A LEARNING ANALYTICS MODEL FOR MEASURING AND EVALUATING THE IMPACT OF TRAINING PROGRAMMES IN ORGANISATIONS

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Abstract

Measuring and evaluating the impact of training programmes in organisations has been challenging for decades. To tackle this challenge, plenty of evaluation models have been proposed to assess the grade of satisfaction, learning, application and return on investment that training brings to organisations. Notwithstanding, these models are not designed to present data so that decision-makers can evaluate the effectiveness of training programmes using learning analytics. Hence, this study aims to design a learning analytics model (LAM) that provides the missing analytics piece of the existing evaluation models. In addition, this investigation should answer the research question: How can a learning analytics model provide relevant data to measure and evaluate the impact of training programmes in organisations? In addition, the research strategy proposed by this study is based on theoretical research as a research methodology. The Thematic Analysis (TA) method was adopted to analyse qualitative data from existing literature, research studies and books.

The proposed LAM was built on the basics of the *Theory Development Process,* from which three building blocks were defined: elements, relationships, and assumptions. In this manner, a solid model can be understood and implemented successfully in organisations. The LAM poses five themes that cluster the identified elements and relationships according to their nature: data sources, external and internal factors, measures, metrics and indicators, data preparation and reporting. Compared to the existing analytical models, this model's novelty comprises the elements required to measure and evaluate the impact of training in organisations by considering perspectives of the data generated before, during and after learning processes are delivered. Those perspectives involve elements of different natures, for example, data sources, external factors that impact the organisation, learning processes, learning experience, stakeholders, business goals, financial goals, analytical models, measures, metrics and indicators. In addition, this model establishes the conditions and assumptions for those who desire to implement or replicate the LAM effectively.

Further studies may adopt the proposed LAM to measure and evaluate the impact of training by implementing reports or dashboards based on their organisational needs.

Furthermore, future studies also may explore other dependencies among the elements to identify and widen the number of relationships proposed by this investigation.

Key Words: Corporate training – learning analytics – learning analytics models – effectiveness – evaluation – measuring – training.

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1 Introduction

1.1 Overview

According to Argote et al. (2021), training in organisations is the process of enhancing soft skills, hard skills, competencies and knowledge to keep employees updated in aspects such as the latest best practices in methods, technologies and tools required to execute workplace tasks with a high degree of productivity. Erina et al. (2015) claim that human resources departments are responsible for establishing strategies aligned with the business goals to deliver employee training programmes. For example, suppose the business goal consists of selling products in English-speaking countries to increase revenue and market share participation. In that case, the human resources department should design and deliver training programmes focused on developing English skills for their employees. Consequently, the organisation will remain competitive and stable in the marketplace because its labour force is able to interact with other cultures, increasing the probability of selling cutting-edge products.

Some studies (Franklin et al., 2014; J. Phillips & Phillips, 2012) have found that training, performance and business outcomes have a strong relationship. This hypothesis has been addressed in case studies implementing surveys and subsequent inferential analysis. For example, Franklin et al. (2014) concluded that providing training programmes to employees will improve the business objectives positively. Namely, this research study discovered that in scenarios where employees enhance their skills and competencies in relation to customer satisfaction, the impact on quality-of-service delivery increases substantially since employees are more aware of the importance of executing tasks correctly and timely. As a consequence, the quality-of-service indicator is affected positively which means that the customer is happy with the service and willing to refer the service to others. Thus, it is concluded that organisational training and development are vital processes for achieving success. Sahay et al. (2018) demonstrate that a positive impact on individuals leads to maximising business outcomes. It is evidenced by the significant increment in customer satisfaction, which affects the retention process. Some factors also influence the training impact: environmental factors, that is, individual goals, employees' commitment, and organisational objectives. Another paramount factor is the ability to design training programmes aligned with strategy and business goals. An example of lack of alignment is found in scenarios where training programmes are only focused on short courses (1 or 2 hours) or seminars, from which employees cannot learn and develop competences that may apply to their job and impact the strategy.

Other studies have addressed whether training programmes have succeeded in organisations and what conditions are required to achieve outstanding effectiveness. These have been carried out as meta-analyses and case studies. The conclusion is that training programmes positively impact employees' performance and business outcomes. The following factors influence the impact of programmes: internal and external motivation, content, attendance policy, duration, business needs analysis and feedback (Gegenfurtner et al., 2020; Lacerenza et al., 2017; Sahay et al., 2018).

Other authors (Barnett & John Mattox, 2010) claim that business goals are critical during training programmes. Business goals are specific targets that an organisation sets to achieve during a particular time. Business goals should drive training strategies and initiatives to guarantee worthwhile and effective investments (Barnett & John Mattox, 2010). For example, suppose the company rolls out a new product to its customers. In that case, the training process should be aligned with this new initiative to ensure that the sales and service teams understand how the product works and fits into the current portfolio. Designing a training course with this sort of alignment increases the effectiveness of training.

Technological solutions have been supporting training programmes by offering Virtual Learning Environments (VLEs) and Learning Management Systems (LMSs). In this way, employees can access courses that organisations have designed for them. Then, satisfaction, apprenticeship and behaviour are evaluated to validate whether training indicators have complied. As a result, organisations make decisions regarding programme continuity (Mouaici et al., 2018). The challenges that current applications ought to tackle are the implementation of learning analytics models, considering the whole training process; the implementation of automatic methods for collecting, transforming and presenting data; presenting indicators and visualisations easy to interpret and analyse (Mouaici et al., 2018; Sousa & Rocha, 2020; Tamkin et al., 2002).

Argote et al. (2021) concludes that in organisations where there is a definition of a training programme strategy and a time plan to deliver training programmes, the multifaceted benefits that contribute to the organisational success comprise productivity, efficiency, competitiveness and cutting-edge products. These benefits' origins lie in upskilling and reskilling employees following the organisational business goals.

Thus, despite the benefits and advantages of designing and implementing a training process in organisational settings, an investigation (Barnett & John Mattox, 2010) revealed that most organisations spend less than 4% of their learning and development investments on evaluation and metrics. Of those, 59% spend less than 1% on measurement. In addition, it was found that 39% of companies spend less than 1% of their training budget on measurement; 94.3% spend less than 5%.

The measurement and evaluation processes of training programmes allow organisations to determine the impact of learning on individuals and business goals (Choudhury & Vedna Sharma, 2019; Sousa & Rocha, 2020). These two processes provide insights regarding whether a programme causes an effect on internal operations or services delivered to the client. Hence, decision-makers may have certainty about increasing or decreasing the training budget in light of business performance and training programme impact (Barnett & John Mattox, 2010; Tamkin et al., 2002).

Thus, Mohammed (2019) defines data analytics as an alternative to measure and evaluate training programmes systematically by extracting, transforming, interpreting and delivering insights to make informed decisions. Then, decision-makers should design and implement actions based on the revealed information to optimise processes, increase processes efficiencies, and obtain a competitive advantage in an organisation. Data analytics is a knowledge area applied in multiple domains such as education, finance, healthcare and marketing due to its flexibility and ease of implementation (Duan & Da Xu, 2021). In this thesis, the term data analytics is changed to learning analytics because data are addressed from the educational and organisational context to measure and evaluate the impact on training programmes.

According to Argote et al. (2021), learning analytics aims to measure, collect, present and analyse data about trainees and their settings to understand and optimise learning processes and the environment where it occurs. This discipline has been adopted in educational institutions to improve learning processes, student outcomes and teaching outcomes. The principal data source are LMSs since interactions, engagement and performance are stored in these learning platforms. For example, assessments, completion rates, quizzes and attendance are variables to design and deliver compelling reports that support decisions during the learning processes. In this thesis, the term learning processes refers to a set of processes in which an employee is involved, that is, teaching process, training process, pedagogic process and didactic process.

Duan et al. (2021) and Hernández et al. (2022) claim that three analytical models exist that support learning analytics: (1) descriptive; (2) predictive; and (3) prescriptive. The descriptive model refers to historical data to answer the question of ‘what happened?’, for example, the number of trainees that passed an assessment. Then, at-risk students are identified on time to design personalised strategies that may support their learning processes successfully. Prescriptive models are considered the next step in learning analytics since they combine data, algorithms and statistics to forecast and warn in scenarios where students’ outcomes and behaviours are adverse. These models answer the question ‘what will happen?’ In this manner, trainers may anticipate adverse results during the learning processes. For instance, prescriptive reports may anticipate that a group of students may fail a course considering past results and current behaviours. The last step in learning analytics is the application of prescriptive models, which combine data, algorithms, statistics and experts’ experiences (i.e., trainers) to offer different alternatives and the best option to make a decision. These models respond to the question of ‘what should be the optimal outcome?’ For example, these models may suggest that trainers should adapt some academic content to obtain favourable outcomes during the learning processes. In addition, business intelligence as a discipline plays a significant role in learning analytics because it provides sophisticated tools and matured techniques to orchestrate and implement these three analytical models.

In addition, learning analytics has been expanded beyond educational settings, especially to organisational training processes, so that training strategies can be measured and evaluated based on the information provided by descriptive, predictive and prescriptive models (Mohammed, 2019). In this manner, investment in training can be justified, monitored and controlled since the impact on the organisational processes is measured and evaluated. It is evidenced in scenarios where it is demonstrated that employees have developed skills that make their work more efficient and effective, affecting operational excellence. Hence, the following are the reasons to measure and evaluate training programmes in organisations:

1. To improve the training programme strategy. Thus, learning and development processes are sustainable over time (Gegenfurtner et al., 2020).
2. To ensure a real transfer of knowledge and skills to the workplace. Hence, efficiencies are implemented in daily activities at work, which are reflected in time and money savings (C. Lee et al., 2014; Sousa & Rocha, 2020).
3. To demonstrate the value of training in organisations. For instance, highly motivated employees stay for several years in the same company because they can acquire new proficiency and skills while working without paying for education. Subsequently, creativity and innovation become part of the organisational culture (Gegenfurtner et al., 2020; Sousa & Rocha, 2020).

1.2 Statement of the problem

1.2.1 Aims of study

This study aims to design a Learning Analytics Model (LAM) that evaluates and measures the impact of training programmes in organisations. The proposed LAM comprises internal and external variables, relationships, data sources, actors, processes, and indicators required for designing dashboards and reports in an organisational context. From that, decision-makers may analyse, interpret and take action concerning the training process. Moreover, it will include the LA cycle: data collection, storage, transformation, measuring, and presentation of reports, which is essential for measuring the impact (Mônaco De Moraes et al., 2016; Patwa & Phani, 2018; Perez et al., 2018; Siemens, 2013a; Zhang et al., 2017).

1.2.2 The problem

The problem tackled in this study is the lack of a LAM in organisations capable of consolidating data generated from the training process. Consequently, decision-makers are not able to monitor, control, measure and evaluate the impact of training in terms of employee behaviour, return on investment and business goals. The importance of designing a LAM stems from providing guidance and description of the elements required for measuring and evaluating the value of training in organisations.

1.2.3 Justification

1.2.3.1 Previous research studies

Organisations have adopted frameworks and models to measure the impact of training programmes. The following are the most used in the corporate world: Kirkpatrick model, Phillip model, The Organisational Elements Model, and the CIRO model (Abich et al., 2019; Bell et al., 2017; Sousa & Rocha, 2020). However, some studies have found that these models still struggle to evaluate organisational impact, although they have been used for decades (Abich et al., 2019). Kirkpatrick confirms it; the most cited and experienced author on this topic has stated in one of his studies, “I have obviously not answered the question how to do it” (D. L. Kirkpatrick, 2006, p.8). The following are the suggestions from other researchers who justify that the problem identified in this proposal requires further research:

- Sousa and Rocha (2020) claim that there is no LAM for corporations that supports the training process’s impact and dimensions. It means that organisations make decisions with low accuracy and effectiveness, even though they live a digital transformation based on data drivers. It is one of their conclusions after they performed a literature review and a survey analysis. Therefore, further endeavours are required that develop a model based on learning analytics.
- Existing models and frameworks provide different techniques and methods to evaluate the impact on the organisation. However, there is no clear guidance to articulate and analyse the whole training process to measure the effect (Abich et al., 2019; Bell et al., 2017). It is also confirmed by Bell et al. (2017) and D. L. Kirkpatrick (2006), who state that existing models do not provide a

path to identify and consolidate variables, relationships, internal and external factors required for measuring and evaluating the impact of training.

- Most of the models are similar to Kirkpatrick's model (Reio et al., 2017; Ulum, 2015). Thus, the majority replicate the same problem. Namely, none of them provides a systematic approach for measuring and evaluating the impact of the training process (Abich et al., 2019; Choudhury & Vedna Sharma, 2019).
- The companies that try to evaluate programmes fail to implement strategies because variables are not appropriate, relationships among components are not considered, and they lack validity, consistency, accuracy, and completeness (Buganza et al., 2013a; Ferguson et al., 2019; Mouaici et al., 2018; Tamkin et al., 2002). It is corroborated by Szabó (2020) who states that only 8% of CEOs see business impact from learning and development.
- Instruments and technological artefacts that present relevant data for organisations require refinement to measure the training process (Bell et al., 2017). Thus, it is essential to develop a LAM that acts as the basis for technological artefacts such as dashboards and reports capable of describing a useful definition of processes, variables, and indicators that support corporate decisions (Hirsh & Carter, 2002).

1.2.3.2 Researcher's experience

The researcher of this thesis has been working for nine years actively in executive education and continuing education programmes that HEIs design to leverage the training processes in organisations with different profiles, sectors, sizes and ages. The role in each project changed from one to another since the needs varied according to the circumstances. Nevertheless, the primary role has been as project technical manager and academic coordinator. Thus, the researcher found out that these companies have defined a well-structured development and training process thanks to the adaptation of evaluation models such as Kirkpatrick (D. Kirkpatrick, 2006) and Phillips (P. Phillips & Phillips, 2018). Depending on the maturity level of the organisational processes, individuals, programmes and behaviours are evaluated considering the methods offered by these models. Nevertheless, the missing piece of these evaluation models is a LAM, able to gather strategic, operational, and learning data to measure training impact on financial, innovation, customer experience and competitiveness aspects.

1.3 Beneficiaries and significance of this research

The direct beneficiaries of the proposed LAM are organisations, namely decision-makers, because they will have the key elements to measure and evaluate the training process as a whole process. They will identify the variables and the factors required to determine indicators such as productivity and ROI. In that way, they will find the value of investing in training, even though they may design strategies in development and training based on learning analytics, which is more accurate than the current scenario.

