants integrated into LMS platforms shows that these tools can be deployed within learning environments and support user interaction with digital learning systems [4].

GenAI also appears to be a relevant technology for LMS-supported onboarding, especially for content creation and adaptation. GenAI can support the development of summaries, quizzes, scenarios, examples, microlearning materials, and role-specific explanations. In onboarding, this may help transform long or complex organizational documents into more accessible learning resources.

LLMs may also support adapting training content to different roles, levels of experience, or learning needs. However, the use of GenAI requires careful validation. Training content generated or adapted through AI must be reviewed by HR, trainers, managers, or subject-matter experts to ensure accuracy, consistency with organizational rules, and alignment with internal procedures. The SLR identified AI-based content creation and adaptive e-learning as relevant areas for improving learning resources and supporting more flexible training experiences [11], [23], [29].

Learning analytics provides another important layer for LMS-supported onboarding. By collecting and organizing data on user activity, learning progress, assessment results, and feedback, LMS platforms can support continuous monitoring of the onboarding process. When combined with AI techniques, learning analytics may help identify patterns that are difficult to detect through manual observation alone.

For example, the organization may identify modules with low completion rates, questions that generate frequent errors, or onboarding stages where employees tend to disengage. This information can support the continuous improvement of onboarding content and training design.

In this way, AI not only supports employees during onboarding but also supports the organization in improving the onboarding process over time [2], [5], [7], [14], [27].

The SLR also indicates that these technologies require adequate data structures. AI-supported systems depend on the availability, quality, and organization of data. In LMS-supported onboarding, this may include data on user profiles, roles, training history, module completion, quiz results, interaction records, and feedback. Poor data quality, fragmented systems, or insufficiently structured learning records may reduce the usefulness of AI functionalities. For this reason, the technical implementation of AI cannot be separated from data governance, platform integration, and organizational readiness. The literature reviewed highlights educational datasets, LMS evaluation, and technological requirements as relevant dimensions for AI-supported learning environments [5], [6], [24].

At the same time, the technical potential of AI must be balanced with ethical and organizational safeguards. AI-supported onboarding involves processing employee-related data, raising questions about privacy, transparency, fairness, accountability, and human oversight. The literature shows that AI systems may create risks if recommendations are not transparent, if monitoring is excessive, if data are not properly protected, or if users do not understand how the system supports their learning path.

These concerns are especially important during onboarding, as new employees may be in a vulnerable phase of organizational integration. The use of AI should therefore be accompanied by clear communication, limited and purposeful data collection, human oversight, and regular review of AI-supported outputs [2], [9], [22], [25], [26].

From a technical perspective, the most appropriate model for LMS-supported onboarding is not a fully automated system, but a hybrid architecture. In this architecture, the LMS provides the structure for organizing content, managing users, tracking progress, and delivering training. AI technologies support personalization, recommendation, prediction, conversational guidance, content adaptation, and monitoring.

Human actors remain responsible for validating content, interpreting results, supporting employees, and making decisions that require contextual judgment. This combination reflects the main direction identified in the SLR: AI can strengthen onboarding when it is used as an intelligent support layer within the LMS, while the human dimension of onboarding remains central to the process [14], [15], [20], [23].

Overall, the SLR identified technologies that suggest AI-supported LMS onboarding can be understood as a combination of several technical components rather than a single tool. Recommender systems can guide employees toward relevant content; adaptive learning can personalize the onboarding sequence; predictive analytics can identify training risks; NLP and AI assistants can support information access; GenAI and LLMs can help create and adapt learning resources; and learning analytics can support continuous improvement.

These technologies provide the technical basis for the implementation proposal developed in Chapter 5, where AI is positioned as a support mechanism integrated into a broader LMS-based onboarding model.

2.8 Synthesis of the SLR Findings

The SLR shows that AI can support LMS-based onboarding through personalization, content recommendation, adaptive learning, skills assessment, predictive analysis, feedback mechanisms, and intelligent support systems. These findings directly inform the empirical phase of this dissertation by helping define what should be examined in the survey.

The review also indicates that AI implementation must be approached carefully. Privacy, data protection, ethical concerns, monitoring, technical complexity, lack of digital skills, and the need for human oversight are recurring challenges in the literature.

These challenges are especially relevant for onboarding because employee integration is not only a technical process. It is also social, relational, and organizational.

The **findings** also show that AI may improve onboarding and internal training by increasing flexibility, accessibility, personalization, and effectiveness. However, the literature does not support the idea that AI should replace human intervention. On the contrary, the selected studies reinforce the importance of human monitoring, ethical control, and contextual decision-making.

Overall, the SLR provides the theoretical foundation for the dissertation's subsequent phases. It supports the construction of the survey methodology, informs the interpretation of the empirical results, and contributes to the development of orientation guidelines for an AI-supported LMS onboarding model in a real organizational context.

Chapter 3 – Survey Methodology

3.1 Purpose of the Survey

Following the Systematic Literature Review presented in Chapter 2, an empirical phase was developed to contextualize the theoretical findings within a real organizational setting. The literature review identified possible applications of Artificial Intelligence in learning environments, the challenges associated with its implementation, and its potential impact on onboarding and continuous internal training. The survey allowed these themes to be examined from the perspective of professionals working in the analyzed organizational context.

The empirical component was conducted within an organization in the Physical Activity, Leisure, and Health sector with more than 4,300 employees globally. The survey gathered information on participants' onboarding experiences, internal training practices, use of Learning Management Systems, perceptions of e-learning, knowledge of Artificial Intelligence, perceived barriers to implementation, and expectations regarding the possible use of AI in onboarding processes.

The survey was designed in alignment with the Systematic Literature Review and the research questions guiding this dissertation. Its purpose was twofold: to examine whether the theoretical findings identified in the literature were reflected in the organizational context and to support the development of a practical contribution grounded in empirical evidence. Through this connection, the survey served as a bridge between the dissertation's theoretical foundation and the later implementation-oriented proposal.

By combining literature-based knowledge with data collected from the organization, the research moved from conceptual analysis to a more situated understanding of how to approach AI-supported LMS onboarding in practice. The survey, therefore, played a central role in identifying organizational needs, employee perceptions, and contextual constraints relevant to developing orientation guidelines for an AI-supported onboarding model.

3.2 Survey Design and Administration

The survey was administered via *LimeSurvey*, which enabled digital distribution of the questionnaire, organization of questions into sections, and asynchronous participation. This format was appropriate for the organizational context, where respondents may have different schedules, operational responsibilities, and availability constraints.

The questionnaire was made available in English, French, and German. English was used for dissertation purposes, while French and German correspond to the main languages spoken within the organization. The multilingual format supported accessibility and encouraged participation from respondents working in different linguistic contexts.

The valid questionnaire responses were collected between March 9, 2026, and April 13, 2026. A total of 49 responses were initially recorded, and 27 fully completed questionnaires were retained for statistical analysis. The final dataset, therefore, included only complete responses, ensuring consistency across the variables analyzed. The data were extracted from LimeSurvey and later analyzed using Microsoft Excel.

The questionnaire included closed-ended, structured questions designed to yield quantitative data suitable for descriptive statistical analysis. Most attitudinal items were measured using Likert-type scales, allowing the responses to be analyzed through percentages, means, and standard deviations. This approach facilitated a clear interpretation of the empirical findings and enabled each response pattern to be linked to the study's objectives.

In methodological terms, the survey focused on three main dimensions of the research problem: the current state of onboarding and internal training practices; the organizational perceptions of LMS, e-learning, and AI; and the opportunities and barriers to the adoption of AI-supported onboarding. These dimensions shaped the questionnaire's structure and guided the organization of its thematic sections.

3.3 Questionnaire Design and Research Alignment

The questionnaire followed the dissertation's conceptual logic and was organized into thematic sections. Each section explored a specific dimension of the research problem and contributed to one or more research questions. This structure supported both respondent clarity and analytical coherence, as the collected data could later be interpreted in line with the study's theoretical and empirical objectives.

The sections were organized progressively. The questionnaire began with informed consent and respondent characterization, then moved to onboarding experience, internal training, and LMS usage, perceptions of AI, barriers to implementation, and final recommendations. This sequence enabled the questionnaire to move from contextual information to more specific perceptions of AI-supported onboarding.

3.3.1 Informed Consent

Before accessing the questionnaire, respondents were presented with an informed consent section. This introductory part explained the purpose of the study, the estimated completion time, the voluntary nature of participation, the anonymity of responses, and the academic purpose of the data collection. It also informed participants that their responses would be treated confidentially and used exclusively within the scope of the dissertation.

The informed consent section established the ethical basis for participation. It ensured that respondents had access to the necessary information before deciding whether to participate, thereby reinforcing the transparency of the research process.

The Use of Artificial Intelligence in Onboarding Processes, Supported by LMS

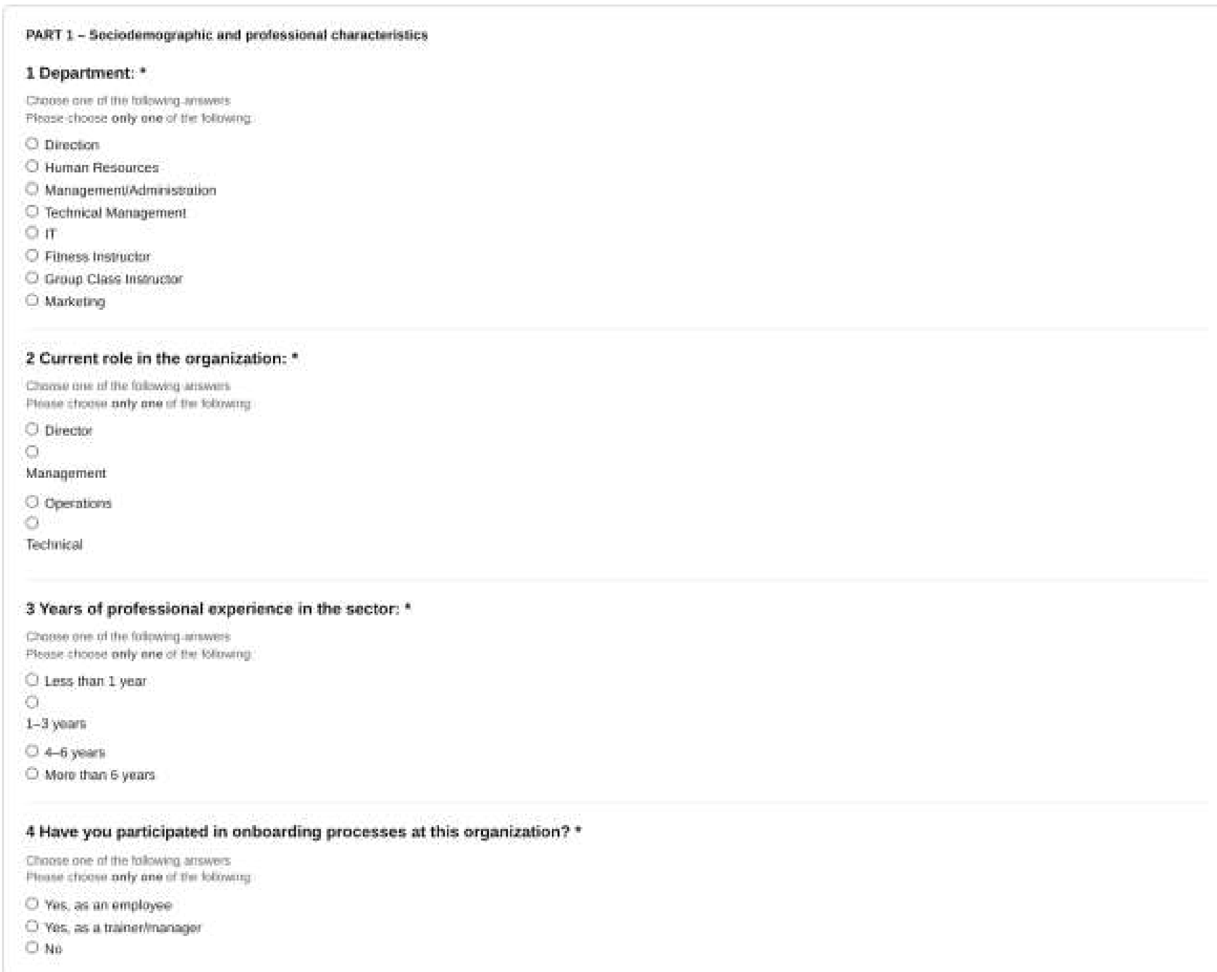
Objectives: This questionnaire is part of an academic study (Master's degree in Information and Business Systems, supervised by Professor Arnaldo Santos from the Universidade Aberta) on Onboarding and the use of Artificial Intelligence (AI) supported by Learning Management Systems (LMS) within organizations in the Physical Activity, Leisure, and Health sector and it is organized as follows : **Data Collection and Processing:** This questionnaire consists of 6 parts, with a total of 20 questions. The estimated time required to complete this questionnaire is approximately 10 to 15 minutes. Questions marked with an asterisk (*) are mandatory. Participation in this study is entirely voluntary. All responses will remain strictly anonymous. Personal information such as age, gender, or professional position will not be disclosed or linked to individual responses. The data collected will be used solely for statistical analysis and interpretation within the scope of this research, specifically regarding the implementation and use of Artificial Intelligence (AI) in Onboarding and Learning Management System (LMS) in an organizational context. **Informed Consent:** I confirm that I have been informed that all data provided will be treated confidentially and used exclusively for academic purposes. I understand that my participation is voluntary and that I may withdraw from the questionnaire at any time without any consequences. **Further Information:** If you have any questions concerning this research, the questionnaire, or issues related to privacy and data protection, please contact: Vanessa Donga vandongart@gmail.com Thank you very much for your valuable contribution to this research. To proceed, please select the "I authorize" option and then click the "Next" button below.