Another beneficiary is the technology sector because the proposed LAM is the basis for developing software tools that provide strategic and operational data through reports and dashboards. The specific contribution of the proposed model is evidenced in the financial and operational variables that the model will define to implement KPIs such as ROI, impact and productivity.

The proposed model will contribute to the learning analytics field because it implements and combines different mature models, such as those of Kirkpatrick and Phillips, into an analytical model to make informed decisions. Therefore, experiences and best practices collected from decades are considered to create a LAM that consolidates variables, external factors, characteristics, relationships and indicators, which are essential elements to evaluate the impact of training programmes. Furthermore, this model is an answer to studies (Bell et al., 2017; Katkalo et al., 2019; D. L. Kirkpatrick, 2006; Sousa and Rocha, 2020) that have suggested further research in this area to provide guidelines for measuring and evaluating the impact of learning in organisations using learning analytics.

1.4 Research questions

The overarching question that this research will answer is:

How can a learning analytics model provide relevant data to measure and evaluate the impact of training programmes in organisations?

The sub-questions are:

- What elements are required to build a LAM that measures and evaluates the impact of training programmes in organisations?
- What are the relationships among elements that define the interactions within the LAM?
- What are the required assumptions and boundaries of the LAM that guarantee a successful application in organisational settings?

1.5 Overview of the thesis

The following chapter (chapter 2) reviews and analyses the existing research about learning analytics models. In this manner, it is possible to understand how current models work and how they have been implemented. Hence, this chapter is divided into three parts: learning analytics, learning analytics models and gap analysis. The learning analytics section presents the definition, evolution, process and challenges of learning analytics and how this topic relates to this thesis. The second part validates existing LAMs in educational and organisational settings; then, a comparison is performed to define the elements that should be considered and included in this thesis. In addition, some LAMs are analysed deeply to understand how they were designed and implemented in the corporate world and what the gaps are. The last part presents an analysis of what has been developed in organisational and educational settings in terms of models and frameworks and what further research should be done. Consequently, this section defines the focus and gap this research study will cover.

The third chapter presents the theoretical research strategy to answer the research question. Thus, secondary data are gathered from existing studies to design and build the LAM. Then, a thematic analysis method is presented and explained as a mechanism to collect qualitative data by following six phases: familiarisation, coding, generating, reviewing, defining, and conceptualising. In addition, flexibility and adaptability are also presented as advantages of this method in scenarios where data are qualitative. This chapter also defines the criteria for selecting the sample data and their saturation point, for instance, language and the sort of indexed databases as data sources.

The fourth chapter comprises the outcomes obtained during the implementation of the TA method. These outcomes are summarised through a thematic map analysis which reveals four themes: inputs, business impact, reporting and data processing. The inputs theme presents the data sources that provide raw data to the LAM, for instance, LMS, training request forms and human resources systems. Business impact presents the elements required to measure and evaluate learning processes, learning experience and the application of the acquired knowledge in the workplace. In addition, this theme reveals the elements that allow measuring of the monetary benefits that a training programme brings to organisations and the impact on delivering services or products to customers when employees participate in the training process. The third theme comprises the elements required to present consistent data in reports or dashboards. Hence, it encompasses descriptive, predictive and prescriptive models that should be evaluated before decision-makers analyse data. Through them, visualisations are explained and grouped in pie charts, scatterplots, line charts, tables, and metrics. In this manner, they are used adequately by the LAM. The last theme is named data preparation. The importance of this theme is in guaranteeing the quality of data used in the LAM. Hence, this theme comprises the data transformation process to obtain the desired content. For example, changing dollar currency into pound currency. Then, data can be used by the LAM. This theme also involves the elements required to remove duplicates, remove nulls or remove formats which are defined as a data cleaning process.

The fifth chapter presents a discussion of this research study. It shows the key findings to answer the research question: *How can a learning analytics model provide relevant data to measure and evaluate the impact of training programmes in organisations?* This chapter is divided into three sections: the underlying variables, the underlying relationships and the assumptions and conditions to implement the LAM. These sections are proposed according to the *Theory Development Process* (Storberg & Chermack, 2007; Whetten, 1989), from which a clear and experienced guideline was adapted to build a solid model. Hence, the first section reveals the essential elements that represent attributes or characteristics of the LAM. They are explained and grouped in themes according to the outcomes obtained in the TA method. In addition, it is explained how the elements can be defined, measured and evaluated to determine the impact of training in the organisation. The second section reveals the relationships between themes, domains, categories and elements. For example, data preparation has a causal relationship with data sources because data cannot be transformed or cleaned without the raw data provided by the LMS. It means one theme is the consequence of a previous one. However, this sort of relationship is not presented in all scenarios. The third section comprises the assumptions and conditions for implementing the LAM in organisational settings. Hence, the discussion is developed considering two perspectives: conceptual assumptions and contextual assumptions. Contextual assumptions define the set of conditions required to successfully apply the model; for instance, the logical order of execution of the elements and relationships. Contextual assumptions answer three premises: where, who, and when.

The sixth chapter presents the summary of the findings, the limitations of this study, and the gaps that should be covered in future research studies.

1.6 Limitations

The proposed model defined more than 90 elements in its structure and 11 relationships among elements. However, these relationships are very few compared to the number of elements. Therefore, further research may overcome the current number of relationships by analysing the potential interactions among elements. This study did not find many relationships because the selection was based on identifying relationships across the elements based on their causality, that is, by discovering which element is the consequence of one or more elements. Then, they were compared with previous studies to ensure trustworthiness. Hence, these two conditions reduced the possibility of discovering a relationship. In summary, further studies should focus on finding other relationships that may contribute to improving the LAM. In this manner, the information provided by the LAM will be more accurate because data are presented and computed according to their relationships.

Given that this research study is based on theoretical research, it is not devised to validate or apply the proposed model in organisational settings. This statement is corroborated by Trinajstić (1996), who states that theoretical studies lead to the design and development of experimental studies that may predict the outcomes based on theoretical predictions. Hence, future studies should be developed to validate the application of the LAM, considering the assumptions and boundaries defined in section 5.3, which are fundamental to implementing the model successfully. Namely, it poses conceptual assumptions involving the data flow process required to collect, transform, compute and present information. In addition, reports show KPIs and visuals that reflect learner experience, the level of acquired knowledge, the degree of knowledge applied in the workplace, the return on investment and some other elements that show benefits to the business goals. Furthermore, contextual assumptions are also defined to establish where the proposed model may be used, who the potential stakeholder involved in the process is, and when the model should be used.

2 Literature review

The studies included in the literature review are those whose topics are associated with measuring and evaluating training programmes and their impact on business goals. Hence, it includes models, variables, stakeholders, learning analytics and technology that have been incorporated into the learning processes to determine the effect of training.

2.1 Learning analytics (LA)

2.1.1 The concept and evolution of LA

The most common and accepted definition across the community is "*the discipline whose objective is the measurement, collection, analysis and reporting of data about the trainees and their contexts to understand and optimise learning and the environment where it occurs*" (Ferguson et al., 2019, p.43; Mônaco De Moraes et al., 2016, p.3; Siemens, 2013b, p.1382; Stewart, 2017b, p.97). Thus, extrapolating this definition considering organisational contexts, LA also is implemented in organisations to measure and evaluate the impact of training on internal processes or customers. In this manner, it validates whether training leverages the commitment to business objectives. It intends to provide insights for making informed decisions in learning and administrative processes. Decision-makers at the strategical and operational levels perform actions to improve indicators of efficiency, efficacy, quality and return on investment (ROI) (Cadavid & Corcho, 2018). (Mônaco De Moraes et al., 2016)

LA has its roots in fields such as educational data mining, business intelligence and data mining. Unlike these fields, LA was originated in 2011 to support informed decisions about learning and teaching processes in real or near real-time (Ifenthaler et al., 2021). The first adaptations of LA in educational settings took place to track the interaction between students and technological tools such as LMS and LVEs (learning virtual environments), namely in online education. Then, the concept was incorporated into MOOCs to improve the learning experience process. Finally, LA was implemented in organisations to evaluate the experience of learning and knowledge acquired by employees.

Comparing the scope of the proposed LAM to the widely accepted definition of LA, this study suggests widening the definition by incorporating the concepts of preparation and evaluation. The LAM refers to preparation as transforming and cleaning data to ensure a certain level of data quality. In this manner, the LAM becomes highly reliable in making informed decisions. Omitting this step will lead to making decisions wrongly, due to the low data quality (section 3.3). It is evidenced when it is required to obtain values in the same date format or when it is requested to remove duplicated and null values.

On the other hand, the term evaluation in this study indicates the process of assessing the results coming from metrics, indicators and measures aligned to learning processes and business objectives. The significance of this evaluation has a high impact on LA because it is the cornerstone of the whole process, it is where criteria or business rules are compared to the results, and information is presented as reports to enable analysis and interpretations (see details in section 5.1.3). For example, if the training experience indicators are negative, it means that trainers' pedagogy or content may have problems related to quality. Thus, decision-makers should notify trainers to evaluate what is impacting the learning processes and change the elements that are causing the problem. Therefore, considering the significance of these two terms, the updated definition of LA should be:

The discipline whose objective is the measurement, evaluation (*new*), collection, preparation (*new*), analysis and reporting of data about the training process (*new*) and its contexts to understand and optimise learning and the environment where it occurs.

2.1.2 Learning analytics process

According to the literature review, there is no standard process for implementing learning analytics. However, some studies have admitted that it is fundamental to have a definition of the required phases to address learning analytics as a process. In this manner, objectives, stakeholders, activities, resources and business rules are identified systematically to meet the decision-maker's expectations. Hence, the literature review carried out in this study has discovered common steps that are part of the LA process.

2.1.2.1 Collection/capturing/gathering

Some studies (Chatti et al., 2012; Jülicher, 2018; Nguyen et al., 2021; Şahin et al., 2019; Šereš et al., 2022) coincide that the first step of the LA process consists of collecting raw data from multiple sources and formats. Other names given for this step are data capturing and data gathering. The most common data source is LMSs because they are flexible to configure and use in different settings such as universities, schools and organisations. A LMS is designed to support learning processes and store data related to learning interactions, learning outcomes, demographics attributes and logs. For example, a LMS stores data derived from navigation behaviour, quizzes, assessments and even student affectivity, that is, motivation or emotional states. In addition, the authors propose other data sources such as student information systems (SIS), social networks, intelligent tutoring systems and institutional databases.

In contrast to the literature reviewed, the proposed LAM includes HRMS and digital request forms as a source of data. These sources store data related to organisational learning, such as trainers' positions, departments, years of work experience or previous experience. These data are combined with educational data to evaluate the probability of success during the training programme execution. Another difference from the literature (Nguyen et al., 2021) is that this study does not contemplate where to store the collected data since it is part of the implementation of the proposed model. Therefore, organisations or entities that desire to implement or adapt the proposed model should define the tools and places to store the collected data.

2.1.2.2 Data preparation

Authors (Chatti et al., 2012; Romero & Ventura, 2020; Şahin et al., 2019) agree on the step of data preparation in the LA process. This comprises transforming the raw data into desired formats or aggregations to present information as it is expected. In this manner, the interpretation and analysis of reports become easy. For example, date variables are in the format year/month/day, but the desired format is day/month/year. Another situation is when it is required to obtain the sum of trainees participating in the training process during a year. Hence, this step should perform statistical operations to satisfy this requirement. In addition, the authors are aligned with identifying in this step the variables required in reports or further analysis because not all data generated by data sources are helpful for research; it depends on the situation and business requirements.

The proposed LAM is also in line with this step and its objectives. The only difference is that the LAM suggests cleaning activities to ensure a certain degree of quality. Consequently, decision-makers may define strategies and plans based on reliable data. Romero and Ventura (2020) claim that personal data are not helpful for learning analytics; that is, name, email, telephone number, and address are data that should be removed or anonymised in this step. The reason is that sum, average, or any statistical operation cannot provide results with these variables. Another reason is associated with data privacy and confidentiality compliance, which should be accomplished in this step.

2.1.2.3 Analytics, reports and action

In the literature, some authors agree (Cadavid & Corcho, 2018; Chatti et al., 2012; Romero & Ventura, 2020; Şahin et al., 2019) that this step comprises the implementation of descriptive, predictive and prescriptive models which present data through visualisations to analyse and interpret information regarding learning processes. Descriptive models describe historical data and its behaviour. For example, the number of programmes delivered to employees in a year or the number of employees attending programmes monthly. Predictive models combine historical data with statistical or machine-learning techniques to anticipate events that may occur in the future. It can be evidenced when trainees with specific demographic characteristics dropped out of the onboarding programme due to its content. Therefore, the model may predict a high probability that the programme will have similar results with trainees with similar characteristics. The prescriptive models combine historical and predictive data to simulate different possible scenarios and suggest the best suitable scenarios for learning. For instance, if the learning experience indicator is adverse, the model will evaluate possible scenarios that should be modified to obtain desired results. Hence, the model should propose changing the content, pedagogy, or trainer based on historical data and algorithms. Chatti et al. (2012) state that three problems may arise during this step - an overload of information, inappropriate information and incomprehensible information. Hence, presenting information with the correct volume and understandably is the key to guaranteeing a straightforward way to analyse and interpret data. This activity can be addressed by planning and designing the reports before they are built.

According to the investigations, reports are the means to present data regardless of the analytical model. Although there is no standard way of designing and implementing reports using visualisations, the literature agrees that tables, charts and graphs are used to show data as information. The proposed model also considers reports as a key element to group visualisations that should support KPIs, metrics and measures defined to monitor, control and improve learning processes.

The last and most crucial step in LA is to take action based on the information presented in reports (Chatti et al., 2012). Some authors approve of this claim because decision-makers should analyse and interpret information to improve learning processes. The first activity is to monitor and control learning processes, for instance, collecting surveys about the educational content, pedagogy and the trainer's experience and ease of delivering knowledge. The second activity consists of changing or adapting strategies to improve the negative variables affecting learning processes. In this study, the proposed model provides the necessary elements to perform actions to reach learning objectives and business objectives. However, the number and type of actions depend on the people responsible for analysing learning analytics data.

2.1.3 Challenges in Learning analytics

2.1.3.1 A need to measure and evaluate performance post-training

Bell et al. (2017) performed a literature review from 1918 to 2016. In this study, it was declared that organisations should measure and evaluate the training process by connecting three elements, learning, transfer and performance. Learning refers to the knowledge level reached during the training. Transfer indicates the degree of knowledge applied in the workplace or knowledge transferred from the trainee to his colleagues or other employees. Performance measures the impact of training on trainees' productivity. For example, productivity is affected positively when the acquired knowledge reduces the time executing a task, improves service quality, increases innovations, or increases the number of products in less time. Bell et al.