Figure 3.1. Informed consent section of the questionnaire

3.3.2 Section I – Respondent Profile

The first section characterized respondents in professional terms. It included questions related to department, professional function, organizational role, years of experience, and previous participation in onboarding processes.

This section provided the contextual basis for interpreting the empirical results. Since perceptions of onboarding, LMS, e-learning, and AI may vary by professional role, experience, or department, respondent characterization was necessary to understand the sample's profile and the organizational perspectives represented in the survey. Although this section did not independently answer one research question, it supported the interpretation of RQ1, RQ2, and RQ3 by clarifying the professional context from which the responses emerged.


PART 1 – Sociodemographic and professional characteristics

1 Department: *

Choose one of the following answers
Please choose **only one** of the following:

- Direction
- Human Resources
- Management/Administration
- Technical Management
- IT
- Fitness Instructor
- Group Class Instructor
- Marketing

2 Current role in the organization: *

Choose one of the following answers
Please choose **only one** of the following:

- Director
- Management
- Operations
- Technical

3 Years of professional experience in the sector: *

Choose one of the following answers
Please choose **only one** of the following:

- Less than 1 year
- 1–3 years
- 4–6 years
- More than 6 years

4 Have you participated in onboarding processes at this organization? *

Choose one of the following answers
Please choose **only one** of the following:

- Yes, as an employee
- Yes, as a trainer/manager
- No

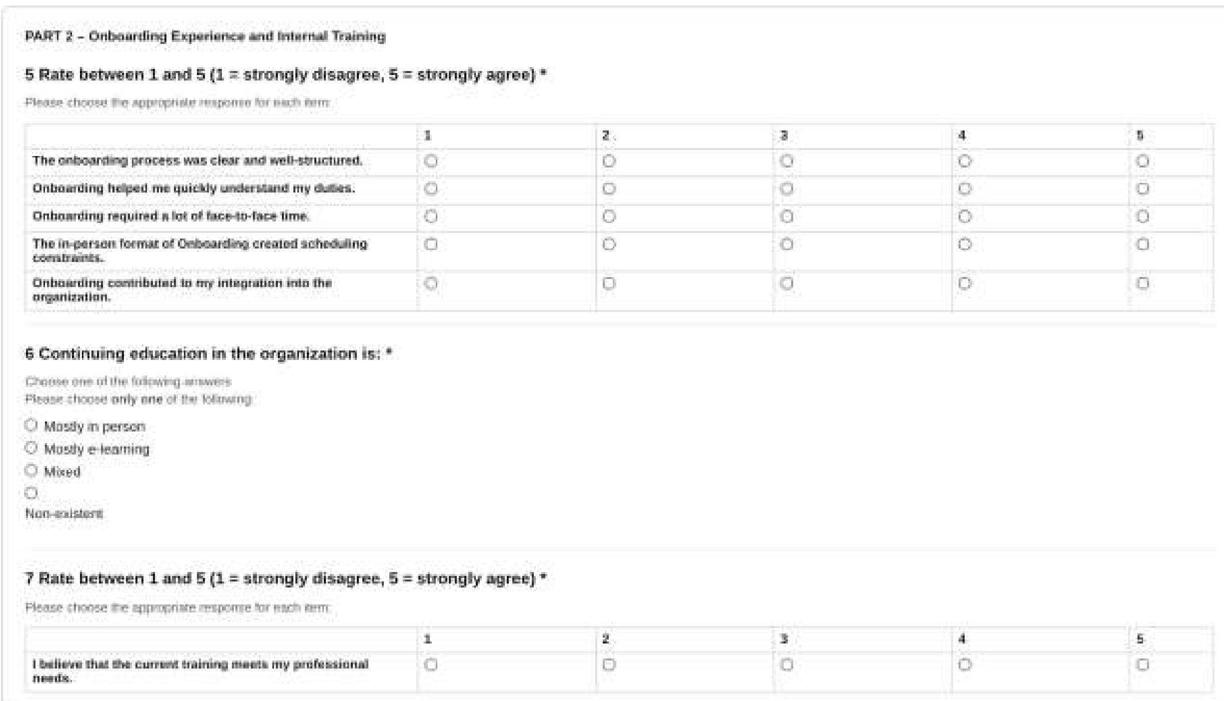
Figure 3.2. Section I – Respondent profile

3.3.3 Section II – Onboarding Experience

The second section focused on respondents’ experiences and perceptions of onboarding within the organization. The questions addressed aspects such as the clarity and structure of the onboarding process, the extent to which it helped employees understand their responsibilities, the role of face-to-face interaction, scheduling constraints, and the contribution of onboarding to organizational integration.

This section was essential because onboarding is the central organizational process examined in the dissertation. Understanding how respondents perceived the current onboarding process provided a basis for identifying areas where AI-supported LMS functionality could be improved.

The data collected in this section primarily contributed to RQ3, helping establish the current state of onboarding and the potential impact AI-supported approaches could have on this process. They also offered indirect support for RQ1, as the limitations or needs identified during onboarding helped clarify where AI-based functionalities might be useful.



PART 2 – Onboarding Experience and Internal Training

5 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
The onboarding process was clear and well-structured.	○	○	○	○	○
Onboarding helped me quickly understand my duties.	○	○	○	○	○
Onboarding required a lot of face-to-face time.	○	○	○	○	○
The in-person format of Onboarding created scheduling constraints.	○	○	○	○	○
Onboarding contributed to my integration into the organization.	○	○	○	○	○

6 Continuing education in the organization is: *

Choose one of the following answers
Please choose only one of the following:

- ○ Mostly in person
- ○ Mostly e-learning
- ○ Mixed
- ○ Non-existent

7 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
I believe that the current training meets my professional needs.	○	○	○	○	○

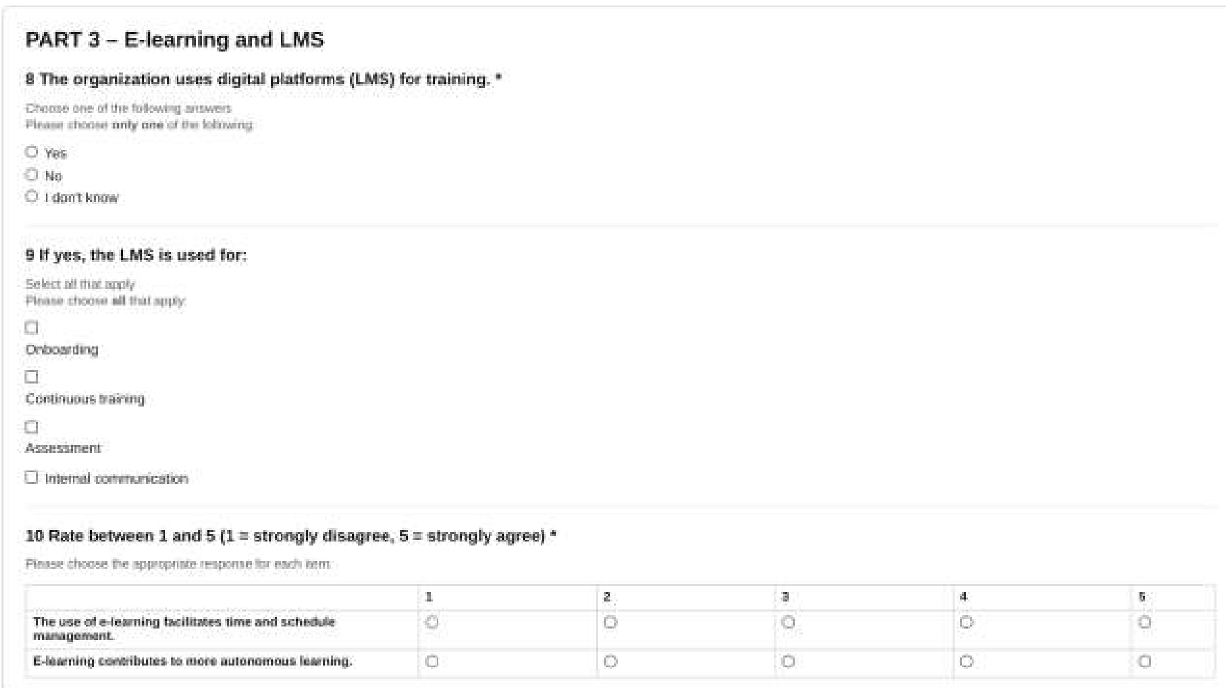
Figure 3.3. Section II – Onboarding experience

3.3.4 Section III – Internal Training, LMS, and e-Learning

The third section examined internal training practices, the use of LMS platforms, and perceptions of e-learning. It addressed the predominant training format, the presence and use of LMS platforms, the purposes for which LMSs are used, and respondents' views on e-learning in relation to time management and autonomous learning.

This section connected the research problem to the organization's existing digital training infrastructure. Since the dissertation investigates AI-supported onboarding through LMS platforms, it was important to understand whether LMS and e-learning were already part of the training culture and how employees perceived these tools.

The data collected in this section contributed mainly to RQ1 and RQ3. In relation to RQ1, the section clarified whether an LMS-based structure could support the integration of AI functionalities. In relation to RQ3, it provided evidence on the perceived value of digital learning in terms of flexibility, accessibility, and training effectiveness.



PART 3 – E-learning and LMS

8 The organization uses digital platforms (LMS) for training. *

Choose one of the following answers
Please choose **only one** of the following:

- Yes
- No
- I don't know

9 If yes, the LMS is used for:

Select all that apply
Please choose **all** that apply:

- Onboarding
- Continuous training
- Assessment
- Internal communication

10 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
The use of e-learning facilitates time and schedule management.					
E-learning contributes to more autonomous learning.					

Figure 3.4. Section III – Internal training, LMS, and e-learning

3.3.5 Section IV – Perceptions of Artificial Intelligence

The fourth section explored respondents' familiarity with Artificial Intelligence and their perceptions of its possible role in onboarding and internal training. The questions addressed knowledge of AI in training contexts, expectations regarding AI's contribution to onboarding, the possibility of fully reducing in-person onboarding, the potential effect on retention, and the usefulness of combining AI with LMS platforms.

This section was central to the dissertation because it directly addressed the integration of AI into onboarding processes. It provided empirical evidence on whether AI is understood, accepted, or perceived as useful by employees in the organizational context under analysis.

The section contributed mainly to RQ1 and RQ3. It supported RQ1 by identifying which AI applications may be considered relevant in LMS-supported onboarding. It supported RQ3 by showing how respondents perceived the possible impact of AI on onboarding, training effectiveness, and organizational integration.

PART 4 – Perception of Artificial Intelligence (AI)

11 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
I am knowledgeable about Artificial Intelligence (AI) applications in training.	○	○	○	○	○
AI could improve onboarding processes.	○	○	○	○	○

12
AI could be useful for: *

Select all that apply
Please choose all that apply:

☐ Customizing training paths.

☐ Recommend content.

☐ Supporting new employees.

☐ Collecting feedback.

☐ Assessing skills.

13 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
AI could reduce the need for fully in-person onboarding.	○	○	○	○	○
The use of AI could improve employee retention.	○	○	○	○	○

Figure 3.5. Section IV – Perceptions of Artificial Intelligence

3.3.6 Section V – Barriers and Challenges

The fifth section examined the perceived barriers to implementing AI in onboarding and training processes. The questions addressed privacy and data protection, digital skills, resistance to change, ethical concerns, lack of management support, and financial costs.

This section introduced the organizational and ethical dimensions of the research problem. The implementation of AI depends not only on technological possibilities but also on employees' trust, organizational readiness, data governance, and the capacity to manage change.

The data collected in this section directly relates to RQ2, as they identify the main challenges associated with AI implementation.

They also informed RQ3, because the potential impact of AI depends on the organization’s ability to address these barriers responsibly and effectively.


PART 5 – Challenges and barriers

14 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
I believe there are barriers to implementing AI in the organization.	○	○	○	○	○

15
Main challenges: *

Select all that apply
Please choose all that apply:

- ☐ Financial costs.
- ☐ Lack of digital skills.
- ☐ Resistance to change.
- ☐ Ethical issues.
- ☐ Privacy and data protection.
- ☐ Lack of management support.