(2017) and Gegenfurtner et al. (2020) agree in implementing post-training assessment to evaluate these three elements. Then, feedback to trainers and trainees can be performed to change what is affecting the training process. In addition, it is recommended that LA provide real-time information to act immediately. Bell et al. (2017) identified that not all organisations evaluate transfer and performance because of their complexity or time consumption. However, this study emphasised that evaluating transfer and performance was vital to determine the benefits learning brings to organisations. Shen and Tang (2018) corroborate in their empirical study that learning, transfer and performance have direct and indirect relationships. This study posed that job satisfaction was a crucial mediating mechanism to reach positive results, which in turn affect the business objectives of organisations (Sung & Choi, 2021).

2.1.3.2 Information overload

Learning analytics is a powerful tool to analyse data generated by trainers and trainees with the objective of distributing information to the right people at the right time. These data are presented employing reports in the form of visuals and KPIs. Despite the LA benefits, Hernández-de-Menéndez et al. (2022) state that organisations are facing the challenge of storing and processing vast amounts of information reflected in reports with the risk of presenting irrelevant data. Therefore, decision-makers do not know what to do with the information. Consequently, decisions are not made timely, and people feel frustrated and confused, affecting their productivity and effectiveness during the analysis process. This challenge is addressed and controlled in this study during the activity of aligning business objectives, learning objectives and desired outcomes. Hence, the information presented in reports is pertinent and appropriate to analyse and interpret to evaluate learning processes. Romero and Ventura (2020) corroborate that it is fundamental to define the aims of LA from the beginning to ensure a successful implementation. In addition, it is also suggested to evaluate and select adequate visuals to present information.

2.1.3.3 Reduced understanding of learning analytics

Some authors (Hernández-de-Menéndez et al., 2022; Selwyn, 2019) agree that decision-makers are only interested in grades, persistence, non-completion of metrics, completion of business KPIs, setting trainers' motivation, engagement and level of satisfaction aside. Ferguson et al. (2019) pose that LA help to transform and innovate the training process. However, LA should accommodate that learning is a dynamic and non-linear process with successes and failures within a qualitative and quantitative world. Şahin et al. (2019) propose a conceptual solution that may address this challenge. Thus, the authors claim that learning analytics may help to personalise the learning process by providing metrics to instructional designers. Then, they analyse and interpret the results. If the results are adverse, instructional designers or trainers may change activities and interventions to improve their effectiveness. In turn, satisfaction, engagement and motivation are affected positively. However, this potential solution should be implemented in an organisational context to validate its significance. Hence, the authors propose that technological solutions are the means to validate this solution by adopting existing frameworks such as Analytics Layers for Learning Design (AL4LD), Learning Analytics Design, among others.

The LAM proposed by this study responds to this challenge in the following manner: by considering measures, indicators and metrics that are not only related to the completion of business objectives and learning objectives but also posing the people perspective, which involves analysis of data associated with trainers' behaviours, experience, motivation and engagement since they are a fundamental part of learning processes. Suppose they are reflected as unfavourable in the reports. In that case, decision-makers should intervene immediately to diagnose the origin of the problem and propose strategic and tactical activities that may help trainers to change the negative results into positive ones (see details in section 5.1.3.1).

2.1.3.4 Limiting LA to technological tools

Guzmán-Valenzuela et al. (2021) and Romero and Ventura (2020) state that technological tools have been developed to support LA and innovations in learning processes during the last decade. For example, mobile education, virtual reality, holograms and augmented reality. However, LA is not yet prepared to prepare and present adequate data from multiple data sources. Thus, further research is fundamental to analyse the manners to process and present very large quantities of data generated by different tools involved in learning processes. Hernández-de-

Menéndez et al. (2022) and Kaliisa et al. (2021) complement this LA challenge by stating that IT specialists only design LA tools, which means that decision-makers, trainers and trainees are not involved in the design and implementation of LA. They have an observational role; thus, their point of view and needs are not considered, leading to biased information (Guzmán-Valenzuela et al., 2021). For example, trainees' levels of motivation and engagement are not considered. In addition, Kaliisa et al. (2021) and Selwyn and Selwyn (2012) critique technology tools used in LA because they ignore contexts and complexities of the real world, that is, students, classrooms and their interactions. The authors claim that software tools are technologically innovative but socially stupid. The reason is that learning processes are dynamic and full of uncertainties which every individual in a classroom generates. It means that every training programme differs, and variables may change among trainees, for example, the degree of engagement or motivation. On the other hand, LA works well when variables are systematically adapted and calculated, for example, the programme's cost and the ROI.

2.1.3.5 Data security

Ferguson et al. (2019), Hernández-de-Menéndez et al. (2022) and Romero and Ventura (2020) conclude that data privacy, security, and ethics are challenging in LA. Hence, it is fundamental to design and implement policies in organisations that prevent LA from unauthorised access or use of data. For example, students monitored and measured during the programme execution should authorise through a consent form before the training begins. In this manner, the institution shows a profound respect for the individual's privacy. In addition, Guzmán-Valenzuela et al. (2021) propose that this challenge should respond to the following question: who gathers the data, where are they stored, who is accountable, what levels of security should be implemented, to whom the data are shared, i.e., government or educational entities, and what are the proposes of using data, that is, marketing, educational or business purposes. Therefore, organisations that desire to incorporate LAMs into their processes must define guidelines or policies that meet data security best practices.

2.2 Learning analytics models (LAMs)

2.2.1 What is a model?

A model describes situations, processes, relationships, factors, and systems in a simplified form to improve understanding of decision-making (Colin Sanderson, 2006). It comprises income, exogenous, endogenous (intermediate), outcome variables and elements with properties. There are three types of models: iconic, conceptual, and mathematical. Iconic models refer to physical or spatial relationships between objects. A typical example is a train route map defining the physical interconnections between stations. Conceptual models are diagrams and relationships that represent and communicate an abstract system, process or situation qualitatively. They can be represented using a logical sequence of activities to define a process and influences or effects to understand conditions in which a system is exposed. These two sorts of representation may be combined in a single model (Colin Sanderson, 2006; Common, 1978). In comparison to conceptual models, mathematical models provide a quantitative representation to understand a phenomenon. Variables, symbols and expressions are the elements that compose these models (Common, 1978).

2.2.2 Characteristics of a LAM

Several studies have concluded that learning analytics should fulfil the following characteristics to provide relevant and accurate data regarding training impact. Hence, a LAM should be:

Aligned with the organisation's strategy and business goals: Studies performed by Sciarrone and Temperini (2019) and Taylor (2019) indicate that learning analytics should measure and evaluate the direct impact of training on the customer, namely, in the dimensions of satisfaction, quality of service, innovation and creativity. Other studies have emphasised that it is paramount that learning analytics measure the training outcomes and the relationship to process optimisation, that is, the reduction of time to complete tasks once proficiency has been developed in training (Reio et al., 2017). Kirkpatrick's (D. Kirkpatrick, 2006) and Phillips's (P. Phillips & Phillips, 2018) evaluation models validate this characteristic as training results.

Designed to measure the impact of training on employee behaviour: Studies from Reio et al. (2017) have indicated that employees' behaviour should be considered as an outcome of learning processes, evidenced in their productivity. Franklin et al. (2014) complement that "as human performance increases, the business performance and turnover also improves". Thus, as it is established and confirmed in Kirkpatrick's model (D. Kirkpatrick, 2006), this is a level that the learning analytics model must consider evaluating the impact of training.

Designed to implement different types of analytics: Studies carried out by Mohammed (2019) have highlighted that learning analytics should include descriptive, prescriptive and predictive analytics. Descriptive analytics refers to historical data, behaviour and outcomes. For example, presenting data related to training costs per year and course completion rates; prescriptive analytics aims to find the best decision for a given data. A typical indicator is the ROI (Barnett & John Mattox, 2010). If it is low, decision-makers should change the strategy regarding the training process to increase this strategical indicator; predictive analytics comprises forecasting behaviours and outcomes using historical data. For example, obtaining the probability of employees' success in the workplace after they finish training (Reio et al., 2017).

Rich in quality: Ferguson et al. (2019) and Siemens (2013a) suggest that a model for learning analytics should fulfil several quality dimensions. Coherence, completeness and availability are examples of dimensions that require attention because they usually are pitfalls in human resource departments (Rasmussen & Ulrich, 2015). However, due to the variety of dimensions in data quality, the LAM must define the criteria to select the most appropriate dimensions according to the organisational context. This definition will be carried out during the development of this study.

A unique source of information: The learning analytics model should consolidate the data generated by the entire training process (Bruno et al., 2003). It means that the end-to-end process should be tracked through the LAM. General activities that belong to this process are data storing, transformation and presentation. Moreover, Stewart (2017) recommends that despite the data being collected during the entire process, it is also essential to find a balance to present data because it sometimes may be overwhelming or meaningful. Hence, how and what data should be collected are questions that the proposed model should respond to (Rasmussen & Ulrich, 2015; Stewart, 2017a).

2.2.3 Learning analytic models in educational settings

In the literature, there are LAMs designed for educational settings such as universities and schools. These LAMs focus on the process of collecting, transforming, and presenting data associated with retention, students' performance, success, interactions, feedback, and grades, among others. Relevant learning models are the Learning Analytics Reference Model, the learning analytics model principles, the learning analytics continuous improvement cycle, Siemens learning analytics model, and the 4-Dimensions Model (Mônaco De Moraes et al., 2016). Another study found 18 frameworks that conceptualise LA for HEIs. These frameworks provide guidelines to articulate pedagogical processes and data generated from Learning Management Systems (LMSs).

A review article addressed by Quadir et al. (2021) identified 101 LAMs for higher education from 2011 to 2019. This investigation grouped LAMs into four categories: data models, interactive models, meta-cognitive models, and performance models. Data models focus on the data flow process, collecting, measuring and executing informed decisions based on the results. Interactive models comprise the events generated between people and computers, for instance, assessments performed by a learner using an LMS. Meta-cognitive models evaluate the educators' experience when they interact with learning tools; for example, an indicator may be the ease of use. Performance models aim to improve the learner's proficiency.

To complement the study carried out by Quadir et al. (2021), a new review of LAMs was performed on Scopus, Web of Science, and Google Scholar from 2018 to 2022. The condition applied to search on these indexed platforms and select the investigations was that models were part of the data models category because the LAM proposed by this research involves the entire learning analytics process. Thus, models and frameworks dismissed in this review did not cover the learning analytics process required for designing and implementing a LAM. For instance, studies that only cover descriptive, predictive and prescriptive models were dismissed because they focused on algorithms and machine learning techniques, omitting the data flow process that involves learner experience, learning assessments, learning application, data quality and data representation.

Thus, the outcomes showed only 7 LAMs. Table 2.1 presents the selected models that may have common elements with the proposed LAM addressed in this study. The potential elements may comprise measurement, collection, analysis and reporting. In addition, the title, publication year, objective, the set of elements that are part of each model and the limitations are presented.

Title	Year	Objective	Elements/Components	Limitations
Study on Learning Analytics Data Collection Model using Edge Computing (Cowman & McCarthy, 2012; H. Lee & Chui, 2019; M.-S. Lee et al., 2021; Mejía et al., 2011; Park & Jo, 2019; X. Wu & Zhu, 2015)	2021	This study presents a model that collects and processes data during the learning processes. Then, data are processed on the students' smartphone to provide quick feedback.	Data collection, data storage, data analyse, data reporting and action.	This study did not incorporate a data quality phase to guarantee reliable and consistent data.
Predicting students' behavioural engagement in microlearning using learning analytics model (Mohd et al., 2021)	2021	The objective of this investigation was to conduct an analysis of students' behavioural engagement. It incorporates neuronal networks as predictive method.	(1) Data collection , (2) data storage, (3) data cleaning and filtering, (4) analyse and predict outcomes, and (5) action	Although this study comprises the LA data cycle, it only focuses on predicting behavioural engagement.
A comprehensive approach to learning analytics in Bulgarian school education (Gaftandzhieva et al., 2021)	2021	The aim of this study was to evaluate the education of a secondary school. The study poses six learning analytics models which are mapped to the following stakeholders: students, parents, teachers, class teachers, managers and governmental agencies. These models helped to improve the learning and teaching processes.	(1) Stakeholders, (2) data sources, (3) indicators and (4) actions	This study did not address data quality and reporting phases. The main findings of this study where indicators related to the six groups of stakeholders. This study suggest implementing technological tools that support the proposed model.
International Forum of Educational Technology & Society Analytics 2.0 for	2021	This study aims to present the progress and suggestions to achieve a better performance during	(1) The brain collects data and centralises the communication.	The study suggests further studies that involve data

Title	Year	Objective	Elements/Components	Limitations
Precision Education (J.-Y. Wu et al., 2021)		the learning processes. The model collects data from different social media platforms and interactions that are involved in the classroom. Then, data are analysed using statistics and intelligent artificial methods. Finally, the data are presented through dashboards.	(2) Social networking behaves as data source, (3) smart classroom provides the interaction among peers and teachers, (4) intelligent component applies statistics and artificial intelligence and (5) dashboard presents data.	privacy and data security to protect learners' identity and behaviour from cyber delinquents. In addition, the authors also propose to include a data transformation phase.
Refining the Learning Analytics Capability Model: A Single Case Study (Knobbout et al., 2020)	2020	This study aims to define the required capabilities to design and implement a LAM. This study is peculiar in this field because it is the first to propose a capability model in LA that can be used in educational and organisational settings.	(1) Data (quality, reporting, collecting analytics, and usage), (2) management (strategy, performance and monitoring), (3) people (stakeholder, skills, training, engagement and knowledge), (4) technology (automation, infrastructure, software and connectivity) and (5) privacy and ethics	The sample data was limited to four stakeholders working for the same organisation. It implies that further research should be developed in this respect to make this model generic. In this manner, it can be used in different contexts. In addition, this model did not identify two essential building blocks analytical models and actions. Analytical models comprise descriptive, predictive and prescriptive approaches. Actions relate to performing activities based on the results provided by the LAM.
Learning Analytics for Educational Innovation: A Systematic Mapping Study of Early Indicators and Success Factors (Okoye et al., 2020)	2020	The investigation aims to improve the learning processes and classroom experiences by means of a Learning Analytics Educational Process Innovation Model which collects data from different	Learning environments, datasets, algorithms, models, visualisations, analysis, process monitoring and action	This case study did not incorporate a data transformation and cleaning phase that ensures data quality. This study

Title	Year	Objective	Elements/Components	Limitations
		sources to monitor and present data and performs actions		considered learners' and institutional perspectives. Thus, further studies should incorporate other views such as external factors.
Applying Learning Analytics to Assess Learning Effect by Using Mobile Learning Support System in U-learning Environment (Duan & Da Xu, 2021; Song et al., 2016; Zhou et al., 2017)	2019	This model aimed to present a software tool that measures learning processes in a Virtual Learning Environment. It consists of collecting multi-dimensional data provided by learners through surveys, educational platforms and terminal tools. Then, data are organised and presented employing an interactive dashboard. Finally, decision-makers interpret the information to identify potential drop-outs, behaviour patterns and how to make optimisations in the learning processes.	(1) Data collection, (2) data organisation, (3) data analysis and (4) data application.	This study omitted the data quality phase which ensures a reliable LAM. In addition, this LAM cannot be extrapolate to other scenarios because it is designed only for a specific educational context.

Table 2.1 Literature review of existing LAM from 2018 to 2022

Comparing the previous LAMs, it can be concluded that at least four elements are fundamental to designing and implementing a LAM in educational settings. In this manner, stakeholders may measure and evaluate learning processes from different perspectives. Hence, the four elements are data storage, data collection, reports and actions.

2.2.3.1 Data storage

This is a set of software tools that store data generated by educators and learners during learning processes. That is demographic data, academic assessments, logs, surveys, satisfaction assessments or other mechanisms that serve as a means to capture data. LMS and VLE are well-known tools that capture interactions or events that are fundamental to updating indicators. However, these two are not exclusive because they depends on the software tools defined by the educational institution. The data storage in the LAMs is essential because it acts as a data source for further phases such as collection and actions. If this element is omitted, measurements and evaluations cannot be performed.

2.2.3.2 Data collection

This describes the process of identifying data sources, extracting data and incorporating data into the LAM. The data to be collected are categorised into quantitative or qualitative groups. Quantitative refers to data whose nature is numeric. For example, the number of learners attending an academic programme. Hence, this variable can be used in statistical operations such as sum, average, minimum and maximum. Qualitative encompasses descriptive data, for instance, the city where the learner lives. Therefore, some of the statistical operations cannot be applied. Frequency is the standard operation that is performed over these sorts of data. This element should incorporate a data quality process to ensure a reliable model. However, neither of the reviewed studies included variables such as completeness or consistency as quality indicators. In addition, some authors are emphatic about the importance of considering the data ethics phase. In this manner, data are collected legally and used ethically.

2.2.3.3 Reports

This is known as the effective manner to present results related to learning processes. Before information is shown through reports or dashboards, the first step consists of defining the objective of the report and what the stakeholders are, for instance, whether learners, educators or managers. The second step consists of implementing the report using visuals categorised into four groups - charts, scatter plots, 3D representations and maps. Thus, depending on the data type and the visualisation objective, the report designers should use visualisations such as tables, diagrams or pie charts. In addition, reports may support basic statistical operations such as average, mean, sum, standard deviation, maximum and minimum. In this manner, variables and KPIs defined in the report can present the required data. For example, the number of attending sessions, the number of visits to the LMS or the frequency of posting and replies. However, it is worth noting that the data and KPIs defined for one situation may not be helpful for another case or context. There are two metrics that reports should fulfil to ensure that people use them as a support to make informed decisions. The first one is known as user-friendliness. It means that the colours, forms, shapes and navigation are set up so that people can interact with the reports easily. The second metric is named ease of interpretation. It refers to the adequate use of visualisations, and the appropriate manner data are presented. The result is that decision-makers may analyse and interpret data rapidly without asking others how to read the data shown in the report.

2.2.3.4 Actions

This element involves two activities, the analysis of data and the execution of actions. The analysis includes recognising patterns and trends by understanding data generated during the student's learning processes. Execution of actions is designed and implemented based on the analysis with the objective of adapting, personalising, reflecting or evaluating aspects of the apprenticeship. For example, adapting or personalising academic content when it is not adding real value. It is interpreted through indicators that consolidate data collected during the programme assessment. Alerts or warnings provided by reports are also the means to take action immediately regarding social, cognitive and behavioural aspects.

2.2.4 Measurement and evaluation models in corporate settings

Studies suggest that it is essential to evaluate the training programmes from the processes' perspective (J. Phillips & Phillips, 2012). It is claimed that measurement and evaluation should be before, during and after the training programme is finalised. Before the training, the purpose is to align business goals to the course. During the training, it is to obtain the participants' perceptions, and after the training, to validate whether knowledge, skills and attitudes are applied on the job. Furthermore, it is necessary to corroborate whether the programme reaches the business goal. The last activity is to calculate the ROI of the programme (Tamkin et al., 2002). Sousa and Rocha (2020) stated that neglecting the whole process analysis leads to inaccurate results in learning analytics since data are incomplete. According to Sahay et al. (2018), other models and methods have been designed to measure the performance and benefits of training programmes. Namely, the study addressed the Discrepancy Evaluation Model; Cervero's Continuing Education evaluation; trend analysis evaluation process method; the cost-benefit analysis method, whose peculiarity is based on identifying the potential benefits before the training; and the transactional model, which monitors and evaluates the training through regular feedback sessions between evaluator and staff.

Kirkpatrick's model is a tool used by organisations to measure and evaluate the impact of training (Bell et al., 2017; Sahay et al., 2018). It has been used for more than five decades because it allows breaking down the training process into manageable levels (Choudhury & Vedna Sharma, 2019). This model is the most used framework, thanks to its business approach. It comprises four levels. The reaction level evaluates the employee's perception towards the course; the learning level evaluates the level of knowledge acquired during the course; the behaviour level evaluates to which extent the learning is applied in the workplace; and the results level focuses on evaluating the effects on business goals (Bell et al., 2017; Sahay et al., 2018; Ulum, 2015). The second most used model is the Phillips model, which added another level, return on investment (ROI), that evaluates the ratio of training costs and the monetary value of business outcomes (Choudhury & Vedna Sharma, 2019). Moreover, it is worth noting that CIRO's model added the organisation's context as part of the evaluation to obtain the real need and objectives of the training (Reio et al., 2017; Tamkin et al., 2002).

The importance of adopting these models in this study is that they have been used and proved to evaluate the impact in organisations from different perspectives over time. Thus, these models will leverage and guide the identification of variables and relationships according to their levels. For example, in Phillips's model, it is fundamental to classify variables and relationships associated with financial aspects to obtain the payoffs after the investment in training processes. In summary, the levels, processes, variables, contexts and other aspects provided by these models will be indispensable for answering what factors, relationships and characteristics are required for designing a LAM.

2.2.5 Learning analytics models in corporate settings

During the literature review, only six LAMs were found within organisational settings. The search was performed in Scopus, Web of Science and Google Scholar. However, despite the wide combination of words like corporate learning, organisational learning, learning analytics, training and evaluation, and analytical models, the results were scarce. Kaliisa et al. (2021) corroborate these very few studies by claiming that there is no concrete application of LAM in business processes or data flows. Also, studies developed by Mouaici et al. (2018) and Sousa and Rocha (2020) concluded that there are scarce studies and documentation about LAMs for measuring training impact in organisations. In summary, there is a clear gap in the field of corporate learning that should be covered concerning LAMs.

2.2.5.1 Model for measuring the performance

The analytical learning model for measuring performance in organisations proposes four dimensions - participants, learning contexts, learning processes and facilitators (Sousa & Rocha, 2018). The participants' dimension measures new knowledge, new skills and learning outcomes acquired by participants. Learning contexts refer to how learning is developed, for instance, via YouTube. Learning processes encompass feedback, test results, skill level, and performance. The facilitator dimension involves the pedagogical strategy, that is, project-based learning or problem-based learning, and their indicators, for example, the degree of participants' engagement in discussion activities, tools or learning activities. However, the authors highlight that the participants' dimension is the key element to measure the impact of learning in the organisation because it has a direct effect on organisational performance, which can be measured by computing variables such as revenue, cost reductions, productivity, efficiency, new strategies, new practices, new business models, new management models, new products or services. The disadvantage of this model is that only the participants' dimension is explained. Therefore, it is crucial to define and detail the elements and measures that comprise the three remaining dimensions. In this manner, the model can be implemented in real scenarios. In addition, there is no evidence of the relationships among the elements and the conditions that should be considered before the model is applied in real cases. The critique of this study (Sousa & Rocha, 2020) is regarding the objective of the research because the authors used the terms efficiency, effectiveness, and performance equally. Notwithstanding, there is a significant difference between them. While efficiency focuses on the process, that is, how tasks are executed in less time or with fewer resources, effectiveness measures the quality of the results. Consequently, this study entails ambiguity and a lack of clarity in interpreting the results.

2.2.5.2 *Prescriptive Action Model (PAM)*

The second analytical model is proposed by Jenny Dearborn (2015), which is known as the Prescriptive Action Model (PAM). The PAM was designed to increase sales in a corporate setting by implementing a business process that comprises four steps, collecting sales data about every representative, analysing data, forecasting performance data and recommending actions based on the model outcomes. This model primarily focuses on measuring the impact of training on sales through the KPIs' average deal size, unique products sold and percentage of partner involvement. Then, the model provides actionable recommendations that decision-makers should prioritise and implement. The authors highlight that these models lead to tailoring training programmes according to individual needs instead of delivering general courses to everyone.

Consequently, the organisation can measure the effectiveness of training on sales using the ROI as an indicator. In addition, the PAM success depends on the participation of different departments, not only Human Resources, that is, sales, sales operators, IT, Marketing and Human Resources. Although the proposed model did not mention the drawbacks, it is worth noting that data quality is a missing step to guarantee a reliable LAM. Therefore, criteria such as consistency, completeness and timeliness should be incorporated into this model to enhance its quality. In addition, this model's most significant omission is associated with learning processes. Namely, the model did not recognise outcomes from academic assessments, teaching assessments and demographic data related to trainees.

2.2.5.3 *Other models with similar objectives*

Namely, these studies focus on measuring participants' satisfaction, knowledge, or behaviour acquired during the programme (Abich et al., 2019; Agrawal et al., 2017; Widayanti, 2019). For instance, Abich et al. (2019) focused on evaluating the effectiveness of LMSs oriented to virtual reality (VR), augmented reality (AR) and mobile platforms. They conclude that measuring the grade of knowledge applied to the job and its impact on business outcomes are variables that are complex to measure, given their difficulty in gathering data. Other models and frameworks have been proposed in research (Greller & Drachsler, 2012a). However, these are designed for HEIs, which means that variables, relationships, contexts, assumptions, and restrictions are associated with educational institutions. Namely, they consider variables such as students, teachers, academic policies, and marks. In conclusion, these studies neglect organisational settings.

2.3 Gap analysis

Figure 2.1 summarises the gap that was found in the literature review. Hence, the three circles represent the main clusters that were built upon the analysis of the current state of LAMs. The first cluster comprises studies focused on LAM designed for organisations, from which only two research articles met the criterion of concentrating on the learning analytics process: measurement, collection, analysis and reporting of data. Hence, this cluster is characterised as partially fulfilled, which means further studies are required to strengthen this field of knowledge since it is immature. In summary, these two models provide the means to make informed decisions in organisations. However, they have missed or omitted the following aspects:

- Relationships among components: these studies did not present a clear relationship among elements. It is fundamental in a model because it helps to determine the dependencies and order of execution of the elements that are part of the model. For example, it is not clear how the dimensions of participants and learning processes are related. The significance of this aspect is evidenced in real contexts where organisations are required to apply the LAM, but they lack clarity on the execution order of the elements and the variables that are needed by other dimensions. For example, the data transformation process should be executed before the information is presented through reports. If this process is ignored, there will be problems with data quality. It is evidenced in scenarios where data should be transformed into desired formats to perform calculations, for instance, changing or normalising date formats because they come from different data sources with different regional settings.
- Limitations and conditions: the investigations did not reveal the boundaries or factors that should be considered to implement the LAM. Therefore, this lack of clarity may lead to finding difficulties while organisations adapt the LAM. Even worse, decision-makers may make wrong decisions since they are omitting

fundamental variables to determine the training effectiveness, for instance, the cost of investment or the degree of knowledge applied in the workplace.

- Data quality: the authors did not consider including an essential step, data quality. This step ensures the LAM's reliability so that decision-makers may expect high data quality in the models presented in reports or dashboards. The mechanism to implement this step depends on the stakeholders involved in learning processes. For example, trainers, trainees and managers may decide the set of criteria to determine the degree of quality, i.e., completeness and timeliness.

The second cluster contains the models that have contributed to the body of knowledge associated with the measurement and evaluation of training in corporate settings, for instance, Kirkpatrick (D. Kirkpatrick, 2006), Phillip (J. Phillips & Phillips, 2012), among other existing models. In this case, cluster 2 is characterised as fulfilled because more than 416 studies were found in the indexed databases concerning these models (Alsalamah & Callinan, 2021a). Therefore, this field of knowledge is sufficiently matured. However, there is no evidence about implementing measurement and evaluation LAMs. This represents a disadvantage for LAMs because they omit relevant data generated from different perspectives, which according to Kirkpatrick is reaction, learning, behaviour and results.

Consequently, decision-makers may make decisions with biased and incomplete information, which may lead to wrong decisions. In contrast, the benefit of adopting these models into LA represents an excellent decision for organisations because they have been evolving year by year according to business needs. Most importantly, they have been proven and implemented in real scenarios. Therefore, they have the experience and a solid structure that may be the basis for LAM.

The third cluster reflects that there are sufficient investigations that propose LAM in educational settings. Namely, more than 100 since 2011. Some coincide in addressing the LA process using storage, collecting, reports and actions as building blocks in HEI and schools. The elements, relationships and conditions defined in these proposed models may be adapted into the corporate context. For example, elements such as students' learning experiences, the perceptions of the training programme or the academic assessment related to the level of knowledge and application of concepts in the workplace and with colleagues. However, these models are limited for organisational contexts because they do not contemplate business variables such as KPIs, sales or service.

Considering these three clusters, it is concluded that further studies are required in the intersections (see Figure 2.1). Although existing studies have proposed LAMs, most of them are designed for educational settings, and very few studies have been developed for organisational settings. Consequently, this study aims to address Gap 1 by designing a learning analytics model (LAM) that provides information by combining measurement and evaluation models such as Kirkpatrick (D. Kirkpatrick, 2006) and Phillips (J. Phillips & Phillips, 2012) with learning analytics in organisational settings. Hence, the proposed model would consolidate characteristics, insights, variables, relationships and boundaries from best practices and models that organisations have adopted for decades. In this manner, organisations may personalise the training for employees and determine how to invest in training to be competitive in the marketplace, thanks to the competencies developed by employees. In addition, the rest of the gaps may be the subject of further research in this field.