16 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
I believe that human intervention should continue to be essential in onboarding processes.	○	○	○	○	○

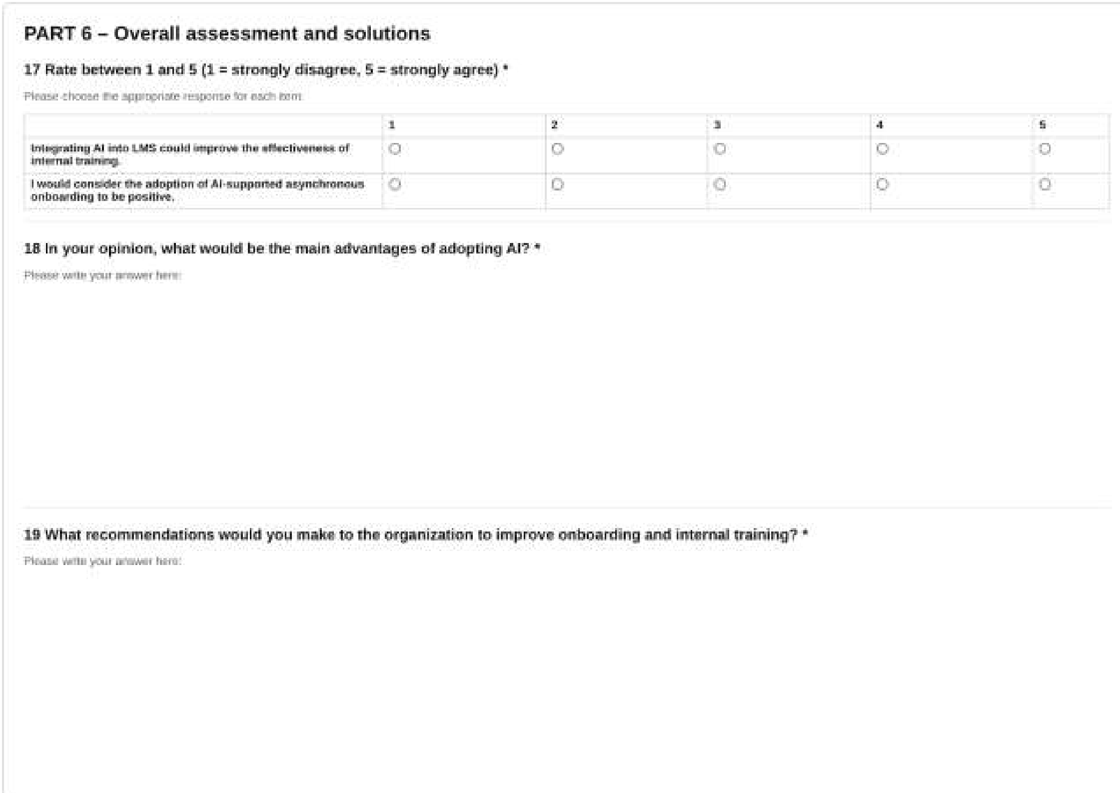
Figure 3.6. Section V – Barriers and challenges

3.3.7 Section VI – Final Assessment and Recommendations

The final section gathered respondents’ overall assessments and recommendations on onboarding, internal training, LMS usage, and the potential integration of AI. This section allowed respondents to express broader views after reflecting on the questionnaire's main themes.

The purpose of this section was to capture a more integrative perspective on the research topic. It complemented the previous sections by enabling the analysis to include not only structured responses but also broader perceptions and recommendations for the future development of onboarding and training practices.

This section contributed to RQ1, RQ2, and RQ3, as respondents’ final recommendations could address potential AI applications, implementation barriers, and expected impacts on onboarding and continuous internal training.



PART 6 – Overall assessment and solutions

17 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
Integrating AI into LMS could improve the effectiveness of internal training.	○	○	○	○	○
I would consider the adoption of AI-supported asynchronous onboarding to be positive.	○	○	○	○	○

18 In your opinion, what would be the main advantages of adopting AI? *

Please write your answer here:

19 What recommendations would you make to the organization to improve onboarding and internal training? *

Please write your answer here:

Figure 3.7. Section VI – Final assessment and recommendations.

3.4 Alignment Between Questionnaire Sections and Research Questions

Table 3.1 presents the relationship between each questionnaire section, its main objective, the research questions it supports, and the type of information collected.

Table 3.1. Alignment between questionnaire sections and research questions

Questionnaire Section	Main Objective	Related Research Question(s)	Type of Information Collected
Informed Consent	Establish ethical participation through transparency, voluntariness, and consent.	Indirect support to the whole study	Ethical and procedural information
Section I – Respondent Profile	Characterize respondents according to their professional context	Supports interpretation of RQ1, RQ2, and RQ3	Contextual and demographic-professional information
Section II – Onboarding Experience	Assess perceptions of the current onboarding process	RQ3 indirect support to RQ1	Perceptions of onboarding effectiveness, clarity, constraints, and integration
Section III – Internal Training, LMS, and e-Learning	Examine the use and perception of digital training practices	RQ1 and RQ3	Perceptions of LMS, e-learning, and internal training
Section IV – Perceptions of Artificial Intelligence	Identify perceptions of AI applications in training and onboarding	RQ1 and RQ3	Perceived usefulness, familiarity, and relevance of AI

Section V – Barriers and Challenges	Identify perceived barriers to AI implementation	RQ2; indirect support to RQ3	Concerns, risks, and organizational constraints
Section VI – Final Assessment and Recommendations	Gather an integrative assessment of the topic	RQ1, RQ2, and RQ3	Overall views and recommendations

The alignment presented in Table 3.1 shows the methodological connection between the questionnaire and the research questions. Section I supports the interpretation of the sample profile; Sections II and III establish the organizational and technological context; Section IV addresses the perceived role of AI; Section V identifies implementation barriers; and Section VI gathers broader recommendations. Together, these sections provide the empirical basis for the analysis developed in Chapter 4.

3.5 Ethical Considerations

Ethical considerations were integrated into the survey design from the beginning. Participation was voluntary, and respondents received information about the questionnaire's purpose before answering. The informed consent section also clarified the anonymous nature of the responses and the academic purpose of the data collection.

The questionnaire did not collect identifying personal information beyond the professional and contextual data required for analysis. This allowed respondents to share their perceptions without personal exposure, which was particularly relevant because some questions addressed organizational practices, onboarding quality, and the possible use of AI in training processes.

The use of LimeSurvey enabled the structured collection of responses and ensured anonymity during data collection. Once the response period ended, the data were extracted and prepared for analysis while maintaining confidentiality.

Ethical care was especially important in this study because the topic involves employee experience and perceptions of emerging technologies. Questions related to AI, data use, monitoring, and organizational change require transparent communication. The informed consent section, therefore, reinforced the study's academic purpose and the responsible handling of the collected information.

3.6 Data Extraction and Analytical Preparation

After the data collection period, responses were extracted from LimeSurvey and organized in Microsoft Excel. Excel was used to structure the dataset, calculate descriptive statistics, and produce tables and graphs.

The final dataset included 27 fully completed questionnaires out of the 49 responses initially recorded. Working with complete questionnaires ensured coherence across the variables analyzed and enabled statistical interpretation based on comparable response sets.

The analytical approach adopted in Chapter 4 is descriptive. It includes percentages, means, and standard deviations, allowing the analysis to identify both response distributions and tendencies across Likert-scale items. Percentages support a clearer reading of response patterns, while means and standard deviations summarize central tendency and variability.

The preparation of the dataset created the basis for the next stage of the dissertation. Chapter 4, titled Data Analysis and Extraction, presents the empirical findings on onboarding, LMS usage, e-learning, AI perceptions, implementation barriers, and the role of human intervention.

3.7 Chapter Summary

This chapter presented the questionnaire's structure and its methodological rationale. The survey was designed in alignment with the Systematic Literature Review and the research questions, allowing the empirical phase to examine the research problem within a real organizational context.

The chapter described the survey design, administration process, questionnaire sections, ethical considerations, and data preparation procedures. It also showed how each section contributed to the research questions and to the empirical foundation of the dissertation.

This methodological structure supports the transition to Chapter 4, where the questionnaire results are analyzed and interpreted in relation to the study's broader objectives.

Chapter 4 – Data Analysis and Extraction

4.1 Introduction

Following the survey methodology presented in Chapter 3, this chapter presents an in-depth analysis of the empirical data collected through the questionnaire conducted within the research framework.

The main objective is to interpret the results in relation to onboarding processes, the use of Learning Management Systems (LMS), and the potential integration of Artificial Intelligence (AI) in organizational training environments.

A total of **49 responses** were initially recorded, of which **27 were fully completed and considered valid for statistical analysis**.

The data were analyzed using descriptive statistical methods, including percentages, means, and standard deviations. The analysis now uses the verified values extracted from the final questionnaire dataset, ensuring consistency between the text, tables, and graphical representations.

Beyond descriptive statistics, this chapter emphasizes analytical interpretation, linking the findings to organizational practices and the research questions defined in the study (RQ1, RQ2, and RQ3).

The structure follows the questionnaire's thematic organization, allowing a systematic exploration of the respondent profile, onboarding experiences, training practices, LMS usage, perceptions of AI, barriers to implementation, and the perceived role of human intervention.

4.2 Profile of Respondents

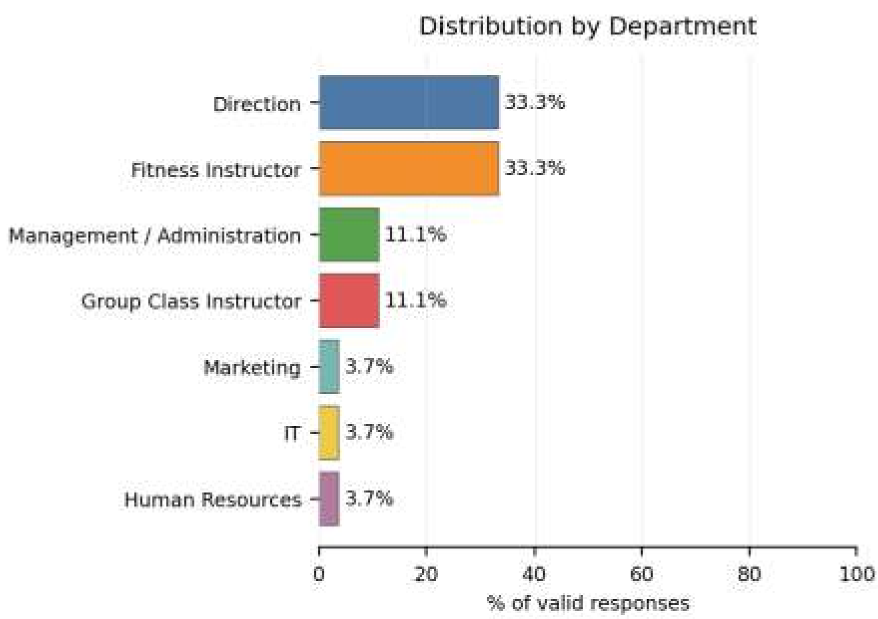
The distribution of respondents across departments provides important contextual insight into the results. Since the study focuses on onboarding and internal training in the Physical Activity, Leisure, and Health sector, it is particularly relevant to understand whether the respondents represent both strategic decision-making roles and operational functions directly affected by onboarding practices.

Table 4.1. Distribution by Department

Department	%
Direction	33.3
Fitness Instructor	33.3
Management / Administration	11.1
Group Class Instructor	11.1
Marketing	3.7
IT	3.7
Human Resources	3.7

Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Figure 4.1. Distribution by Department



Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

The sample is primarily composed of participants from Direction (33.3%) and Fitness Instructors (33.3%), followed by Management/Administration (11.1%) and Group Class Instructors (11.1%). The remaining respondents are distributed across Marketing, IT, and Human Resources (each representing 3.7%). This distribution reflects a balance between strategic and operational perspectives, since management-level participants contribute insights into organizational decision-making, while instructors represent key users of onboarding and training systems.

This dual perspective strengthens the analysis's validity. In a sector characterized by high employee turnover, operational variability, and geographically dispersed work patterns, as highlighted by Rosado et al. [32], onboarding processes must be both efficient and adaptable to diverse professional realities.

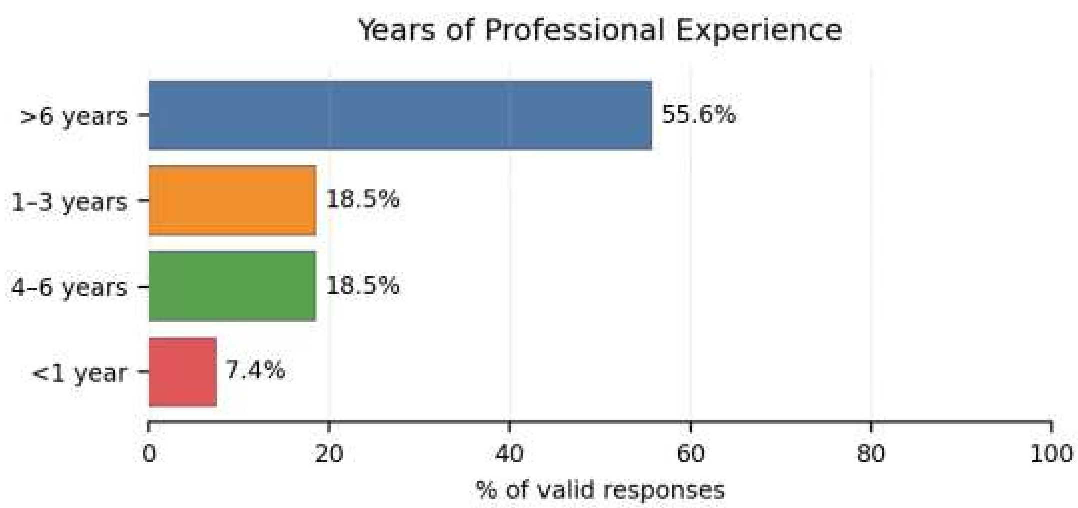
The presence of both decision-makers and employees directly involved in training processes allows the findings to reflect the organizational problem from multiple viewpoints.

Table 4.2. Professional Profile of Respondents

Dimension	Response	%
Current role	Management	48.1
Current role	Operations	29.6
Current role	Director	14.8
Current role	Technical	7.4
Years of experience	More than 6 years	55.6
Years of experience	1–3 years	18.5
Years of experience	4–6 years	18.5
Years of experience	Less than 1 year	7.4
Onboarding participation	Yes, as an employee	66.7
Onboarding participation	Yes, as a trainer/manager	22.2
Onboarding participation	No	11.1

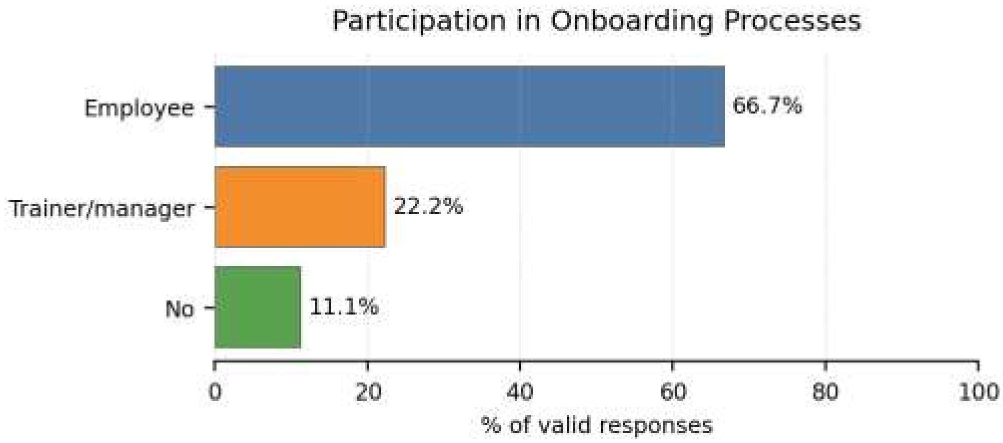
Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Figure 4.2. Years of Professional Experience



Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Figure 4.3. Participation in Onboarding Processes



Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

The professional profile supports the responses' contextual relevance. More than half of the respondents (55.6%) have more than 6 years of experience in the sector, indicating that the perceptions collected are not based solely on recent or superficial contact with the organization.