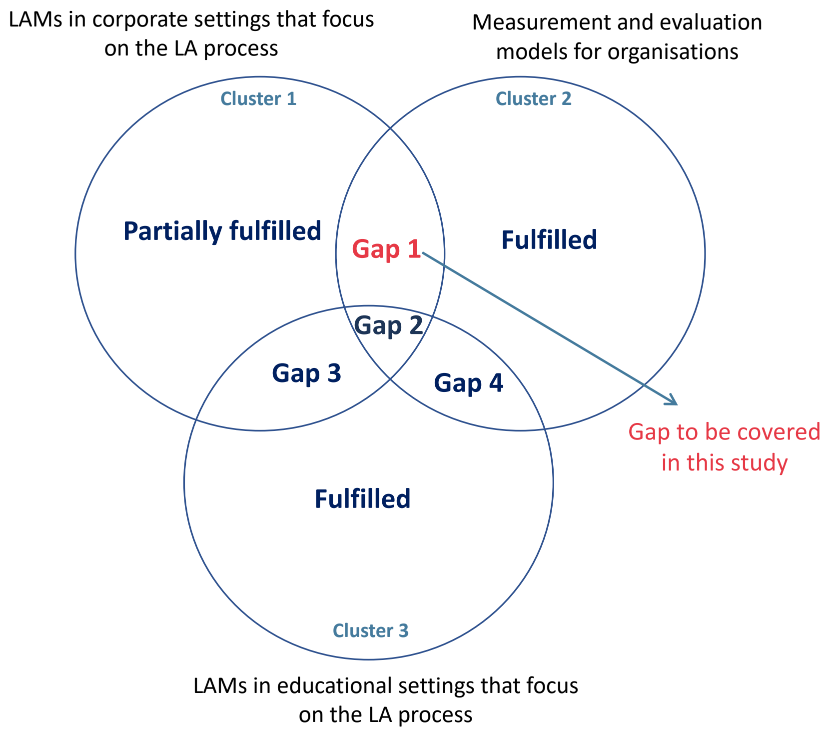

Figure 2.1 Summary of the gap found in the literature review.

3 Methodology

This chapter presents the overall research strategy required to answer the research questions. It presents the characteristics and building blocks used to build the proposed LAM. It also shows the process of collecting data, the criteria, topics of interest, saturation point and sample size. In addition, the data analysis method is discussed by explaining the thematic analysis method and how it was adapted to the data analysis.

3.1 Purpose and research questions

The purpose of this research study is to provide a LAM that measures and evaluates the impact of the training process in organisational settings. In this way, decision-makers could understand and perform actions based on their analysis and interpretations. For example, they may decide whether a particular training programme should be delivered to employees based on the historical benefits that it has brought to the business goals. The LAM also serves as a mechanism to demonstrate that training programmes have been taught to meet external requirements required by regulators. Hence, to address the purpose of this study, the following overarching question is posed:

How can a learning analytics model provide relevant data to evaluate and measure the impact of training programmes in organisations?

The sub-questions are:

- What elements are required to build a LAM that measures and evaluates the impact of training programmes in organisations?
- What are the relationships among elements that define the interactions within the LAM?
- What are the required assumptions and boundaries of the LAM that guarantee a successful application in organisational settings?

3.2 Research design

This section discusses the desk-based research approach as the framework for guiding this thesis. Specifically, the objective, the characteristics and the related process to this approach were detailed in the light of this thesis. Likewise, the method adopted for designing and building the proposed LAM is presented, from which the first step consists of defining the elements that compose the model. The second step comprises the identification of relationships among the elements. The last step defines the conditions required to ensure the correct application of the LAM in organisational settings.

3.2.1 Desk-based research

The proposed model of this study will be built upon qualitative research, namely desk-based research. Desk-based research aims to obtain knowledge that should enable us to understand a specific topic (Trinajstić, 1996; Whetten, 1989). The main characteristic is that it helps to understand and predict any phenomena using secondary data. In that way, empirical research may pose propositions and hypotheses to test the proposed model (Whetten, 1989). Albert Einstein is an example of someone carrying out theoretical research. He always collected data from other studies to build his research studies (Vogt et al., 2012). In this study, the source of data is mainly existing studies (details are shown in section 3.3), namely those with relationships to the corporate world. Then, this research will define and theorise the proposed LAM.

According to Bassot (2022), the process of addressing desk-based research consists of defining the research objectives and research questions, which act as a guiding framework for the entire study. Then, relevant and reliable data sources should be identified to locate literature and data aligned with the research objectives. This thesis used academic search engines, indexed databases and digital libraries as data sources. The following step involves the data gathering process, which aims to define the criteria to filter data provided by the data sources, for example, language, year of publication, publication type and keywords which are fundamental to obtain refined and compelling results. In addition, findings are analysed and synthesised to draw meaningful themes and categories that were defined in this thesis using the thematic analysis method.

It is worth noting that meta-analysis and systematic review approaches were not considered in this thesis. The reason is that meta-analysis is not appropriate to uncover themes and categories based on identifying and analysing text, but its focus is on analysing quantitative results from multiple studies to understand the global effects of a particular finding, ensuring a certain degree of homogeneity in the analysed studies (Lacerenza et al., 2017), which differs drastically from the objective of this thesis; as a consequence this approach is dismissed. On the other hand, the systematic review approach aims to summarise and appraise existing studies that have addressed the same question. In this thesis, this approach is not used because the objective is not to assess previous publications about LAMs but to find the elements and relationships required to measure and evaluate the impact of training in organisations.

3.2.2 Model building method

Some authors (Koskela, 2008; Partington, 2002; Rivard, 2021) concur that building a model or theory is often a challenging task because there is no standard method that proposes guidelines to define a compelling and solid model from scratch. In addition, existing terms and concepts are abstract and overly complex to understand. However, W. Burke (2017), Koskela (2008), Rivard (2021) and Storberg & Chermack (2007) claim that the method defined by Whetten (1989) provides the essential basis to build a model in a systematic manner that ensures a successful application in organisational contexts. In addition, the Google Scholar search engine presents more than 5,000 citations related to this method, which represents the importance and recognition of this method. As a consequence, this thesis will adapt this method to build the proposed LAM.

Whetten (1989) poses that a complete model must contain three building blocks: (1) a set of elements that should be represented as boxes; (2) the relationships among elements which should be depicted as arrows; (3) the conditions that limit the application of the proposed model, and in this case no graphical element is suggested.

In the following sub-sections, the relationship between the research questions and the building block are detailed.

3.2.2.1 The elements

The first building block involves identifying the factors that would be part of the study. An example of factors may be variables, concepts or inputs that are part of the studied phenomenon. Selecting the factors is essential to defining the inclusion and exclusion criteria. The proposed model will cover this building block through the thematic analysis method focusing on research question one. Hence, this building block will comprise factors like stakeholders involved in the process, data sources that provide information about the training process, productivity, return on investment and innovation.

3.2.2.2 The relationships

The second building block stands for establishing the relationships among factors. They are identified by recognising patterns, causality and rules. Hence, like the first building block, the thematic analysis method will leverage the process of defining the relationships among factors and variables. Research questions two and three focus on this block. An example of a potential relationship to calculate the ROI was the worth of investment and the tangible benefits of the training (see details in section **Error! Reference source not found.**).

3.2.2.3 The conditions

The last building block focuses on the conditions that should be considered to apply the proposed model. This means that the researcher should provide underlying justifications for selecting the factors and their relationships. It is recommended to draw the model or theory to understand better what is found. Research question three covers this block by providing the limitations that will serve as criteria to support the selection of the factors and variables. Alignment with business goals and data quality are examples of assumptions that will be part of this block (see details in section 5.3).

In summary, the proposed model fits with the three building blocks suggested in Whetten's model (Whetten, 1989) - the building blocks one and two are covered by research questions one and two (see section 1.4). These questions stand for identifying the factors and their relationships that will be part of the LAM. Building block three is associated with research question three, which focuses on the assumptions that should be satisfied by the proposed model to measure the impact of training.

3.3 Data gathering

Considering that existing works provide benefits like large sets of data, patterns, historical trends, and best and worst practices, this work will use secondary data as the primary data source; namely, case studies and literature reviews. Likely scientific journals and books will be considered a source of information for collecting existing studies. Primary data are neglected in this study because collecting and analysing data will be biased by the restrictions imposed by organisations. Besides, the sample size required for constructing the proposed LAM would be small because the author has no permission to access data from a significant number of companies willing to share their private data.

3.3.1 Topics of interest

The characteristics of the studies that will be considered as data sources are mainly those whose content comprises:

- Training models adopted by organisations to support the training and development processes of human talent. It includes the methods, approaches and techniques required to evaluate training processes from different perspectives, for example, the business and employee perspectives. In this way, variables, insights, and external and internal factors are identified for designing the proposed LAM.
- Business processes that allow identifying stakeholders, activities, business goals, strategic indicators, operational indicators, and events that initialise activities associated with the training process. It entails articulating the strategic and functional objectives set by organisations. It ensures that any academic programme that is designed and implemented points out the business goals. Thus time and money resources are invested adequately.

- Dashboards, reports or technological artefacts that present data in the forms of descriptive, prescriptive and inferential visuals. It allows identifying the process of collecting, cleaning and presenting data to the decision-makers. In addition, these sorts of research studies would help build a reliable LAM that compiles and gathers common elements such as key performance indicators, variables, patterns, and data sources used by organisations.

3.3.2 Selection of secondary data

The criteria to search and select the secondary data comprise language, date, the topic of interest and context, peer-reviewed, search engine and academic databases. They are detailed as follows:

- **Language:** studies in English and Spanish languages are contemplated because the author of this research study can understand both languages. In this case, the number of possibilities to find the required data can increase significantly.
- **Date**: studies published in the past have been considered in this study regardless of year. The rationale is they could provide valuable elements, relationships or restrictions that recent studies did not cover.
- **The topic of interest and context:** studies aiming to measure or evaluate the training process in organisational or educational settings will be considered in selecting secondary data regardless of their nature, for instance, location and industry.
- **Peer reviewed:** studies with and without a peer review process are considered in this research. Although the peer-reviewed process ensures a certain degree of quality due to rigorous evaluation criteria, non-peer-reviewed studies also provide reliable information collected from projects and consultancies performed by well-recognised firms worldwide that have worked in different sectors in the industry. Therefore, they do not focus on the academic audience but on industry experiences that may help future research and the industry itself.
- **Search engine and academic databases**: Google Scholar is used as a search engine to localise and access articles. However, considering that not all

publishers are included in this engine, the *OneSearch* engine provided by Lancaster University is also employed to widen the likelihood of finding relevant articles and complement Google's limitations. In addition, the academic databases considered in this study are Scopus, Web of Science, Science Direct, EBSCO and JSTOR. They were selected thanks to their worldwide recognition, reliability and a high degree of quality.

3.3.3 Saturation and sample size

According to Malterud et al. (2016), Ness (2015) and Probal (2018), saturation is a standard method for collecting qualitative data. This method consists of choosing the number of studies, observations or people without compromising the quality. The significance of this method comprises the combination of the sufficient amount and quality of data to understand a phenomenon in depth. Hence, it is not enough to collect a vast amount of data without quality and vice-versa. The principles to identify the saturation point are the stages where no new themes, no new coding, no new data and the ability to replicate the study is reached. In this study, the saturation point is determined by applying the condition that there are no new data, codes or themes during the execution of the thematic analysis method.

According to Ness (2015), the mechanism to attain sufficient data with a certain degree of quality is known as data triangulation. Triangulation refers to searching multiple sources of data to ensure data are reliable, valid and objective since researchers can create themes and codes by comparing outcomes, theories, methods and methodologies across different studies. Triangulation also helps to eliminate biases originating from researchers.

Hence, collecting data to address the research questions involved the triangulation of recognised academic databases and search engines (see section 3.3.2) that allow comparing and corroborating the elements, relationships and conditions required to define the LAM. The triangulation also incorporated recognised researchers in organisational settings whose primary research field embraced training or learning analytics. Kirkpatrick (D. Kirkpatrick, 2006) and Phillips (J. Phillips & Phillips, 2012) are an example of those well-known authors thanks to their contributions.

The sample size and saturation point were reached with 78 studies. NVivo 12.7.0 for MAC was used for storing, organising and analysing data. The collection of data was performed by importing documents in PDF format to initiate the data analysis process. In addition, connections among studies and relevant concepts were highlighted in NVivo directly to ease the discovery of themes and codes which are part of the thematic analysis method (see details in section 3.4). For example, in Figure 3.1 concepts identified during the data gathering process are shown. On the left-hand side panel, the phases defined for the data analysis process are presented; the second panel consolidates the documents imported into NVivo; the third panel shows the concepts identified during the data collection, namely the paragraph highlighted in yellow colour indicates the relevance of the idea and text highlighted in green colour represents a potential relationship with research question one.

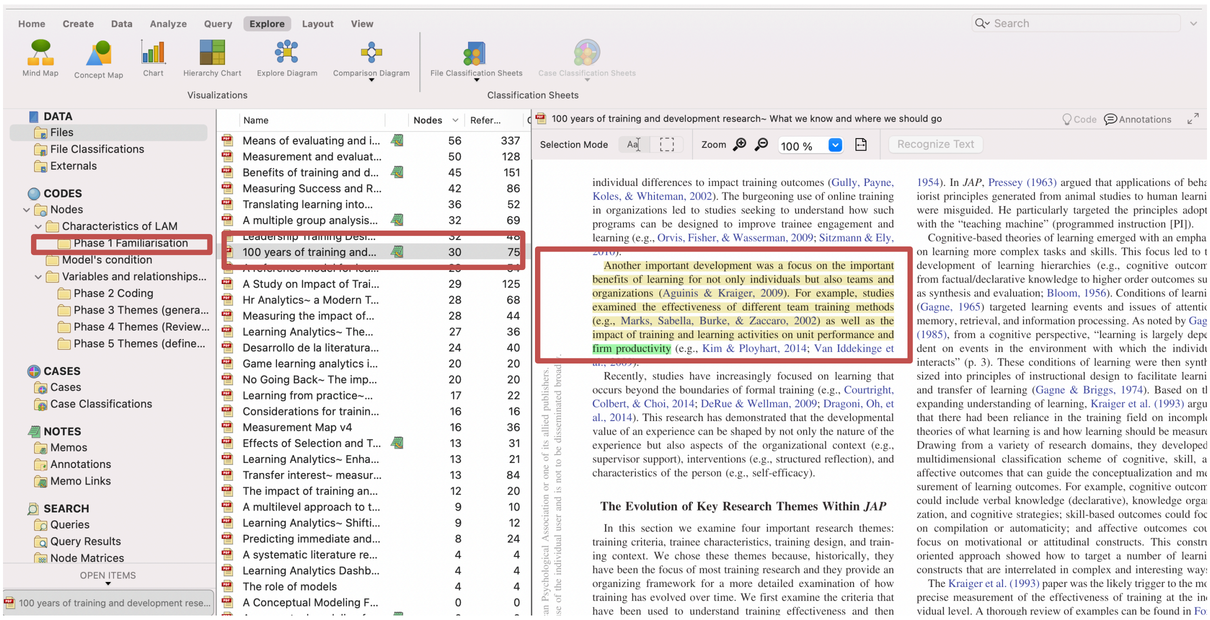

Figure 3.1 Concepts identified during the data gathering process on NVivo.

3.4 Data analysis

The data type gathered in this research is qualitative. The data analysis method used in this study is thematic analysis as the cornerstone for qualitative data analysis (Herzog et al., 2019). This method consists of identifying, analysing and defining themes that are part of a phenomenon. It is one of the most used and influential methods for analysing qualitative data (Herzog et al., 2019; Maguire, 2017). The primary characteristic is flexibility because it does not belong to any methodology or framework and can be used to analyse qualitative data from articles, interviews or any type of text. This method comprises six phases, familiarisation, coding, generating themes, reviewing themes, defining themes and conceptualising.

The adaptation of this method in this research study is planned in the following form:

1. **Becoming familiar with the data**: in this phase, it is planned to read the collected data and make some notes about the early impressions in the light of the variables, relationships and characteristics that the LAM should fulfil, which are related to the research questions. It is known as the top-down approach because the analysis is performed considering the research questions posed in this study (Herzog et al., 2019).
   This phase was created in NVivo with the name Familiarisation in this study. The studies considered in this phase were literature reviews and meta-analysis studies to identify the evolution of training and measurements in organisations since 1918. This phase was helpful to have a depth and breadth context about the most cited authors and models employed to measure the training process using different perspectives. In addition, challenges, gaps and future research in this field were found to evaluate whether the proposed LAM may cover them. The search criteria in this phase considered the words shown in Table 3.1.

Iteration	Criteria
Iteration 1	Training organisations impact
	Training organisations indicators
	Learning analytics
	Training Organisations Learning Analytics Model
	Learning analytics model
Iteration 2	Training organisations Balanced Score Card
	Kirkpatrick training learning analytics
	Phillips training Learning Analytics
Synonyms used in the search: • **Organisations: companies, firms and corporations** • **Learning analytics: educational data mining** • **Impact: measurement, indicators, KPIs and metrics**	

Table 3.1 Searching criteria for phase 1

2. **Coding**: during this phase, data are organised using software tools such as MS-Excel, NVivo or ATLAS. Hence, the data collected are transformed into small chunks of meaning following the research questions to generate the initial

codes (Herzog et al., 2019). Namely, the secondary data are analysed and coded about their relevance and interest.

In this study, inductive coding was performed. Hence, no predefined codes were defined to start the coding analysis. However, the most well-known models and authors were considered in the first step, Kirkpatrick (Alsalamah & Callinan, 2021a) and Phillips (P. Phillips & Phillips, 2018) models, because they provide different organisational perspectives to be analysed. For example, the models pose perspectives such as learning experience, learning implemented at work, return of investment, payoffs, income, and time efficiency at work. Although there are plenty of models in the literature regarding training measurements, all of them are a variation or subset of Kirkpatrick and Phillips (Alsalamah & Callinan, 2021b). It is worth noting that other models were also evaluated because this phase aimed to find as many codes as possible. Then, a refinement was performed to reduce the number of codes based on similarities, duplicates and nonsense concepts or words. NVivo was a crucial tool for grouping codes by colours at this phase, which helped to analyse, interpret and define relationships among codes.

3. **Search for themes**: during this phase, patterns of codes are identified according to their significance or common relationships. Themes result from analysing, combining and comparing how codes relate to one another. Themes do not come from data or the repetition of codes. Therefore, it is crucial to define a theme, and then the researcher should start defining themes and subthemes by interpreting and re-reading the collated codes (Braun & Clarke, 2006; Herzog et al., 2019). For example, in this study, a potential pattern and theme might be the financial aspect in organisations because it is an aspect that is inherent in the training process. Results and discussion chapters detail this aspect in terms of tangible and intangible elements that impact business objectives in organisations. Moreover, thematic maps are the suggested graphical mechanism to identify, understand, describe and present themes and their relationships (Herzog et al., 2019). In addition, the number of initial themes was 24. They are listed in Table 3.2.

Initial themes					
Analytical models	Customer	Data quality	Data representation	Domains	External variables
Finance	Gaps in LA	Indicators	Internal processes	Learning analytic processes	Learning and growth
Satisfaction and experience	Learning outcomes	Behaviour	Impact on programme	ROI	Models
Organisational environment	Participants	Programme variables	Source of data	Stakeholders	Technological tools

Table 3.2 List of initial themes

4. **Review themes**: in this phase, it is essential to validate the coherence and sense of the themes defined in the previous phase to ensure a clear distinction between themes. It implies reorganising codes, renaming, grouping and removing themes to generate the potential final themes (Braun & Clarke, 2006; Herzog et al., 2019; Kiger & Varpio, 2020). In addition, a comparison of themes is required to guarantee that themes do not overlap among them.

   In this case, a preliminary version of the thematic map was defined to represent visually the themes and codes according to their nature and objective. However, during this phase, it was found that within a theme, several codes may be broken down into hierarchical levels to obtain more clarity and effectiveness during the definition of the elements, relationships and conditions that compose the LAM. For example, in the initial thematic map, the reporting theme comprises two levels (see *Figure 3.2*). The first level is composed of analytical models, indicators and visualisations. The second level embraces descriptive, diagnostic, predictive and prescriptive models. Figure 3.2 shows the first iteration of the thematic map from which five themes were defined: inputs, business impact domain, reporting, data flow process and data processing. It is worth noting that these themes changed in further phases.

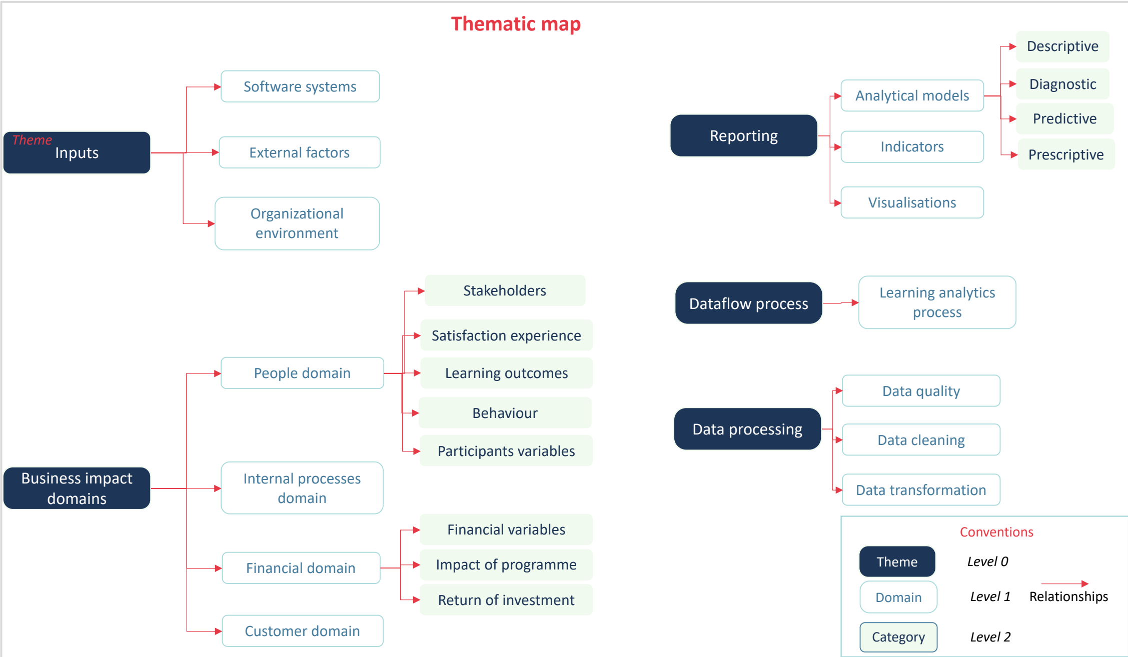

Figure 3.2 Initial thematic map

5. **Define themes**: this step comprises the final refinement of themes and their relationships. The authors of this method proposed that this phase aims to "*identify the essence of what each theme is about*" (Braun & Clarke, 2006, p.92). The themes are finalised when they fully respond to the research questions, and the names are evocative and self-descriptive. They result from several iterations and reorganisations to ensure a solid set of themes and sub-themes (Herzog et al., 2019). Hence, the final themes comprise inputs, business impact, reporting and data processing. The details and levels are

discussed in the Results (see details in chapter 4). Table 3.3 summarises the themes, meaning and quality criteria.

Theme	Summary	Quality criteria
Inputs	This theme comprises the potential sources of data that will feed the LAM. It includes concepts such as type of data sources, type of data, frequency of synchronisation and people or departments that originate the data.	**Triangulation**: by comparing different studies from different data sources to ensure reliability, validity and objectivity (see section 3.3.3)
Business Impact	This theme refers to the backbone of the LAM since it includes the alignment between learning processes and business goals using measures, indicators and metrics.	
Reporting	It acts as an instrument to analyse, interpret and present information employing visuals that vary according to the decision-maker's expectations. For instance, it is desired to evaluate the behaviour of trainees in the workplace in the past. Thus, according to the results, organisations may decide to invest in specific training programmes. This theme also covers artificial intelligence models to make predictions and prescriptions.	
Data preparation	It comprises processes, activities, stakeholders, data and business rules required to guarantee a certain degree of quality in the LAM. This theme also includes the transformation of data.	

Table 3.3 Defined themes for further analysis

6. **Conceptualise**: This phase provides compelling arguments and evidence of how themes and codes respond to the research questions. This phase starts from phase 1 and continues in the subsequent phases (Braun & Clarke, 2006). During this phase, a document, report or chapter is created to describe the entire data analysis process by recognising the patterns and conditions required to determine the codes and themes, including why the selection of themes and codes is considered accurate (Herzog et al., 2019; Kiger & Varpio, 2020). The elements, relationships and conditions required to measure and evaluate the impact of training in organisations are addressed in the Discussion chapter 5.

3.5 Chapter summary

In summary, this thesis is a qualitative study. Specifically, desk-based research was applied to collect secondary data from existing studies. In this manner, scientific studies and documents derived from consultancies were used as raw data to define the codes and themes. The procedure of grouping codes in clusters was leveraged by the model-building process, which comprised three building blocks – the first building block aimed to identify the elements or components that were part of the model; the second building block encompassed the relationships among elements; the third building block defined the conditions to apply the proposed model adequately in an organisation setting. The main topics of interest during the data-gathering process were training models, business processes, dashboards, reports and technological artefacts. These topics were used as criteria to obtain existing studies through the search engine Google Scholar and academic databases such as Scopus, Web of Science, Science Direct, EBSCO and JSTOR. The saturation method was adopted to collect sufficient data and deeply understand a specific phenomenon. The data triangulation method was the mechanism to ensure a certain degree of data quality in terms of reliability, validity and objectivity. Finally, the thematic analysis method was included during the data analysis to identify the themes related to the research questions, which also are required for the Results chapter (see details in chapter 4). Hence, inputs, business impact, reporting and data processing were the themes presented as inputs to identify the elements, relationships and conditions that would be part of the proposed model.

4 Results

Before the results are presented, it is relevant to restate the purpose of this investigation. Thus, this study aims to design a LAM that evaluates and measures the impact of training in organisations. The overarching question related to this aim is: *How can a learning analytics model provide relevant data to measure and evaluate the impact of training programmes in organisations?*

This chapter presents four themes constituting the LAM's pillars: inputs, business impact, reporting and data processing. **Error! Reference source not found.** shows the thematic map analysis, which has three levels. Themes conform to the first level. Likewise, domains correspond to the themes' structure, appearing on the second level of the thematic map. Furthermore, categories are presented in the third level to separate domains into small units due to their topic's profundity.

The first theme is named inputs; it comprises any data source that provides raw data to perform calculations, aggregations or any other operation required by the analytical model. Furthermore, inputs also provide limitations and boundaries that affect the entire LAM, that is, internal and external factors, for instance, organisational policies and international agreements, respectively.

The second theme is business impact; it groups elements and relationships in four domains due to many elements and their nature. The four domains are (1) trainee and learning, (2) internal processes, (3) business objectives and (4) customer. The trainee and learning domain refers to demographic data, prior experience, motivation, and other variables related to the stakeholders involved in the training process, e.g., trainees, trainers, managers, and peers. The internal processes domain refers to the elements that measure the efficiency obtained in the business processes or daily activities thanks to the training delivered to the employees. The business objectives domain relates to the elements that measure the monetary benefits that training programmes bring to the organisation. The customer domain reveals the elements and relationships that allow the impact of the training process on delivering products and services to customers to be measured.

The third theme is *reporting*; It covers the three existing analytical models in data reporting: descriptive, predictive and prescriptive. These models' outcomes are presented through reports and dashboards considering criteria to use adequate visuals, facilitating the data analysis. Accordingly, decision-makers using the LAM may interpret and execute actions based on historical data, forecasting and business restrictions.

The last theme is defined as data processing; it comprises the process of data quality assurance. It is executed before data are presented in reports. The first part consists of cleaning data to detect the errors included in a dataset. Then, data are transformed according to the business needs, for instance, aggregating, deleting or hiding data attributes.