Furthermore, 66.7% participated in onboarding as employees and 22.2% as trainers or managers, meaning that 88.9% of valid respondents have direct or indirect experience with onboarding processes.

This is important for interpreting the results, as the analysis is grounded in respondents who are familiar with the practical realities of integration and internal training.

4.3 Analysis of Current Onboarding Process

The analysis of onboarding experiences reveals several important insights into the effectiveness and limitations of current practices.

Respondents evaluated the onboarding process using a 5-point Likert scale, where 1 indicated strong disagreement, and 5 indicated strong agreement. The verified descriptive statistics are presented in Table 4.3.

Table 4.3. Descriptive Statistics: Onboarding Experience and Internal Training Needs

Statement	Mean	SD
Clear and structured onboarding	3.30	0.91
Helped understand duties quickly	3.19	0.92
Required face-to-face time	2.96	1.16
Created scheduling constraints	2.96	1.06
Contributed to integration	3.41	1.19
Current training meets professional needs	3.19	1.00

Note. M = mean; SD = standard deviation. Statistics are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

The results indicate a moderately positive perception of onboarding, with the highest mean observed for the integration into the organization statement (M = 3.41, SD = 1.19). This suggests that onboarding contributes positively to employees' adaptation and sense of belonging, though the relatively high standard deviation indicates that not all respondents uniformly perceive this experience. This finding is consistent with previous research emphasizing onboarding as a key factor in employee engagement and retention [10].

However, indicators such as clarity and structure (M = 3.30, SD = 0.91) and rapid understanding of job responsibilities (M = 3.19, SD = 0.92) remain only slightly above the neutral midpoint. These results suggest that onboarding processes are functional but not fully optimized. In practical terms, this may translate into variations in onboarding quality depending on department, trainer availability, role complexity, or the degree of standardization across locations.

The items related to face-to-face time (M = 2.96, SD = 1.16) and scheduling constraints (M = 2.96, SD = 1.06) reveal a moderate level of perceived operational difficulty. In the fitness sector, professionals often work across multiple organizations or locations, making it difficult to participate in rigid, time-bound onboarding sessions. This operational reality creates friction between organizational requirements and employee availability, particularly for instructors whose schedules may vary significantly from week to week.

The statement regarding whether current training meets professional needs obtained a mean of 3.19 (SD = 1.00), indicating moderate satisfaction but also room for improvement. From an analytical perspective, these findings directly address RQ3, suggesting that current onboarding practices, while functional, are neither fully efficient nor sufficiently personalized. The identified constraints reinforce the need for more flexible, scalable, and adaptive onboarding solutions, potentially supported by digital technologies and AI.

4.4 Internal Training, LMS, and E-learning

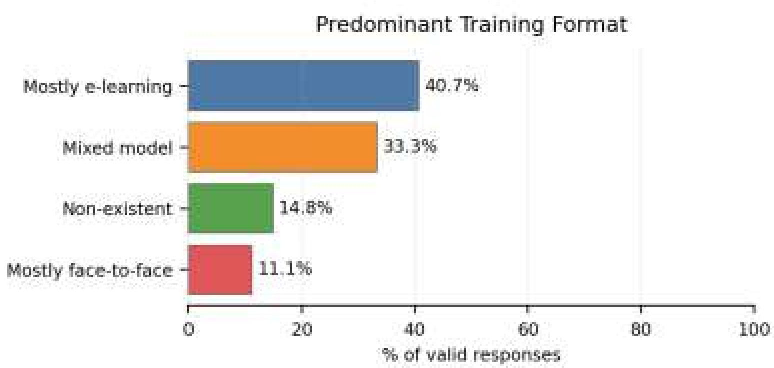
The analysis of internal training practices reveals a clear shift toward digital and hybrid learning models. This is an important element in the research because the feasibility of AI-supported onboarding depends not only on attitudes toward AI, but also on the existing digital learning infrastructure and the organizational acceptance of e-learning.

Table 4.4. Predominant Training Format

Format	%
Mostly e-learning	40.7
Mixed model	33.3
Non-existent	14.8
Mostly face-to-face	11.1

Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Figure 4.4. Predominant Training Format



Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

A significant proportion of respondents (74.0%) indicated that training is either mostly e-learning (40.7%) or a mixed model (33.3%). Only 11.1% reported predominantly face-to-face training. This suggests that the organization has already embraced digital transformation in its training practices and that employees are familiar with technology-supported learning environments.

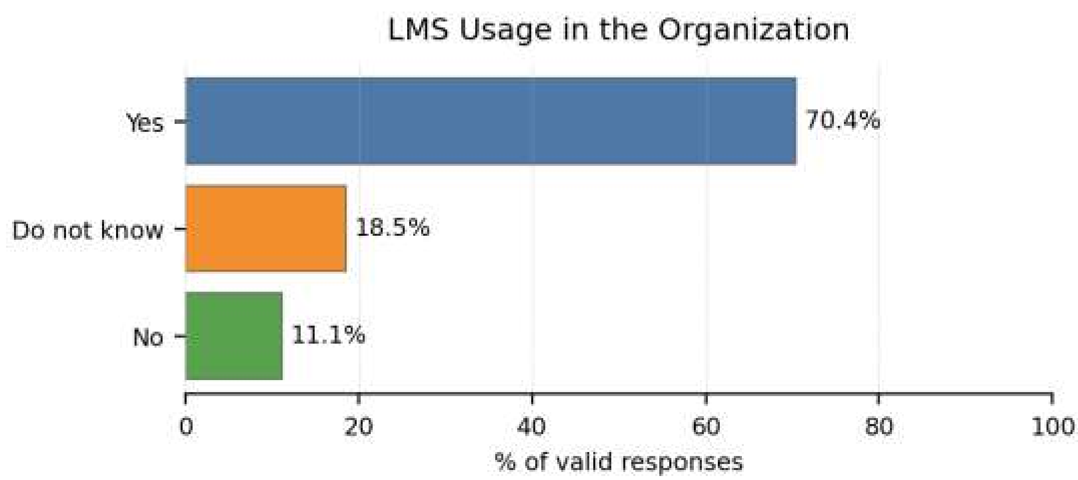
This trend reflects broader changes identified in the literature, where organizations increasingly adopt e-learning solutions to improve flexibility, reduce costs, and enhance accessibility [31]. In dynamic sectors such as fitness, these advantages are particularly relevant given irregular working schedules, the geographical dispersion of staff, and the need for continuous training across different roles.

Table 4.5. LMS Usage in the Organization

Response	**%**
Yes	70.4
No	11.1
Do not know	18.5

Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Figure 4.5. LMS Usage in the Organization



Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

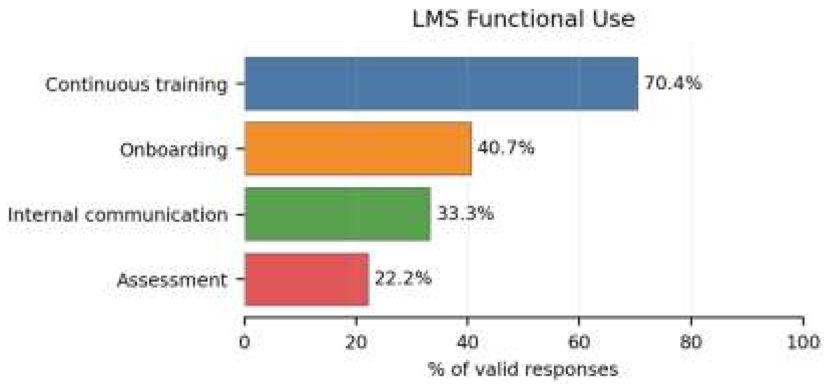
The use of LMS platforms was reported by 70.4% of respondents, indicating a relatively mature technological infrastructure. However, the fact that 18.5% of respondents reported not knowing whether an LMS exists suggests possible communication gaps, uneven system usage across departments, or limited visibility of the LMS as an integrated training platform.

Table 4.6. Functional Use of LMS Platforms

LMS Function	**%**
Continuous training	70.4
Onboarding	40.7
Internal communication	33.3
Assessment	22.2

Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Figure 4.6. Functional Use of LMS Platforms



Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

The functional use of LMS platforms provides a particularly relevant finding for this dissertation. While 70.4% of respondents indicated that the LMS is used for continuous training, only 40.7% identified its use for onboarding. This indicates that the digital infrastructure already exists, but its potential is not fully exploited for the onboarding phase. This gap is central to the proposed intervention developed in Chapter 5.

Table 4.7. Perception of E-learning

Statement	**Mean**	**SD**
Facilitates time and schedule management	4.07	0.87
Promotes autonomous learning	4.26	0.71

Note. M = mean; SD = standard deviation. Statistics are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

The perception of e-learning is positive, with high mean values for time and schedule management (M = 4.07, SD = 0.87) and autonomous learning (M = 4.26, SD = 0.71). These results indicate strong consensus among participants regarding the benefits of digital learning environments, especially in terms of flexibility and self-directed learning.

This is consistent with studies on LMS use in learning environments, which highlight their role in supporting access to learning resources, interaction, monitoring, and autonomous learning [35]. The ability to learn independently and manage one's own schedule is particularly valued in professions requiring flexibility.

These findings support RQ1, indicating that LMS platforms are well established and positively perceived, creating a favorable foundation for integrating AI-based functionalities into existing systems.

4.5 Perceptions of Artificial Intelligence

The analysis of perceptions of Artificial Intelligence reveals a critical and highly relevant dynamic between knowledge and acceptance. This section is central to the dissertation because AI adoption in onboarding cannot be assessed only from a technical perspective; it also depends on users' perceived usefulness, trust, and readiness to engage with AI-supported systems.

Table 4.8. AI Perception Indicators

Statement	Mean	SD
Knowledgeable about AI in training	2.63	1.18
AI could improve onboarding	3.78	0.97
AI could reduce fully in-person onboarding	3.11	1.31
AI could improve employee retention	2.85	1.06
AI + LMS could improve internal training effectiveness	3.59	0.93
AI-supported asynchronous onboarding would be positive	3.52	0.98

Note. M = mean; SD = standard deviation. Statistics are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Respondents reported relatively low familiarity with AI applications in training ($M = 2.63$, $SD = 1.18$), indicating limited exposure to or understanding of the technology. The relatively high standard deviation also suggests differences in knowledge across respondents, which variations in department, role, or previous contact with digital learning technologies may explain. This result indicates that AI is not yet fully integrated into employees' daily practices, or that its presence is not explicitly recognized as part of training processes.

Despite this limited familiarity, respondents expressed positive expectations for AI's potential to improve onboarding processes ($M = 3.78$, $SD = 0.97$) and for the effectiveness of internal training when integrated with an LMS ($M = 3.59$, $SD = 0.93$). This contrast between low knowledge and relatively high perceived usefulness is particularly significant from an organizational perspective.

It suggests that employees may perceive AI as a promising solution even without a detailed technical understanding, which aligns with Kaushal et al.'s [26] findings that AI adoption in HR contexts is often driven by perceived benefits rather than technical expertise alone. The moderate agreement regarding the reduction of fully in-person onboarding (M = 3.11, SD = 1.31) indicates a cautious attitude toward replacing traditional methods. The high standard deviation reveals considerable dispersion, suggesting that some respondents see strong potential in asynchronous AI-supported onboarding, while others remain hesitant. This result is important because it indicates that implementation should not be framed as a complete replacement of human-led onboarding, but as a complementary model.

Similarly, the lower mean for employee retention (M = 2.85, SD = 1.06) suggests uncertainty about the long-term organizational impact of AI. This may reflect the fact that retention depends on multiple variables beyond onboarding technology, including management practices, workload, organizational culture, and career opportunities. From an analytical standpoint, these findings are highly relevant for both RQ1 and RQ3: they highlight a favorable context for AI adoption while emphasizing the importance of awareness, training, and change management strategies.

4.6 Preferred Applications of Artificial Intelligence

The analysis of preferred AI applications provides valuable insights into user expectations and perceived value.

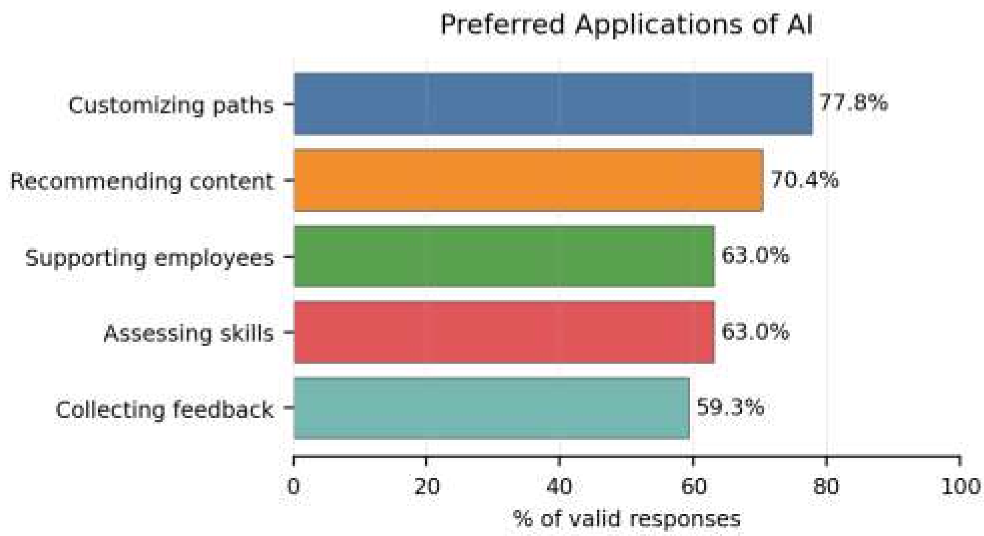
Respondents were asked to identify areas where AI could be useful, enabling a direct connection between the empirical findings and the design of the proposed AI-supported LMS onboarding model.

Table 4.9. Useful Applications of AI

Application	%
Customizing training paths	77.8
Recommending content	70.4
Supporting new employees	63.0
Assessing skills	63.0
Collecting feedback	59.3

Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Figure 4.7. Preferred Applications of AI



Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

The most selected application was the customization of training paths (77.8%), followed by content recommendation (70.4%). Other relevant applications include supporting new employees (63.0%), assessing skills (63.0%), and collecting feedback (59.3%). These results clearly indicate that respondents associate AI primarily with personalization, guidance, and adaptive learning support rather than with replacing human actors.

The strong emphasis on personalization reflects the heterogeneous nature of the fitness sector workforce, where employees may have diverse backgrounds, roles, levels of experience, and training needs. Standardized training approaches may not be sufficient to meet these varied needs. This aligns with the literature, which describes AI as a key enabler of individualized learning experiences and adaptive recommendations [1].

These findings directly support RQ1 by providing empirical evidence of how AI can be applied in LMS-supported onboarding processes. The results justify the inclusion of personalized learning paths, intelligent content recommendation, support tools, feedback mechanisms, and skills assessment in the proposed model. They also provide a practical basis for Chapter 5, where these functions are translated into implementation components.

4.7 Barriers to AI Implementation

The analysis of barriers provides important insights into the challenges of AI adoption. While the previous sections show openness to e-learning and a moderately positive perception of AI, implementation depends on addressing organizational, ethical, legal, and competence-related concerns.

Table 4.10. Perception of Barriers to AI Implementation

Statement	Mean	SD
Barriers to implementing AI exist	3.11	1.05

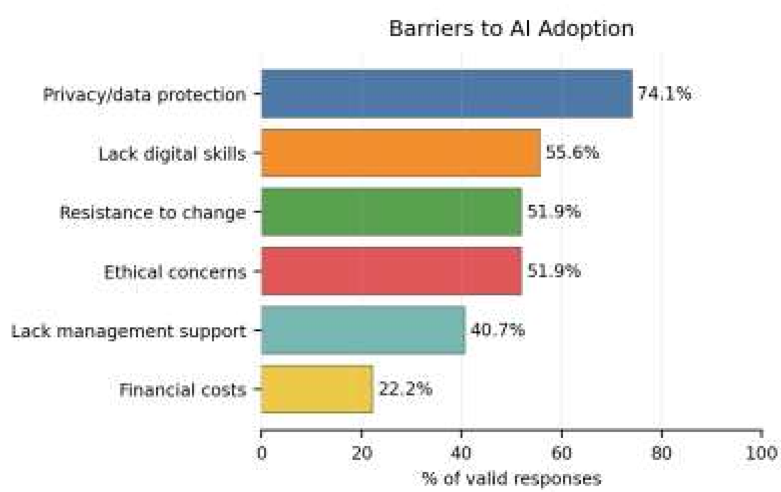
Note. M = mean; SD = standard deviation. Statistics are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Table 4.11. Main Barriers Identified

Barrier	%
Privacy and data protection	74.1
Lack of digital skills	55.6
Resistance to change	51.9
Ethical concerns	51.9
Lack of management support	40.7
Financial costs	22.2

Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

Figure 4.8. Barriers to AI Adoption



Note. Percentages are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

The general statement that barriers to implementing AI exist obtained a mean of 3.11 (SD = 1.05), indicating moderate agreement and some variability among respondents. This suggests that participants recognize the existence of obstacles, though the perceived intensity of those barriers may differ by role, digital maturity, or familiarity with AI.

The most significant concern identified was privacy and data protection (74.1%). This finding is particularly relevant in the European context, where compliance with the General Data Protection Regulation (GDPR) is mandatory. According to the GDPR [34], organizations must ensure lawful, transparent, and secure processing of personal data. In AI systems, which rely heavily on data collection and analysis, these requirements become even more critical.

Other important barriers include lack of digital skills (55.6%), resistance to change (51.9%), and ethical concerns (51.9%). These findings suggest that the main challenges are not exclusively technological but also organizational and human. The relatively low percentage associated with financial costs (22.2%) indicates that budget constraints are not perceived as the primary obstacle. Instead, issues related to trust, competence, transparency, and organizational culture are more significant.

These findings address RQ2 by highlighting the need for a comprehensive implementation strategy that includes training, communication, ethical governance, and data protection mechanisms. They also influence the structure of Chapter 5, which includes preparation, stakeholder alignment, GDPR compliance, pilot testing, and continuous monitoring.

4.8 Human Role in Onboarding

One of the most significant findings of this study relates to the role of human intervention. This dimension is essential because the proposed use of AI in onboarding must be understood as part of a hybrid learning and integration process, not as a fully automated substitution of human guidance.

Table 4.12. Human Intervention in Onboarding

Statement	Mean	SD
Human intervention should remain essential	4.41	0.80

Note. M = mean; SD = standard deviation. Statistics are based on valid questionnaire responses (n = 27). Source: Author's own elaboration based on questionnaire results.

The statement that human intervention should remain essential obtained a very high mean value (M = 4.41, SD = 0.80), indicating strong agreement among respondents. This is one of the questionnaire's strongest results and suggests that employees favor a hybrid approach in which AI complements human interaction rather than replacing it.

This finding aligns with the literature, which emphasizes the importance of human elements such as socialization, emotional support, mentoring, and organizational culture in onboarding processes [36]. AI can support access to information, personalize training paths, recommend content, and collect feedback, but it cannot fully replace the relational and cultural dimensions of onboarding.

From an analytical perspective, this result is critical for RQ3, as it reinforces the need for balanced solutions that integrate technological efficiency with human-centered practices. It also supports the design of the proposed model in Chapter 5, which includes human oversight as a core component of the AI-supported LMS onboarding framework.

4.9 Spearman Correlation Analysis

In addition to the descriptive analysis presented in the previous sections, a Spearman correlation analysis was conducted to explore associations between selected Likert-scale variables. Spearman's rank correlation coefficient, originally proposed by Spearman [37], was used to examine associations between selected Likert-scale variables. This coefficient is appropriate for ordinal data and does not require the assumption of normality.

In this study, it was used to examine whether respondents who valued autonomous learning and flexible e-learning formats also tended to express more positive perceptions of AI-supported onboarding.

The analysis was conducted using the 27 fully completed questionnaires included in the final dataset. The results should be interpreted as exploratory, given the limited sample size and the descriptive nature of the empirical phase. Nevertheless, the correlations provide an additional analytical perspective on the relationship between e-learning perceptions and attitudes toward AI-supported onboarding.

Table 4.13. Spearman correlation analysis

Variables analyzed	Spearman's rho	p-value	Interpretation
Autonomous learning × AI could improve onboarding	**0.493**	**0.009**	Moderate positive association
Autonomous learning × AI + LMS training effectiveness	**0.496**	**0.008**	Moderate positive association
Autonomous learning × AI-supported asynchronous onboarding	**0.506**	**0.007**	Moderate positive association
Time/schedule management × AI-supported asynchronous onboarding	**0.506**	**0.007**	Moderate positive association
AI onboarding improvement × AI + LMS training effectiveness	**0.792**	**< 0.001**	Strong positive association
AI onboarding improvement × AI-supported asynchronous onboarding	**0.861**	**< 0.001**	Very strong positive association
AI onboarding improvement × reduced fully in-person onboarding	**0.692**	**< 0.001**	Strong positive association
AI onboarding improvement × employee retention	**0.627**	**< 0.001**	Strong positive association

Note. Spearman's rho was calculated using the 27 fully completed questionnaires.

Source: Author's own elaboration based on questionnaire results.

The results indicate a moderate positive association between the perception that e-learning promotes autonomous learning and the perception that AI could improve onboarding processes. This suggests that respondents who value autonomy in digital learning environments are also more receptive to AI-supported onboarding. Similar moderate positive associations were observed between autonomous learning and the perceived effectiveness of integrating AI into LMS platforms, as well as between autonomous learning and acceptance of AI-supported asynchronous onboarding.

The association between time and schedule management and positive perceptions of AI-supported asynchronous onboarding also supports this interpretation. Respondents who value the flexibility of e-learning are more likely to view AI-supported asynchronous onboarding positively. This result is particularly relevant in the organizational context under study, where flexible schedules and operational variability are important features of the work environment.

The strongest correlations were found among AI-related indicators. Respondents who agreed that AI could improve onboarding also tended to agree that integrating AI into LMS platforms could improve internal training effectiveness and that AI-supported asynchronous onboarding would be positive. These strong associations indicate internal coherence in the responses and reinforce the interpretation that positive perceptions of AI in onboarding are connected to broader acceptance of AI-supported training models.

These findings should be interpreted with caution, as the sample size does not allow broad statistical generalization. However, the correlation analysis strengthens the descriptive results by showing that positive attitudes toward autonomous and flexible learning are associated with more favorable perceptions of AI-supported onboarding. This reinforces the relevance of the hybrid model proposed in Chapter 5, which uses AI to support personalization, flexibility, monitoring, and guidance while maintaining human supervision.

4.10 Discussion by Research Question

The results provide relevant insights into the research questions and serve as a bridge between the empirical analysis and the implementation proposal.

For RQ1, the findings show that AI can be applied in LMS-supported onboarding through personalization, recommendation systems, employee support, skills assessment, and feedback automation. This is supported by the high percentages of respondents who selected customization of training paths (77.8%) and content recommendations (70.4%) as useful AI applications.

For RQ2, the main challenges include privacy and data protection, lack of digital skills, resistance to change, and ethical considerations. The fact that privacy and data protection were selected by 74.1% of respondents indicates that implementation should be supported by robust governance and GDPR-compliant data practices.

For RQ3, AI is expected to improve flexibility, efficiency, and training effectiveness while maintaining the need for human involvement. The high mean associated with human intervention (M = 4.41) supports the interpretation that a hybrid model combining AI-supported learning with human supervision and social integration is more appropriate than full automation.

4.11 Conclusion

The findings indicate that the organization is already transitioning toward digital learning models and shows openness to AI integration. The confirmed use of LMS platforms, the positive perception of e-learning, and the preference for AI-supported personalization create a favorable foundation for the proposed intervention.

Although knowledge about AI remains limited, its perceived usefulness is relatively strong. However, successful implementation depends on addressing organizational, ethical, and regulatory challenges, particularly those related to GDPR compliance, digital competencies, resistance to change, and the preservation of the human dimension of onboarding.

Overall, the results support the development of a hybrid onboarding model, where AI enhances efficiency and personalization while human actors remain central to employee integration, motivation, and development. These conclusions provide the empirical basis for the implementation proposal and orientation guidelines presented in Chapter 5.

Chapter 5 – Implementation Proposal and Orientation Guidelines

5.1 Purpose and Scope of the Proposal

This chapter presents the implementation proposal developed from the findings of the Systematic Literature Review, the survey methodology, and the data analysis presented in the previous chapters. Its purpose is to translate the dissertation's theoretical and empirical results into a structured, applicable proposal for an AI-supported LMS onboarding model.

The proposal was developed for the organization under study, operating in the Physical Activity, Leisure, and Health sector and employing more than 4,300 people globally. Although grounded in this specific organizational context, the model may also be adapted to similar organizations facing comparable onboarding, training, and digital transformation challenges.

The chapter translates the diagnosis developed throughout the dissertation into orientation guidelines for a real organizational case. Grounded in survey results and analyses of onboarding, LMS usage, AI perceptions, and implementation barriers, the proposal offers a structured path for introducing AI-supported functionalities into LMS-based onboarding.

The proposed model positions Artificial Intelligence as a complementary layer within the LMS. Its role is to improve personalization, access to information, content recommendation, feedback collection, and monitoring, while preserving the relational dimension of onboarding. Human support, mentoring, and supervision remain essential elements of the model, especially because onboarding involves not only information transfer but also integration, belonging, and professional confidence.

5.2 Empirical Basis for the Proposal

The implementation proposal is grounded in the results presented in Chapter 4. These findings indicate that the organization already has conditions that may support the development of an AI-supported onboarding model, while also revealing gaps that justify a more structured and adaptive approach. The results showed that onboarding is perceived as moderately positive, but not fully optimized. Respondents evaluated the clarity and structure of onboarding with a mean of 3.30 and the ability of onboarding to help employees understand their duties quickly with a mean of 3.19. These values indicate that the current process is functional, while still presenting opportunities for improvement in consistency, clarity, and role-specific guidance.

The analysis also highlighted operational constraints associated with traditional onboarding formats. The items related to face-to-face time and scheduling constraints both obtained moderate mean values of 2.96. Although these results do not indicate a severe limitation for all respondents, they suggest that some respondents experience difficulties with rigid or in-person formats. In a sector where professionals often work variable schedules, this finding underscores the need for more flexible onboarding options.