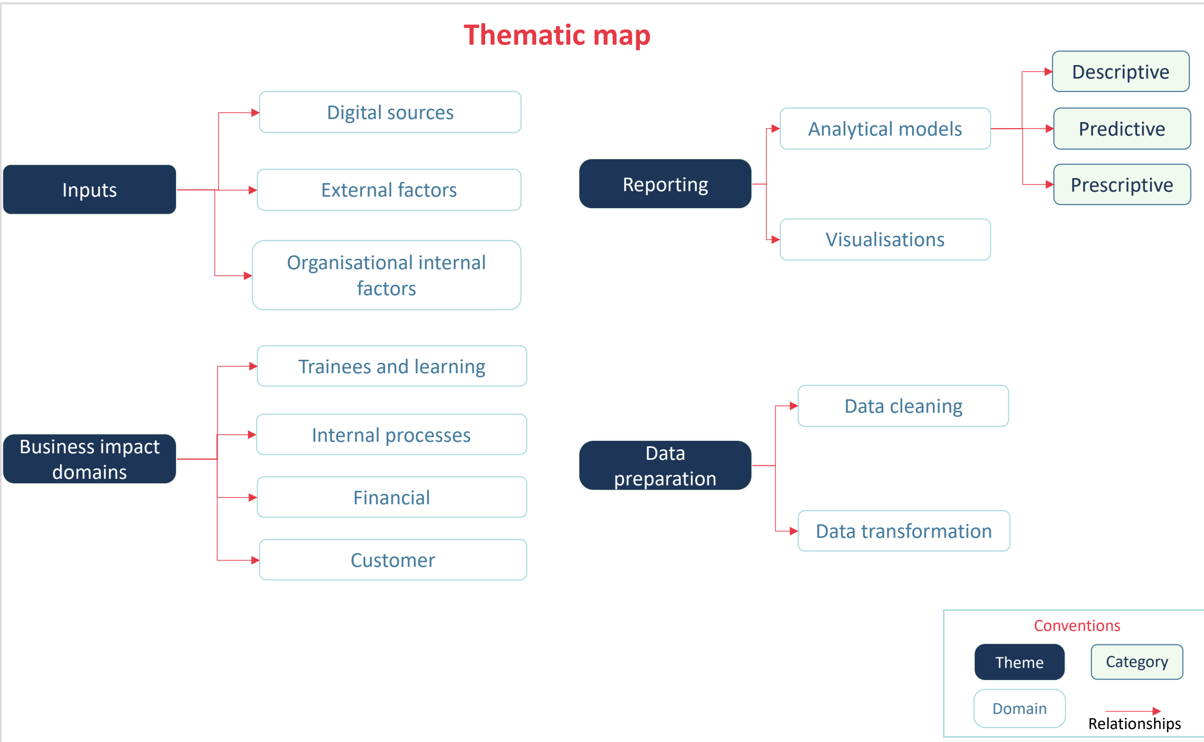

Figure 4.1 Thematic map analysis

4.1 Theme 1: Inputs

This theme refers to the input data required to perform any process associated with a LAM. Hence, three categories of inputs were identified: from software systems such as a Learning Management System (LMS), Human Resources Management Systems (HRMS) and some other digital software. The second category is the external factors that affect the training process, that is, policies defined by a nation or regulator which obligate organisations to implement training courses in a mandatory form. The last category comprises the organisation's environment, which refers to the ease of transferring knowledge into the workplace.

4.1.1 Digital sources

Data sources are an essential element that provides raw data to be transformed and presented as reports (Gasevic, 2018). In a LAM, sources are found through LMS, HRMS, databases and flat files like Microsoft Excel. The type of data provided by these data sources varies according to their nature; for instance, LMS provides data regarding the performance of employees in a specific course, and HRMS contains data related to salaries and individual training indicators.

4.1.1.1 LMS

LMS aims to support the training process aligned with the business goals regardless of the teaching format, whether face-to-face or online (Barnett & Mattox, 2010; Greller & Drachsler, 2012b). This software stores, tracks, and provides data from the employees' interactions and activities using a web browser or mobile device (Lee et al., 2014; Siemens, 2013b; Wong & Li, 2020). In this way, the training process is measured to make informed decisions regarding employee satisfaction and programme performance. For example, using this tool, decision-makers may assess whether the programme has been helpful or not, considering the employees' comments and evaluation. If negative comments are identified, strategies to improve the programme's quality are implemented during the programme's execution (Barnett & Mattox, 2010; Sahay et al., 2018).

LMSs have the capability to provide analytics in different formats acting as an output (Kaliisa et al., 2021). In this way, LAMs may benefit from metrics such as the number of people trained, departments that have participated along with the courses, number of online and face-to-face courses, course satisfaction indicators, employees' participation, cost per employee and hours of training (Barnett & Mattox, 2010; Katkalo et al., 2019). In addition, this tool captures employee performance based on academic assessments, business goals, interviews and feedback from trainers, managers and colleagues (Cadavid & Corcho, 2018; Sahay et al., 2018).

4.1.1.2 Training requests forms

This source of information condenses the requests made by departments or employees to the training team for the viability analysis and subsequent incorporation into the annual training programme (Bruno et al., 2003). Request information is collected and stored in different ways: information systems, Microsoft (MS) Excel, or any digital software that helps manage the training process.

Viability analysis is based on the relevance of the request, and it should be aligned with the organisation's strategy to guarantee a business impact after the training is performed (Lacerenza et al., 2017). Another justification for making the training viable is when a regulatory authority asks to implement courses that meet regulations. For example, courses teach how to manipulate personal data to guarantee compliance with international data protection law (Ferguson et al., 2019; Swanson, 1987).

The training request form collects the following data: the department that requests the programme, that is, marketing, sales or operations; the training topic and why it is relevant for the organisation; the business goal's impact after the course finishes, for example, increasing the volume of sales, reducing the time and effort to perform operational tasks, growing customer satisfaction and the desired return on investment. Other variables are the desired behavioural or skills change; rate of employees' retention (Barnett & Mattox, 2010; Lacerenza et al., 2017; Sahay et al., 2018; Swanson, 1987).

The training request form also includes the programme's general attributes: initial date, ending date, syllabus, learning objectives, cost of investment, cost of having employees doing the course, the number of hours, type of course (such as seminar, conference and certification programme); the number of potential employees that will participate in the programme; the number of assessments pre-and post-training and the programme's format (self-paced, online or face-to-face) (Barnett & Mattox, 2010; Huang et al., 2009; Lacerenza et al., 2017; Lee et al., 2014; Rasmussen & Ulrich, 2015). Once the course has finished, the grade of satisfaction is measured to evaluate whether the course was helpful or not (Barnett & Mattox, 2010).

Another variable incorporated as a programme's variable is the delivery method, which depends on the programme's purpose. Thus, there are three methods. The first one is named information-based, which is evidenced in lectures or presentations. Second, demonstration-based refers to examples of the competency using means such as audio, videos, or simulated medium. Finally, practice-based methods comprise role-play, simulations or guided practice (Lacerenza et al., 2017).

4.1.1.3 Human Resources Training System (HRTS)

This sort of data source is in charge of managing the entire training process. It collects data from the programme's design until its execution, including data representation through reports (Mohammed, 2019).

The variables that an HRTS consolidates to be shown using a LAM are the number of requests and their status, approved or rejected; the number of trained employees, areas and locations; the time invested in training which involves the number of hours per training per person; the budget and expenses associated to the programmes; the return on investment; individual and team performance to measure whether the skills are applied into the job; the employees' salaries and the cost per employee (Barnett & Mattox, 2010; International Atomic Energy, 2003; Swanson, 1987).

4.1.2 Organisation's external factors

This sort of input proposes the need to accommodate external factor entities such as industry regulators, governmental institutions or international corporations that demand local organisations to develop training programmes that meet compliance requirements (Barnett & Mattox, 2010; Greller & Drachsler, 2012b). For example, in the pharmaceutical industry, sales representatives must acquire deep knowledge regarding medicine, components, and dosages before they engage doctors. After that, pharmaceutical companies demonstrate descriptive data associated with the training programmes to regulators. In cases where descriptive data are not available in the form of reports, regulators impose fines because there is no evidence about the training programmes delivered to employees.

Another external factor relates to the new marketplace needs from which customers require new products and services. Similarly, there is a need when new products or services become standard in the marketplace, leaving current products out of the market. Consequently, it entails organisations creating strategies to overcome these new customer expectations. Namely, organisations should update competencies and skills in their labour force to be sustainable over time (Barnett & Mattox, 2010; Greller & Drachsler, 2012b). An example of a training strategy is evidenced in the context of the constant evolution of technological tools, from which employees should learn through training courses how to use them to optimise business processes or develop new forms of doing tasks. In this case, the metrics that serve as input to the LAM are similar to the compliance requirements scenario.

Power economic blocks such as the European Union are another external factor that affect organisations indirectly because they impose on countries to improve the indicator of human capital development (Aguinis & Kraiger, 2009). In turn, organisations are obligated to implement training programmes as part of national policies. The metrics encompassing this factor are educational enrolment, completion rates, and skills developed in specific areas such as data science, marketing, and law. Other metrics comprise the time and expenditure of workplace training and demographic data such as age, sex, location and level of education (Balcerzak, 2016; Lee & Chui, 2019).

4.1.3 Organisational internal factors

This refers to the factors inherent to the organisational environment that influence an organisation's training process (Bell et al., 2017). These factors are essential because they have an implicit effect on training effectiveness. Namely, they impact participants' motivation and performance (Brown et al., 2012; Lee et al., 2014). Although these factors have not been considered in important models such as Kirkpatrick (Alsalamah & Callinan, 2021b) and ROI models (J. J. Phillips, 2011b), they impact the effectiveness of the training process (Bates, 2004).

According to Bell et al. (2017), the factors may vary from one organisation to another because they depend on the organisational policies, values and culture. Nevertheless, C. Lee et al. (2014) identify two standard environmental factors regardless of the organisation's nature or industry: organisation learning support and work climate to transfer the training.

Organisation learning support measures employees' attitudes towards learning at work. Metrics are obtained from a survey that considers variables such as overall satisfaction, career development, recognition, rewards and learning conditions. The survey outcome provides insights concerning trainees' alignments with the training strategy and the organisation's commitment in terms of time and financial resources, which are the required means to attend training programmes. For example, if the training session needed two hours of attendance, the organisation would respect and provide the necessary time to participate. In this case, it is evidenced by high organisational interest and support.

Working climate comprises the commitment of managers and peers to support the transfer of knowledge from those who have developed a skill or competence in a training course (Lee et al., 2014). It means that managers are aware of the importance of supporting the training process, which entails increasing the effectiveness of the training because participants are motivated and empowered to incorporate what they learned in the course (Aguinis & Kraiger, 2009; Buganza et al., 2013a). It is evidenced in the scenarios where participants have the time and freedom to apply the acquired knowledge to the job (Bell et al., 2017; Lee et al., 2014). It leads to employees' promotions, compensations and benefits due to their performance and commitment.

4.1.3.1 Relationships

The first relationship identified in this theme is between data sources and external factors. Namely, this is when external entities ask for evidence in the form of metrics to validate the compliance of requirements, for instance, the number of courses, courses' status (finished or ongoing), the number of participants, results of the individual assessments and dates. They indicate whether participants demonstrated sufficient knowledge in a specific field (Barnett & Mattox, 2010; Greller & Drachsler, 2012b). Consequently, the LAM should provide data from predefined data sources to meet the regulators' requirements.

Another relationship is evidenced between data sources and data preparation themes. Specifically, the association is established when data flow from data sources to the data cleaning process is to ensure a high quality of data in upcoming activities (Frazzetto et al., 2019a; Raghupathi & Raghupathi, 2021). Then, data are transformed to obtain consolidated figures regarding the training process (Siemens, 2013b). For example, data from a specific programme is extracted from an LMS and HRTS, but there are some duplicated trainees' names, and their demographic data are incomplete. Then, the data preparation process is in charge of rejecting data that does not fulfil duplicates and completeness quality rules. Then, trainers or a human resources department should correct the inconsistencies to initiate the process from the beginning: data extraction and preparation.

4.2 Theme 2: Business impact domains

This theme presents the business pillar variables and measures related to the training process in organisations. Thus, four domains are proposed to group variables and measures: trainees and learning, internal processes, finance and customers. The trainee´s domain comprises trainees' characteristics that affect a training programme, i.e., demographic data, motivation and course expectations. The internal processes domain presents the efficiency and quality of business processes thanks to skills and knowledge acquired in a training programme. The financial domain focuses on the measures impacted by training programmes, which in turn contribute to the financial performance of an organisation. ROI and NPV are part of the financial domain. The last domain identifies time, quality, service and cost as variables affecting customer interactions due to the training programmes.

4.2.1 Trainees and learning

This domain embraces categories related to the stakeholders and learning processes involved in training programmes, including the relationships with the LAM. A particular emphasis is granted to trainees and how they learn and apply their knowledge in the workplace because they are the principal actor in an organisation's learning path. Furthermore, other individuals are considered in this domain since they interact with trainees implicitly or explicitly during learning processes, such as managers and instructors. The first category is trainees, describing individual characteristics collected before the training programme starts. Specifically, this category proposes the following variables: demographic factors, employees' performance and motivation. The second category is named learning experience, which is associated with the learning experience process. Therefore, the variables identified are content quality, teaching experience, and course logistics. The third category is denominated learning path. It focuses on the proficiencies gained by the trainees after the training programme is taught to employees; the variables suggested in this category are learning results and behaviour. The last category condenses the remaining stakeholders of the process, namely trainers, managers and peers who interact with trainees.

4.2.1.1 Trainees' characteristics

In this context, employees attend the training programme; they are encouraged to learn concepts and develop skills to improve the manner of executing tasks at the workplace, enhancing their motivation, creativity and organisational commitment (Aguinis & Kraiger, 2009). Metrics related to trainees' characteristics are collected before and after the training through a questionnaire which is responsible for defining trainees' profiles by collecting demographic data, anticipating the trainees' performance, adapting the course's content, measuring the knowledge and skills acquired, and how trainees apply the gained proficiency to the workplace.

Demographic data

These sorts of data identify the context of the trainees' characteristics and the course's profile. For example, the data comprises age, tenure, department, region, country, career, and organisational position (Ediger, 2019; Gegenfurtner et al., 2020). These data are also helpful in segmenting participants into groups and adapting the academic content and pedagogy of the course. In this way, teachers may engage the audience with the content.

Employees' performance level

This refers to the category that an employee belongs to. It is determined through periodic assessments led by a human resources department, from which employees are classified as low, medium or high performers. This classification measures the degree of self-efficacy in the workplace. For example, if the degree is low, the employee requires support from the work environment to be motivated and execute tasks autonomously (Lee et al., 2014). Thus, if an employee is part of the low-performers group and participates in a training programme, she/he is likely to perceive the course negatively, even before it starts. The reason is that she/he is unwilling to participate in the programme alone. In contrast, high performers will have an active participation in the training process, and they are willing to transfer knowledge into the workplace, leading to an effective training strategy (Aguinis & Kraiger, 2009; Lee et al., 2014).

Motivation to learn

This is the desire to participate actively and learn the programme's content (Aguinis & Kraiger, 2009). This component is paramount to increasing employee performance and achieving business goals by acknowledging the training programme's benefits (Subha & Bhattacharya, 2012). It ensures that the training process is initiated and finished without interruptions because there is a perceived benefit when a skill or competency is developed, for instance, by changing the way trainees perform tasks at the workplace based on the acquired knowledge (Ferguson et al., 2019). There is no unique way to measure this variable since it depends on numerous factors inherent to each organisation (Ferguson et al., 2019; Lacerenza et al., 2017).

Prior experience

According to Bell et al. (2017), this variable measures trainees' experiences regarding a specific topic. It impacts the training programme's success because if trainees have prior knowledge and the programme content does not provide new insights, they may be discouraged during the training course. In turn, expectations and motivation will be affected negatively. The measurement unit is years or months.

Training expectations

This variable indicates the grade of interest before the training course starts. It refers to the training reputation, instructors' experience and qualification, programme content, and quality (Bell et al., 2017).

4.2.1.2 Learning experience

Learner satisfaction is a metric that measures how the training course meets or surpasses the trainee's expectations (Buganza et al., 2013a). Kirkpatrick defines the satisfaction experience as to how well trainees liked a particular training programme

(Kirkpatrick, 2006). Including the learner's satisfaction experience in a LAM is paramount because decision-makers may identify whether trainees are motivated or not during or after the course finishes (Buganza et al., 2013a; Ediger, 2019).

Satisfaction experience results from applying a questionnaire during or after the course finishes. The questionnaire comprises trainees' attitudes toward the instructor, programme content, and course logistics. In summary, these three topics condense the trainees' reactions to measure the outcomes of training courses (Lacerenza et al., 2017; Sahay et al., 2018; Ulum, 2015). This metric is obtained using a five-point scale: excellent, very good, good, fair and poor. Similar scales can be used (Ediger, 2019; Kirkpatrick, 2006). Kirkpatrick recommends applying the questionnaire during the class session to obtain the responses from all the participants because they may not be eager to spend time responding at another time.

Trainers are in charge of delivering academic content considering teaching strategies to reach learning objectives and keep motivation among trainees (Lacerenza et al., 2017). Trainers participating in the training phase may differ from the designing phase (Lacerenza et al., 2017). The trainer term is also found in the literature as a facilitator, instructor, teacher, educator and mentor, which depends on the context (Patwa & Phani, 2018).

The instructor's evaluation topic includes questions about the levels of experience and knowledge on a specific topic, the ability to express and communicate ideas using a methodology, and whether the instructor stimulates the trainees' participation. This feedback is essential to determine whether a change or improvement on the learning path is necessary. This way, motivation and engagement are kept during the training process (Buganza et al., 2013a; Reio et al., 2017; Ulum, 2015).

The content evaluation topic comprises the relevance of the topics, for example, whether the employee may apply the new skills on the job or not. Thus, some questions that may be included in the questionnaire are: Did I learn new knowledge or skill? Have I changed the way I do my job? Can I see how the tools shared fit my needs? Was the content engaging and held my interest? The analysis of the answers is crucial because it determines whether the content should be adequate. Hence, if the content is relevant to the learners, the effectiveness of the course will increase (Ulum, 2015).

The course's logistics topic refers to the opportunity to access the academic content and the training platform. For instance, providing trainee users with the password to access the platform before the course or sessions start is crucial for learners (Kirkpatrick, 2006; Ulum, 2015). Other factors are part of the logistics: facilities, quality of meals, schedules and cleanliness (Kirkpatrick, 2006).

4.2.1.3 Learning path

Learning

This component measures the grade of knowledge or skill the trainee has developed after a training course finishes (Lacerenza et al., 2017). Kirkpatrick defines learning as the attitudes, knowledge, and skills learned (Kirkpatrick, 2006). A questionnaire is designed to measure the learning outcome and identify what proficiency or skills need to be developed in employees. The results of this component are usually numerical, and it depends on the scale and design of the questionnaire.

The questionnaire can be applied before and after the course finishes (Kirkpatrick, 2006). However, it is also recommended to apply an ongoing assessment as soon as the topic finishes since trainees have a fresh understanding of it. In this way, the organisation determines the course's impact, including how well and how much trainees learn (Ulum, 2015). The evaluation activity may be written, oral or technical when it is required to demonstrate a skill with a specific tool or equipment (Bruno et al., 2003).

Positive results associated with these variables mean that trainees have developed their proficiencies. However, it does not mean that the entire training course has been effective because the knowledge or skill should be applied to the workplace to achieve the desired effectiveness (Reio et al., 2017).

Learning outcomes are categorised as affective, cognitive and skill-based. Affective learning concerns the change in internally-based states, which is evidenced when soft skills such as leadership and communication are developed in a training course. Cognitive learning enhances intellectual skills, for instance, the apprenticeship of a new process model that the organisation needs to adapt more efficiently. Skill-based learning refers to developing or strengthening a capacity to manipulate equipment or adequately use a software tool reflected in the workplace (Lacerenza et al., 2017).

Behaviour

This component encompasses the application of learning after a programme finishes, that is, the capacity of the employee to change the manner of doing work tasks by incorporating the proficiencies and skills acquired in a training course. The results may differ across organisations since the transfer of knowledge into the workplace differs for each trainee (Aguinis & Kraiger, 2009; Ulum, 2015). The importance of this variable consists in measuring the grade of application of what trainees have learnt because attending the course is not sufficient for an organisation. Consequently, organisations could determine the effectiveness of a training programme (Ulum, 2015).

The assessment method comprises short-term or long-term observation and productivity data (Abich et al., 2019; Buganza et al., 2013b; Choudhury & Vedna Sharma, 2019). The questionnaire measures the impact on job performance which is linked to the reduction in time to complete a task thanks to skills acquired in the training programme (Bell et al., 2017; Blankenship & Taylor, 1938; Cowman, 2012; International Atomic Energy, 2003; Lee et al., 2014; Van Iddekinge et al., 2009). Thus it encompasses changes in variables such as:

- Productivity: refers to the grade of efficiency that tasks are executed. It is usually considered the ratio of the quantity produced and the number of resources required to generate a product or service. It is also known as efficiency (Aguinis & Kraiger, 2009; Barnett & Mattox, 2010; Bell et al., 2017; Cheng & Ho, 2001; DiazGranados, 2010; Van Iddekinge et al., 2009).
- Accuracy: it is linked to the correct value or standard reached while a task is being executed (Aguinis & Kraiger, 2009; Bell et al., 2017; Cowman, 2012).
- Reduction of error rates or accidents: it points to the decrease of errors while service is provided or product is produced. This variable is also analysed from the training quality perspective, which affects the outcomes directly (Barnett & Mattox, 2010).

- Time: refers to the reduction of time to perform an internal process. It might be a repetitive task that is digitalised based on the proficiency acquired in the training programme (Barnett & Mattox, 2010).
- Innovation refers to the number of new efficient processes or activities created thanks to the skills or competencies developed in the training programme (Axtell et al., 1997; Bell et al., 2017).

The author Ulum suggests that if a negative result is obtained in this assessment, it is crucial to validate the trainees' experiences and learning outcomes variables because they may show the reason for this negative result (Ulum, 2015). For example, the course's expectation may not have been surpassed, or the trainee's motivation was low. Employees feel satisfied when they apply new knowledge to the workplace because their work becomes efficient and motivated (Lacerenza et al., 2017; Sahay et al., 2018).

Kirkpatrick (2006) suggests aggregate questions into the questionnaire that comprise the following conditions that organisations should consider to measure the application of the learned concepts into the workplace: a desire to change, knowing what and how to implement the acquired knowledge, a proper environment that allows implementation or updating processes, help in applying what was learned in the training course, for instance, colleagues support to make organisational changes. The last condition refers to rewarding for transferring. The potential responders may be trainees, bosses, subordinates, and colleagues who may assess the knowledge transfer (Choudhury & Vedna Sharma, 2019; Kirkpatrick, 2006). Some questions that may be considered are, do you plan to apply what you have learned in your workplace? Has your colleague, boss, or subordinate implemented or changed any activity in his workplace based on the training programme? (Buganza et al., 2013b; Ediger, 2019).

Support from managers and peers is a fundamental factor in ensuring knowledge transfer into the workplace. It is evidenced in cases where a trainee feels empowered to innovate or change activities based on the acquired knowledge due to the freedom of change and the particular time for changing or improving the manner of executing tasks at work (Aguinis & Kraiger, 2009). Managers and peers act as observers to assess whether the trainee has incorporated the knowledge he learned in the training course. Then, the course's effectiveness is determined (Aguinis & Kraiger, 2009). Observations are designed and performed in a digital or physical form, and the number of times it is repeated depends on the assessed indicators.

4.2.1.4 Relationships

Kirkpatrick (Alsalamah & Callinan, 2021b) contends a causality relationship and established order among the following categories: trainees' experiences, learning, behaviour and organisation business goals. Kirkpatrick (D. Kirkpatrick, 2006) also emphasises that omitting one may lead to profound mistakes. Reio et al. (2017) claim that there are correlations among these categories, concluding that positive reactions enhance learning. Once the learning has occurred, desired behaviours will change in the workplace and ultimately impact the organisational results (Alliger & Janak, 1989; Hilber, Preskill & Russ-Eft, 1997; Kirkpatrick & Kirkpatrick, 2005, 2006). However, there are some contradictors about this causality linkages affirmation. For example, Bates (2004) claims a lack of evidence demonstrating a correlation among these categories, evidenced in two meta-analyses in the investigation. Another source, Alsalamah and Callinan (2021a) argue that applying knowledge acquired in the training course to the workplace has no relationship with trainees' experiences. It is evidenced when an employee improves a task thanks to the skills developed in the training programme. At the same time, the authors Alsalamah and Callinan (2021a) experimented with a negative experience during learning processes.

4.2.2 Internal processes domain

This domain refers to the efficiency obtained in a process, service or product before or after a training course finishes, that is, the trainee's performances. This domain seeks to provide numerical results to measure the impact of business goals.

4.2.2.1 Job performance

The typical manner of measuring a process's performance is through Key Performance Indicators (KPIs), whose aim is to monitor the progress of desirable outcomes. The author Kirkpatrick (2006) recommends measuring the variables of this domain by defining two groups. The first group is not part of the training, for instance, the reduction of errors rate thanks to the incorporation of best practices after employees attend the training programme. The second group are variables related to trainees' skills. Then, the performance of both groups should be measured before and after the training. After that, the impact of the training is obtained (Kirkpatrick, 2006; Lacerenza et al., 2017; Ulum, 2015).

Since organisations are unique in their processes, there is no standard list of KPIs that a LAM should incorporate into its structure. However, Kaplan and Norton (2005) suggest the following measures regardless of the organisation's nature: employee productivity, on-time delivery, average lead time, and the number of products or activities with no errors. These measures can be summarised as the reduction of time and the costs of executing an action with a high-quality standard (Kaplan & Norton, 2005).

To obtain the indicator of time reduction, the LAM should incorporate the required time to produce a product in a specific interval before and after the trainees participate in the course. If the final time is less than the initial, the LAM should present a positive indicator showing course effectiveness (Sahay et al., 2018). The same scenario applies to measuring the reduction of costs indicator.

Productivity is the grade of efficiency in which a task is performed. It is usually considered the ratio of the quantity produced and the number of resources required to generate a product or service. It is also known as efficiency (Aguinis & Kraiger, 2009; Bell et al., 2017; Cheng & Ho, 2001; Diaz, 2010; Van Iddekinge et al., 2009). In summary, the productivity indicator is obtained by dividing outputs by input. Output is the number of products an employee produces, such as the number of products, services, or money within a time interval. In contrast, input is the number of resources required to generate an output or profit. Similar to the reduction of time indicator, the LAM should incorporate these variables before and after the training course.

4.2.2.2 Workplace observers

Aguinis and Kraiger (2009) identified the participation of different stakeholders during the training process, that is, design, training, and post-training. Hence, in the design phase a human resources department is involved, which is responsible for the entire training process—managers who request the training programme based on their team's needs. And for the educational institution, which is represented by trainers whose aim is to materialise the organisational needs into a training programme (Greller & Drachsler, 2012b). However, in some cases, organisations decide to be responsible for the design and delivery phases, that is, while universities or training institutions are not contracted to provide educational services, the human resources department defines a team to do so.

The workplace observers are extremely important for the LAM because they evaluate the trainees' performances based on what the observers perceive in their daily tasks. The training phase comprises peers, managers, coordinators, supervisors or other qualified observers that evaluate the trainees' behaviours in the workplace (Barnett & Mattox, 2010; Kirkpatrick, 2006). Since this phase aims to assess the impact of training programmes, managers and peers are requested to provide data regarding trainees' performances, that is, whether concepts and skills are applied in the workplace or not, according to their perceptions and trainees' interactions (Barnett & Mattox, 2010; Sahay et al., 2018). This assessment is accomplished after the training finishes using questionnaires and interviews. Then, data are consolidated and shared by trainers with the human resources department to update the training indicators (Aguinis & Kraiger, 2009).

4.2.3 Relationships

Several authors have identified a direct relationship between productivity and behaviour. Alsalamah and Callinan (2021b) present a study of a group of trainees that took a training programme. The results revealed that after the training finishes, trainees will develop positive behaviour in their workplace, reflecting an improvement in their job performance. Bell et al. (2017) confirm this relationship by examining the positive progress in outputs by taking some samples during a period after the training finished, which means that employees were more efficient in executing tasks or processes in different contexts, for instance, navigation, computer software and radar tracking. Another evidence of the relationship between productivity and behaviour is when a reduction of time required to perform a task originated from the skills developed in the training programme (Phillips, 2011b).

Behaviour has a relationship with quality. It is evidenced when it is required to compare the number of failures, errors and rework rates before and after the training. J. J. Phillips (2011b) asseverated that there is a direct relationship between behaviour and quality as long as the behaviour is positive, that is, knowledge acquired from the training programme is applied on the job (in a nuclear plant in the author's example). The positive results of these two variables will increase the training effectiveness indicators. The researcher proposed that managers monitor and control the output of a specific process to validate personnel errors once the training finishes. The monitor process may be automatic, using software-generated reports or manually (Bruno et al., 2003).

4.2.4 Finance

This domain aims to present the components related to the training process that affect an organisation's financial goals and performance. Sales, profitability, and revenue growth are common goals regardless of the sector or nature of the organisation (Bell et al., 2017). Thus, the importance of this domain stems from providing the elements to measure