The organization already appears to have a relevant digital training foundation. LMS usage was reported by 70.4% of respondents, and 74.0% identified training as either mostly e-learning or mixed. These results suggest that implementing AI-supported onboarding would not require a complete transition from a purely traditional model. The proposal can build on existing digital practices and expand their use toward onboarding.

However, the results also revealed that LMS platforms are not fully used for onboarding. While 70.4% of respondents indicated that the LMS is used for continuous training, only 40.7% identified onboarding as one of its functions. This gap is central to the present proposal. It shows that the organization already has a technological base, but its potential has not yet been fully realized in the onboarding phase.

The perception of e-learning was positive. Respondents agreed that e-learning facilitates time and scheduling management (mean = 4.07) and promotes autonomous learning (mean = 4.26). These findings support the feasibility of using LMS-based onboarding modules, especially for employees who may benefit from asynchronous access to training content.

Regarding Artificial Intelligence, the results showed a relevant contrast between limited familiarity and positive expectations. Respondents reported relatively low knowledge of AI applications in training, with a mean of 2.63. At the same time, they expressed a more positive perception of AI's potential to improve onboarding (mean = 3.78) and to enhance internal training effectiveness when integrated into LMS platforms (mean = 3.59). This indicates cautious openness: employees may not yet be highly familiar with AI, but they recognize its potential value when applied to practical training needs.

The preferred AI applications also provide direct guidance for the proposed model. The most selected applications were customizing training paths (77.8%), recommending content (70.4%), supporting new employees and assessing skills (both 63.0%), and collecting feedback (59.3%). These results indicate that respondents associate AI primarily with personalization, guidance, support, and improvement of the learning process.

The main barriers identified in Chapter 4 must also shape the proposal. Privacy and data protection were selected by 74.1% of respondents, followed by lack of digital skills, resistance to change, ethical concerns, lack of management support, and financial costs. These barriers show that implementation cannot be approached only as a technological project. It must include governance, communication, training, and change management.

Finally, the strongest result of the survey was the importance attributed to human intervention in onboarding, with a mean of 4.41. This finding establishes a clear boundary for the proposal: AI should support and enhance onboarding, while the process remains human-centered. Mentors, managers, trainers, and HR teams continue to play a central role in social integration, motivation, emotional support, and organizational belonging.

5.3 Proposed AI-Supported LMS Onboarding Model

The proposed model integrates AI capabilities into the existing LMS, aiming to improve onboarding consistency, flexibility, personalization, and monitoring. The model is designed as a hybrid approach that combines digital training, AI-supported capabilities, and human supervision.

As illustrated in Figure 5.1, the model comprises six interconnected components: a structured LMS onboarding path, AI-supported personalization, intelligent content recommendation, AI-supported guidance, feedback and monitoring, and human oversight. These components work together to create an onboarding process that is standardized enough to ensure consistency, but adaptive enough to respond to different professional profiles and learning needs.

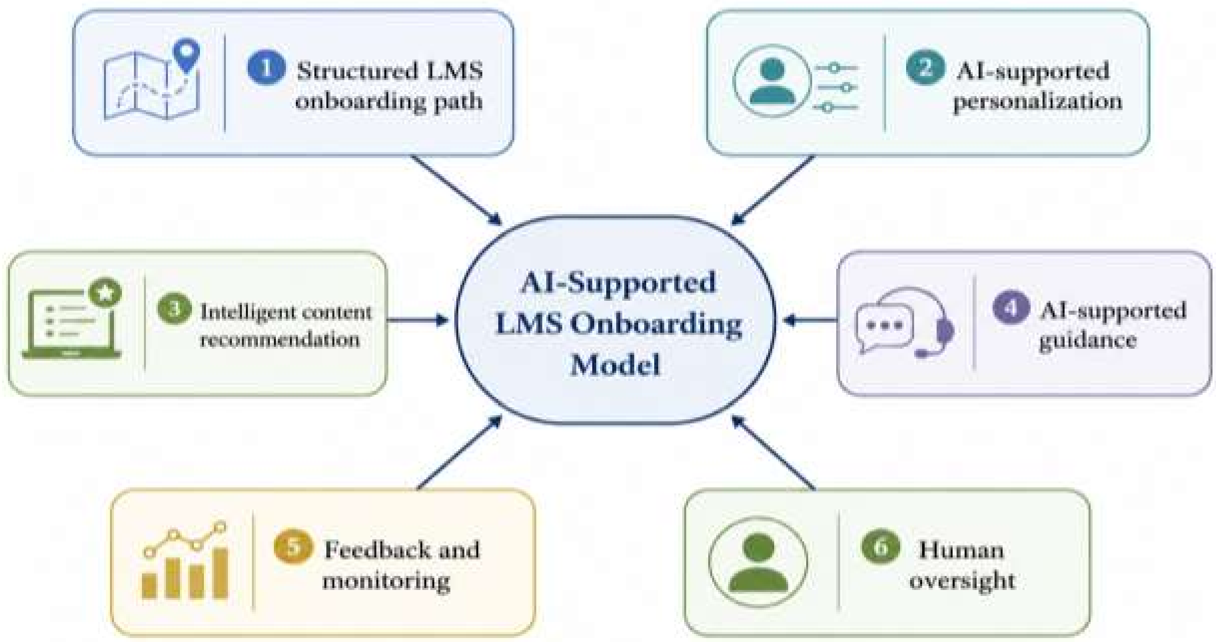


Figure 5.1. Components of the AI-supported LMS onboarding model

The first component of the model is a structured LMS onboarding path. The LMS should provide a centralized onboarding journey containing essential information, organizational procedures, role-specific modules, internal policies, training content, and assessment checkpoints. This structure would help ensure that all new employees receive consistent information, regardless of department, location, schedule, or manager availability.

The second component is AI-supported personalization. Based on the employee's role, previous experience, department, and training progress, AI could support the adaptation of onboarding paths. For example, a new employee with previous experience in the sector may require a different learning path from someone entering the sector for the first time. Similarly, a manager, fitness instructor, group class instructor, or administrative employee may need different onboarding content and priorities.

The third component is intelligent content recommendation. AI could recommend relevant resources based on an employee's progress, knowledge gaps, or training needs. This would make the onboarding experience more targeted and reduce the risk of overwhelming employees with excessive or poorly sequenced information. Content recommendation would also support autonomous learning by guiding employees toward the most relevant materials at each stage of onboarding.

The fourth component is AI-supported guidance. This may include a chatbot or virtual assistant integrated into the LMS to answer frequently asked questions, guide employees through onboarding modules, explain procedures, and provide support outside standard working hours. This functionality would be particularly useful in a sector with flexible schedules, where employees may not always have immediate access to managers or trainers.

The fifth component is feedback and monitoring. AI-supported tools could help collect feedback during onboarding, identify recurring difficulties, monitor completion rates, detect delays, and provide HR or training teams with information about areas requiring improvement. This would transform onboarding from a static process into a continuously monitored and adjustable one.

The sixth component is human oversight. Every AI-supported function should remain connected to human responsibility. HR teams, managers, mentors, and trainers should continue to validate the onboarding experience, interpret feedback, support social integration, and intervene when employees need personalized human guidance. Human oversight is not a secondary element of the model; it is one of its core principles.

5.4 Orientation Guidelines for Implementation

The following orientation guidelines translate the proposed model into practical implementation principles. They are based on the dissertation's empirical findings and intended to support the organization in developing an AI-supported LMS onboarding process in a progressive, responsible manner.

Table 5.1. Orientation guidelines for an AI-supported LMS onboarding model

Guideline	Orientation	Practical Application
Guideline 1	Structure onboarding through the LMS	Create a centralized onboarding path with mandatory modules, role-specific content, procedures, and checkpoints.
Guideline 2	Personalize learning paths with AI.	Use employee role, experience, department, and progress to adapt onboarding content and learning sequences.
Guideline 3	Use AI for content recommendation.	Recommend relevant resources, training materials, and support content according to the employee’s needs.
Guideline 4	Provide AI-supported guidance	Integrate a chatbot or virtual assistant to answer frequent questions and support employees asynchronously.

Guideline 5	Include feedback and monitoring mechanisms.	Collect feedback, monitor progress, identify difficulties, and generate insights for HR and training teams.
Guideline 6	Preserve human supervision	Maintain mentors, managers, and trainers as central actors in the onboarding process.
Guideline 7	Ensure ethical and responsible data governance.	Define clear rules for data collection, access, storage, transparency, and responsible use.
Guideline 8	Implement gradually	Begin with a pilot phase, evaluate results, adjust the model, and scale progressively.

These guidelines reflect the central conclusion of the empirical analysis: AI can add value to onboarding when it supports personalization, flexibility, and monitoring, but its implementation must remain gradual, transparent, and human-centered. The organization should introduce AI as a support mechanism to enhance the existing LMS and strengthen the onboarding experience.

The first guidelines focus on structure and personalization. A structured LMS onboarding path ensures consistency, while AI-supported adaptation allows the process to respond to individual needs. This combination is particularly important in organizations with diverse roles and professional profiles.

The following guidelines focus on support, feedback, and monitoring. AI-supported guidance and feedback collection may reduce repetitive tasks for managers and trainers, while providing employees with more immediate access to information. At the same time, monitoring mechanisms can help the organization identify weaknesses in the onboarding process and continuously improve it.

The final guidelines concern governance and implementation strategy. Ethical data governance and gradual implementation are essential for building trust and reducing resistance. The model should be tested, evaluated, and adjusted before being expanded across the organization.

5.5 Implementation Roadmap

The implementation of an AI-supported LMS onboarding model should follow a progressive roadmap. A phased approach reduces operational risk, allows the organization to test the model with a limited group, and creates opportunities for adjustment before broader deployment.

The proposed ten-month roadmap reflects the need for a gradual, controlled implementation. Since the model involves LMS organization, AI-supported functionalities, data governance, user training, and human supervision, a shorter implementation period could increase the risk of insufficient preparation or weak adoption.

The first months are dedicated to alignment and design, ensuring the model is technically, organizationally, and ethically prepared before testing. The pilot phase allows the organization to identify usability issues, collect feedback, and adjust the model before broader deployment.

Although the roadmap is structured over ten months, a margin of up to twelve months should be considered if technical adjustments, internal approval procedures, resistance to change, or additional training needs delay implementation.

This extended margin would allow the organization to preserve the model's quality and acceptance rather than accelerating deployment prematurely.

It would also align the implementation more naturally with the annual planning cycle, which is relevant when introducing a new organizational process that may require investment decisions, budget allocation, technical resources, and management approval.

Table 5.2. Implementation roadmap for the AI-supported LMS onboarding model

Phase	Timeline	Focus	Key Actions	Main Actors
Phase 1	Month 1	Preparation and alignment	Define objectives, identify stakeholders, map onboarding needs, review LMS capabilities, and establish data governance principles.	HR, training team, IT, data protection, managers
Phase 2	Months 2–3	LMS onboarding structure	Organize onboarding content, define mandatory modules, create role-specific paths, and structure assessment checkpoints.	HR, training team, managers, LMS administrator
Phase 3	Months 3–4	AI functionality design	Define personalization rules, content recommendation logic, chatbot scope, feedback mechanisms, and monitoring indicators.	HR, IT, LMS administrator, data protection
Phase 4	Months 5–6	Pilot implementation	Test the model with a limited group of new employees, collect feedback, monitor completion, and identify usability issues.	HR, trainers, mentors, pilot group
Phase 5	Month 7	Evaluation and adjustment	Analyze pilot results, adjust content, refine AI functionalities, review risks, and improve user support.	HR, IT, managers, data protection
Phase 6	Months 8–10	Progressive deployment	Expand the model to additional departments or roles, train users, and establish continuous monitoring.	HR, managers, trainers, LMS administrators

The first phase should focus on preparation and alignment. Before implementing AI functionalities, the organization should clarify the objectives of the onboarding model, identify the stakeholders involved, map existing onboarding limitations, and define the principles governing data use.

This phase is essential because the survey results showed privacy and data protection as the main barriers to AI implementation.

The second phase should structure the onboarding journey within the LMS. This includes organizing content, defining learning paths, identifying mandatory and optional modules, and creating role-specific training sequences. The objective is to transform onboarding into a more consistent and traceable process.

The third phase should define the AI functionalities to be integrated. This includes personalization rules, recommendation mechanisms, chatbot functions, feedback collection, and monitoring indicators. At this stage, the organization should avoid excessive complexity and focus on the functionalities most clearly supported by the survey findings.

The fourth phase should consist of a pilot implementation. A limited group of new employees should test the model before full deployment. This allows the organization to collect feedback, identify usability issues, assess acceptance, and adjust the model before scaling.

The fifth phase should focus on evaluation and adjustment. The data collected during the pilot should be used to refine the onboarding path, improve content, adjust AI-supported recommendations, and reinforce human support where necessary.

The final phase should involve progressive deployment. The model should be expanded gradually across departments or roles, accompanied by communication, training, and continuous monitoring. This approach supports organizational learning and reduces resistance to change.

5.6 Governance, Human Oversight, and Ethical Safeguards

Implementing AI-supported onboarding requires a governance structure that balances technological innovation with ethical responsibility. Since AI functionalities depend on data collection and processing, the organization must define clear principles for data access, transparency, consent, storage, and use.

Data governance should be established before implementing AI functionalities. Employees should understand what data are collected, why they are collected, how they are processed, who has access to them, and how long they are retained.

This transparency is necessary to build trust and address concerns about privacy and data protection.

The model should also apply the principle of data minimization. Only data that is necessary for onboarding, personalization, monitoring, and improvement should be collected. Sensitive or unnecessary information should not be included in the system.

This principle is particularly relevant because employees may be cautious about AI-supported monitoring if they do not clearly understand its purpose.

Human oversight should remain central throughout the implementation. AI can recommend content, identify gaps, support feedback collection, and provide guidance, but it should not make final decisions about employee performance, integration, or suitability. These decisions require human interpretation, contextual understanding, and managerial responsibility.

Mentors and managers should remain visible throughout the onboarding process. The LMS and AI functionalities may support access to information and training materials, but human interaction is still necessary for belonging, motivation, emotional support, and cultural integration.

The hybrid nature of the proposed model depends precisely on this balance between technological support and human presence.

Ethical safeguards should also include regular review of AI outputs. Recommendations, chatbot responses, feedback summaries, and monitoring indicators should be periodically assessed to ensure that they remain accurate, fair, and useful.

This prevents the system from becoming a rigid or opaque mechanism and supports continuous improvement.

5.7 Risks and Mitigation Measures

Implementing an AI-supported LMS onboarding model involves risks that must be anticipated. These risks are not limited to technology. They also include organizational behavior, trust, skills, leadership involvement, and the preservation of the human dimension of onboarding.

Table 5.3. Risks and mitigation measures

Risk	Possible Impact	Mitigation Measure
Resistance to change	Low adoption or reluctance to use the new onboarding model	Communicate benefits clearly, involve stakeholders early, and begin with a pilot group.
Privacy and data protection concerns	Loss of trust in AI-supported monitoring and personalization	Establish transparent data governance, limit data collection, and clarify access and use.
Lack of digital skills	Difficulty using LMS or AI-supported functionalities	Provide short training sessions, user guides, and ongoing support.
Over-reliance on automation	Reduction of human contact and weaker social integration	Maintain mentors, managers, and trainers as active participants in onboarding.
Low management involvement	Weak implementation and limited follow-up	Define roles and responsibilities for HR, managers, and training teams.
Uneven adoption across departments	Inconsistent onboarding experience	Start with standardized core modules and adapt only role-specific components.
Poor content quality	AI recommendations become less useful or inaccurate	Review onboarding content regularly and update materials according to feedback.

The most significant risk is the perception that AI may replace human support. This concern must be addressed from the beginning through clear communication.

Employees should understand that AI is being introduced to support access to information, personalization, and monitoring, not to eliminate mentors, managers, or trainers from the onboarding process.

Privacy and data protection concerns also require particular attention. Since this was the most frequently identified barrier in the survey, the organization should treat data governance as a foundational element of the model rather than a secondary technical issue. Clear rules, transparent communication, and limited data collection are essential.

Lack of digital skills may also affect adoption. Even when employees perceive AI positively, limited familiarity with AI-supported systems can generate uncertainty. Short training sessions, practical demonstrations, and accessible user guides can help reduce this barrier.

Another important risk is uneven adoption across departments. If some teams use the LMS and AI-supported onboarding consistently while others do not, the organization may reproduce the same inconsistencies that the proposal aims to reduce.

For this reason, the model should include common core modules for all employees, combined with role-specific adaptations.

5.8 Alignment Between Findings and Proposed Guidelines

The proposed guidelines are directly linked to the dissertation's empirical findings. Table 5.4 summarizes this relationship by linking the main findings from Chapter 4 to the corresponding orientation guidelines.

Table 5.4. Alignment between empirical findings and proposed guidelines

Empirical Finding	Proposed Guideline	Expected Contribution
Onboarding is moderately structured but not fully optimized.	Structure onboarding through the LMS.	Improves consistency, clarity, and access to essential information.
Face-to-face onboarding may create scheduling constraints.	Provide asynchronous LMS onboarding modules.	Increases flexibility and reduces dependence on fixed schedules.
LMS platforms are already used in the organization.	Expand LMS usage to onboarding.	Uses existing digital infrastructure more strategically.
E-learning is positively perceived.	Develop digital onboarding paths.	Builds on employee acceptance of flexible learning formats.
AI knowledge is limited, but expectations are positive.	Introduce AI gradually with user support.	Encourages adoption while reducing uncertainty.
Customization and content recommendation are highly valued.	Personalize learning paths and recommend content.	Aligns AI functionalities with employee expectations.
Privacy and data protection are the strongest barriers.	Establish ethical and transparent data governance.	Builds trust and supports responsible implementation.
Human intervention is strongly valued.	Preserve mentoring and human supervision.	Maintains the relational and cultural dimensions of onboarding.

This alignment supports the connection between the proposal and the empirical phase. Each guideline responds to a specific need, perception, or barrier identified in the survey. The model, therefore, reflects both the technological possibilities identified in the SLR and the organizational reality captured in the questionnaire.

The table also shows that the proposal is based on balance. It does not focus only on AI functionalities, but also on structure, governance, training, and human support. This balance is essential because the empirical findings showed both openness to AI and caution regarding its implementation.

5.9 Expected Organizational Contributions

The proposed AI-supported LMS onboarding model may contribute to the organization in several ways. The first expected contribution is greater consistency in onboarding. By structuring onboarding through the LMS, the organization can ensure that essential information is available to all new employees in a standardized format, regardless of department, schedule, or location.

The second contribution is increased flexibility. Asynchronous LMS modules may reduce reliance on fully face-to-face onboarding and enable employees to access training content based on their availability. This is particularly relevant in the Physical Activity, Leisure, and Health sector, where work schedules may vary significantly.

The third contribution is personalization. AI-supported learning paths and content recommendations may help adapt onboarding to different roles, experience levels, and training needs. This can make onboarding more relevant and efficient for each employee.

The fourth contribution is improved monitoring. By collecting data on progress, completion, feedback, and difficulties, the organization can identify weaknesses in the onboarding process and continuously adjust it. This creates a more dynamic approach to internal training, where improvement is based on evidence rather than informal impressions.

The fifth contribution is the better use of existing LMS infrastructure. Since the organization already uses LMS platforms for continuous training, the proposal encourages a more strategic use of existing systems by expanding them to onboarding.

The sixth contribution is the preservation of the human dimension of onboarding. The model reinforces that AI should support, not replace, human actors. Managers, trainers, mentors, and HR teams remain essential to social integration, motivation, and contextual support.

Overall, the proposal contributes to a more structured, flexible, personalized, and human-centered onboarding process. It also provides a practical orientation for organizations seeking to integrate AI into LMS-supported training without losing sight of ethical, organizational, and human factors.

5.10 Chapter Summary

This chapter presented an implementation proposal and a set of orientation guidelines for an AI-supported LMS onboarding model. The proposal was developed from the dissertation's theoretical and empirical findings and designed for a real organizational context in the Physical Activity, Leisure, and Health sector.

The chapter identified the empirical basis for the proposal, described the proposed model, presented implementation guidelines, defined a phased roadmap, and discussed governance, human oversight, ethical safeguards, risks, mitigation measures, and expected organizational contributions.

The proposed model is based on a hybrid perspective. LMS provides structure, AI supports personalization and monitoring, and human actors preserve the relational and cultural dimensions of onboarding. This balance constitutes the chapter's central contribution and prepares the transition to the dissertation's final conclusions.

Chapter 6 – Final Conclusions

6.1 Closing the Research Path

This dissertation examined the use of Artificial Intelligence in onboarding processes supported by Learning Management Systems, with particular attention to the relationship between e-learning, organizational training, employee integration, and AI-supported personalization. The study was developed in the Physical Activity, Leisure, and Health sector, a context in which onboarding and continuous internal training are especially relevant given operational variability, heterogeneous professional profiles, flexible schedules, and frequent training needs.

The research followed a progressive path from theoretical understanding to empirical analysis and practical orientation. The Systematic Literature Review provided the foundation for identifying how AI may support LMS-based learning environments, the challenges associated with implementation, and the potential impact AI may have on onboarding and internal training. The survey then allowed these dimensions to be examined within a real organizational context, gathering perceptions about onboarding, LMS usage, e-learning, AI, implementation barriers, and the continued role of human intervention. The final implementation proposal translated these findings into orientation guidelines for an AI-supported LMS onboarding model.

Three research questions guided the study. Together, they allowed the topic to be examined not only as a technological possibility but also as an organizational, methodological, and human-centered challenge. The findings suggest that AI may enhance onboarding when integrated into LMS platforms as a support layer, particularly through personalization, content recommendations, feedback collection, monitoring, and asynchronous guidance. At the same time, the study indicates that the value of AI depends substantially on ethical governance, organizational readiness, data protection, digital skills, and continued human supervision.

The central contribution of this dissertation lies in the development of a hybrid perspective. AI is understood as a tool that may strengthen the structure, flexibility, and adaptability of onboarding processes. At the same time, human intervention remains essential to the relational and organizational dimensions of employee integration. This perspective is particularly important in organizations where employees need access to consistent information, but also require mentoring, social integration, contextual support, and human judgment.

6.2 Main Conclusions

The first research question focused on how Artificial Intelligence can be applied to Learning Management Systems for onboarding. The literature reviewed in this study indicates that AI can support LMS environments through personalization, recommendation systems, adaptive learning paths, predictive analysis, content creation, intelligent tutoring, and feedback mechanisms. These possibilities are especially relevant for onboarding, as new employees may differ in their roles, previous experience, digital readiness, availability, and learning needs.

The empirical results suggest that the organization already has a digital foundation that may support this type of development. Most respondents recognized the use of LMS platforms, and the results also indicated a positive perception of e-learning, particularly in relation to time and schedule management and autonomous learning. However, the analysis also showed that LMS platforms are not yet fully used for onboarding. This gap is significant because it suggests that the organization may already have part of the technological infrastructure needed for AI-supported onboarding, while still having room to use it more strategically during the employee integration phase.

The preferred AI applications identified in the survey were also aligned with the proposed model's direction. Respondents selected customization of training paths, content recommendation, support for new employees, skills assessment, and feedback collection as relevant AI-supported functionalities. These results indicate that employees tend to associate AI with practical forms of support rather than with full automation. In this sense, AI appears more acceptable when its purpose is clear, it responds to concrete training needs, and it supports the employee experience in a way that is visible and understandable.

The second research question addressed the main challenges in implementing AI in LMS-supported onboarding processes. The findings suggest that these challenges are not only technical. Privacy and data protection emerged as the most relevant perceived barriers, followed by a lack of digital skills, resistance to change, ethical concerns, a lack of management support, and financial costs. These results indicate that AI implementation depends on more than technological feasibility. It also requires trust, communication, governance, training, and organizational commitment.

The role of human intervention was one of the strongest findings of the empirical phase. Respondents attributed high importance to maintaining human support in onboarding processes, which establishes a clear boundary for the proposed model.

AI may support onboarding, but the role of managers, mentors, trainers, and HR teams remains central. Onboarding involves more than access to information. It also includes integration, belonging, motivation, cultural understanding, and emotional support. These dimensions require human presence and contextual judgment.

The third research question examined the potential impact of AI on onboarding and continuous internal training. The findings suggest that AI-supported LMS onboarding may contribute to greater flexibility, consistency, personalization, and monitoring.

It may also reduce dependence on fully face-to-face formats, especially in contexts where employees work with variable schedules or across different locations. Through AI-supported recommendations and adaptive paths, onboarding may become more responsive to each employee’s role and experience level.

The results provide a structured understanding of the potential, perceived usefulness, and organizational conditions associated with AI-supported LMS onboarding. They also support the development of a model that may guide future implementation in a real organizational context.

However, the scope of the study remained exploratory: it did not include implementing an AI system, testing algorithms, developing a prototype, or integrating AI functionality into an LMS.

For this reason, the proposed model should be understood as an orientation framework for future implementation and validation, rather than as evidence of an already tested technological solution.

Overall, the dissertation indicates that AI-supported LMS onboarding may be a valuable direction for organizations seeking to improve internal training and employee integration. Its value depends on a careful balance between digital innovation and human-centered practice.

AI can help organize, recommend, personalize, and monitor learning processes, but the quality of onboarding still depends on human guidance, ethical decision-making, and organizational support.

6.3 Contribution of the Study

This dissertation contributes to the discussion on AI-supported onboarding by connecting three domains that are often examined separately: Learning Management Systems, Artificial Intelligence, and employee onboarding. By bringing these areas together, the study offers a structured perspective on how AI may support LMS-based onboarding in an organizational context.

From a theoretical perspective, the study organizes the literature around three central dimensions: applications of AI, implementation challenges, and potential impact on onboarding and internal training. The Systematic Literature Review identified themes including personalization, content recommendations, adaptive learning, predictive analysis, ethical concerns, data privacy, human monitoring, and organizational readiness. These themes provided the foundation for the empirical and practical phases of the dissertation.

From a methodological perspective, the study contributes by aligning the literature review, research questions, survey design, data analysis, and implementation proposal. The questionnaire was structured to examine the same dimensions identified in the SLR, thereby maintaining the empirical phase's connection to the theoretical framework. This alignment strengthened the coherence of the research process and supported the development of guidelines grounded in both literature and organizational data.

From a practical perspective, the main contribution is the proposed AI-supported LMS onboarding model. This model translates the findings into orientation guidelines that may support organizations in structuring onboarding through LMS platforms, personalizing learning paths, recommending relevant content, providing asynchronous support, collecting feedback, monitoring progress, and preserving human supervision.

The implementation roadmap developed in Chapter 5 also contributes to practice by proposing a gradual, realistic path to adoption. Instead of presenting AI implementation as an immediate technological transformation, the roadmap outlines progressive phases: preparation, LMS structuring, AI functionality design, pilot testing, evaluation, adjustment, and deployment. This staged approach reflects the organizational complexity of implementing AI-supported onboarding and recognizes the need for planning, governance, and user acceptance.

The study may also contribute to managerial reflection. The results indicate that employees may be open to AI-supported onboarding when its role is practical, transparent, and supportive. However, the same results also show that privacy, data protection, digital skills, and human oversight must be treated as central elements of implementation. For managers and HR teams, this means that communication, training, ethical safeguards, and continued human involvement should accompany AI adoption.

6.4 Research Limitations

The limitations of this dissertation are closely tied to the organizational conditions under which the research was conducted. The empirical phase depended on internal authorization, access to organizational data, management availability, and voluntary employee participation. These conditions shaped the study's rhythm, scope, and reach. Internal procedures, cautious attitudes toward data sharing, resistance to change, limited availability from management, and modest institutional encouragement for participation affected the research process. They delayed the survey phase by more than one year.

This delay has methodological implications. Artificial Intelligence is a field in rapid transformation, where new academic publications, technical applications, and organizational practices emerge continuously. The time gap between the initial literature review and the empirical phase may therefore have affected the currency of the theoretical foundation. More recent studies on generative AI, large language models, adaptive learning systems, recommender systems, or AI-supported LMS functionalities may have been published after the original search period and were not included in the review.

The same organizational context also influenced the number of valid responses to the questionnaire. Of the 49 responses initially recorded, only 27 fully completed questionnaires were retained for analysis. The final sample, therefore, reflects the conditions under which participation was possible, including employee availability, voluntary participation, and the limited institutional support for the survey. This reduced sample limits the representativeness of the findings and prevents statistical generalization to the organization as a whole or to the broader Physical Activity, Leisure, and Health sector.

The sample size also shaped the analytical approach. The empirical analysis used descriptive statistics, including percentages, means, and standard deviations. These indicators allowed the study to identify response patterns, tendencies, and perceptions within the organizational context. However, no inferential statistical tests were applied, so the analysis does not establish statistically significant relationships between variables. The findings should therefore be understood as exploratory and context-specific, rather than as definitive conclusions applicable to all organizations or all onboarding contexts.

The exploratory nature of the research also defines the scope of the proposed model. The study offers a structured interpretation of the organizational potential for AI-supported onboarding and provides practical implementation guidelines for future use. At this stage, however, the model has not yet been implemented, tested through a prototype, or integrated into a real LMS environment. For this reason, the dissertation cannot evaluate the operational performance, usability, accuracy, or organizational impact of an AI-supported onboarding system after deployment.

The Systematic Literature Review was developed within a defined methodological scope. The search was conducted through EBSCO, which provided access to peer-reviewed, full-text academic publications relevant to the intersection of Artificial Intelligence, Learning Management Systems, e-learning, and onboarding. This choice allowed the review to remain focused and aligned with the dissertation's objectives, particularly in identifying studies that could inform the empirical and practical phases of the research. At the same time, the use of a single academic platform should be understood as a delimitation of the review. Future research could broaden the search strategy by including additional databases with stronger coverage in computer science, educational technology, and AI system development.

The search strings were designed around the dissertation's core concepts: LMS, Artificial Intelligence, multimedia content, and learning management systems. This strategy supported a focused selection of studies directly connected to the research questions. However, the rapid evolution and diversity of AI-related terminology mean that other relevant studies may have used different expressions, such as generative AI, recommender systems, intelligent tutoring systems, adaptive learning, natural language processing, or AI-supported human resources management. Future reviews could therefore expand the search strategy by including a broader set of synonyms, more specialized technical terms, and additional Boolean operators.

The focus on a single organizational context also limits the transferability of the results. The proposed model may be adaptable to similar organizations, but the empirical findings reflect the organization under study's characteristics, culture, constraints, and perceptions. Organizations with different levels of digital maturity, management support, LMS usage, workforce structure, or data governance practices may experience different challenges and opportunities.

The nature of the data collected must also be considered. The survey captured respondents' perceptions of onboarding, LMS, e-learning, AI, and implementation barriers. These perceptions are valuable because they show how employees understand and evaluate the organizational context. They may also be influenced by personal experience, professional role, familiarity with digital tools, or attitudes toward technological change. The study did not include interviews, observations, LMS usage data, or performance indicators that could triangulate these perceptions.

Artificial Intelligence was approached as a broad organizational concept rather than as a technically differentiated set of systems. The dissertation identifies possible AI-supported functionalities, including personalization, content recommendations, guidance, feedback collection, monitoring, and skills assessment. Still, it does not examine in depth the technical differences between machine learning, recommender systems, natural language processing, generative AI, large language models, or adaptive learning architectures. This choice is consistent with the study's exploratory and organizational focus and defines a relevant opportunity for future research.

These limitations do not diminish the dissertation's relevance, but they define the scope within which its findings should be read. The study offers an exploratory, context-specific, and practice-oriented contribution. Its results indicate possibilities, tensions, and organizational needs, while future research is required to test, refine, and validate the proposed model in practice.

6.5 Future Work

The limitations identified in this dissertation open several possibilities for future research. A natural continuation would be to test the proposed AI-supported LMS onboarding model in a real organizational context. A pilot implementation would enable evaluation of usability, employee acceptance, completion rates, training effectiveness, feedback quality, and the practical role of AI-supported functionalities in onboarding.

Future research could also develop a prototype based on the model proposed in Chapter 5. Such a prototype could include a structured LMS onboarding path, AI-supported content recommendation, adaptive learning sequences, automated feedback collection, and a virtual assistant or chatbot to support new employees. Testing a prototype would allow future studies to move beyond perceptions and evaluate how AI-supported onboarding tools function in practice.

The empirical component could also be expanded. A larger sample would support more robust quantitative analysis and enable the application of inferential statistical methods. Future studies could examine whether perceptions of AI-supported onboarding differ by department, professional role, years of experience, prior onboarding participation, or familiarity with LMS platforms. This would strengthen the statistical and organizational relevance of the findings.

A mixed-methods approach would also be valuable. Interviews, focus groups, or observational data could complement survey results and provide a deeper understanding of employee expectations, management concerns, resistance to change, and the conditions necessary for successful AI adoption. Qualitative data would be particularly useful for exploring ethical concerns, trust, perceived usefulness, and the human dimension of onboarding.

The literature review could also be expanded and updated. Future studies may consider additional databases such as Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and ScienceDirect. They may also apply more complex search strings and include recent literature on generative AI, large language models, recommender systems, natural language processing, intelligent tutoring systems, adaptive learning, and AI-supported human resources management. This would provide a broader and more up-to-date theoretical foundation.

Further research could also examine which AI techniques are most appropriate for specific onboarding needs. Recommender systems may support content suggestions, natural language processing may support chatbot-based guidance, machine learning may support predictive analysis, and generative AI may assist in creating or adapting training content. A more technical approach would help organizations understand not only what AI can support, but also which type of AI is best suited to each function.

Ethical and governance models should also receive further attention. Since privacy and data protection emerged as major concerns, future research could investigate how organizations can design transparent, compliant, and trustworthy data governance frameworks for AI-supported onboarding. This includes questions related to consent, data minimization, access rights, algorithmic transparency, bias reduction, and human accountability.

Another possible direction would be to compare different organizational contexts. The model proposed in this dissertation was developed for an organization in the Physical Activity, Leisure, and Health sector. Still, future studies could examine whether similar guidelines apply in other sectors with high turnover, distributed teams, or strong training needs. Comparative research could help identify which elements of AI-supported onboarding are sector-specific and which may be transferable.

Longitudinal studies would also be particularly valuable. Onboarding is not limited to the first days of employment, and the effects of AI-supported LMS onboarding may only become visible over time. Future research could examine whether this type of model contributes to stronger integration, better training completion, higher employee satisfaction, improved retention, or greater alignment between employees and organizational expectations.

6.6 Final Reflection

AI-supported onboarding may strengthen access to information, support more adaptive learning paths, and make training processes more structured and responsive. Nevertheless, onboarding remains a deeply human process, shaped by organizational culture, social integration, professional confidence, and the development of a sense of belonging. In this sense, AI should be understood as a support mechanism, while the relational and interpretive role of managers, trainers, mentors, and HR professionals remains essential.

The proposed model reflects this balanced perspective. LMS provides structure, AI offers adaptive and analytical support, and human actors preserve the social and organizational dimensions of onboarding. This hybrid approach is the dissertation's central conclusion. It suggests that the future of onboarding may not depend on choosing between technology and human intervention, but on designing systems that integrate both in a responsible and meaningful way.

This dissertation contributes to the ongoing discussion of digital transformation in organizational training by offering a practical, theoretically grounded orientation for organizations seeking to explore AI-supported onboarding. The study remains exploratory and context-specific, but it provides a foundation for future implementation, testing, and refinement of AI-supported LMS onboarding models.

The final contribution of this work lies in the balance it proposes. Artificial Intelligence can support the structure, personalization, and monitoring of onboarding processes, but its value depends on the way it is integrated into organizational practice. When implemented with ethical governance, transparent communication, user support, and human supervision, AI may become a meaningful tool for improving onboarding without weakening the human relationships that make employee integration effective.

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Appendix A – Questionnaire

The following pages reproduce the print version of the questionnaire used in the empirical phase of this dissertation.

The Use of Artificial Intelligence in Onboarding Processes, Supported by LMS

Objectives: This questionnaire is part of an academic study (Master's degree in Information and Business Systems, supervised by Professor Arnaldo Santos from the Universidade Aberta) on Onboarding and the use of Artificial Intelligence (AI) supported by Learning Management Systems (LMS) within organizations in the Physical Activity, Leisure, and Health sector and it is organized as follows : **Data Collection and Processing:** This questionnaire consists of 6 parts, with a total of 20 questions. The estimated time required to complete this questionnaire is approximately 10 to 15 minutes. Questions marked with an asterisk (*) are mandatory. Participation in this study is entirely voluntary. All responses will remain strictly anonymous. Personal information such as age, gender, or professional position will not be disclosed or linked to individual responses. The data collected will be used solely for statistical analysis and interpretation within the scope of this research, specifically regarding the implementation and use of Artificial Intelligence (AI) in Onboarding and Learning Management System (LMS) in an organizational context. **Informed Consent:** I confirm that I have been informed that all data provided will be treated confidentially and used exclusively for academic purposes. I understand that my participation is voluntary and that I may withdraw from the questionnaire at any time without any consequences. **Further Information:** If you have any questions concerning this research, the questionnaire, or issues related to privacy and data protection, please contact: Vanessa Donga vandongart@gmail.com Thank you very much for your valuable contribution to this research. To proceed, please select the "I authorize" option and then click the "Next" button below.

PART 1 – Sociodemographic and professional characteristics

1 Department: *

Choose one of the following answers
Please choose **only one** of the following:

- Direction
- Human Resources
- Management/Administration
- Technical Management
- IT
- Fitness Instructor
- Group Class Instructor
- Marketing

2 Current role in the organization: *

Choose one of the following answers
Please choose **only one** of the following:

- Director
- Management
- Operations
- Technical

3 Years of professional experience in the sector: *

Choose one of the following answers
Please choose **only one** of the following:

- Less than 1 year
- 1–3 years
- 4–6 years
- More than 6 years

4 Have you participated in onboarding processes at this organization? *

Choose one of the following answers
Please choose **only one** of the following:

- Yes, as an employee
- Yes, as a trainer/manager
- No

PART 2 – Onboarding Experience and Internal Training

5 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
The onboarding process was clear and well-structured.	○	○	○	○	○
Onboarding helped me quickly understand my duties.	○	○	○	○	○
Onboarding required a lot of face-to-face time.	○	○	○	○	○
The in-person format of Onboarding created scheduling constraints.	○	○	○	○	○
Onboarding contributed to my integration into the organization.	○	○	○	○	○

6 Continuing education in the organization is: *

Choose one of the following answers
Please choose **only one** of the following:

○ Mostly in person
○ Mostly e-learning
○ Mixed
○
Non-existent

7 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
I believe that the current training meets my professional needs.	○	○	○	○	○

PART 3 – E-learning and LMS

8 The organization uses digital platforms (LMS) for training. *

Choose one of the following answers
Please choose **only one** of the following:

○ Yes
○ No
○ I don't know

9 If yes, the LMS is used for:

Select all that apply
Please choose **all** that apply:

☐
Onboarding

☐
Continuous training

☐
Assessment

☐ Internal communication

10 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
The use of e-learning facilitates time and schedule management.	○	○	○	○	○
E-learning contributes to more autonomous learning.	○	○	○	○	○

PART 4 – Perception of Artificial Intelligence (AI)

11 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
I am knowledgeable about Artificial Intelligence (AI) applications in training.	○	○	○	○	○
AI could improve onboarding processes.	○	○	○	○	○

12

AI could be useful for: *

Select all that apply
Please choose **all** that apply:

☐ Customizing training paths.

☐ Recommend content.

☐ Supporting new employees.

☐ Collecting feedback.

☐ Assessing skills.

13 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
AI could reduce the need for fully in-person onboarding.	○	○	○	○	○
The use of AI could improve employee retention.	○	○	○	○	○

PART 5 – Challenges and barriers

14 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
I believe there are barriers to implementing AI in the organization.	○	○	○	○	○

15

Main challenges: *

Select all that apply
Please choose **all** that apply:

☐ Financial costs.

☐ Lack of digital skills.

☐ Resistance to change.

☐ Ethical issues.

☐ Privacy and data protection.

☐ Lack of management support.

16 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
I believe that human intervention should continue to be essential in onboarding processes.	○	○	○	○	○

PART 6 – Overall assessment and solutions

17 Rate between 1 and 5 (1 = strongly disagree, 5 = strongly agree) *

Please choose the appropriate response for each item:

	1	2	3	4	5
Integrating AI into LMS could improve the effectiveness of internal training.	○	○	○	○	○
I would consider the adoption of AI-supported asynchronous onboarding to be positive.	○	○	○	○	○

18 In your opinion, what would be the main advantages of adopting AI? *

Please write your answer here:

19 What recommendations would you make to the organization to improve onboarding and internal training? *

Please write your answer here: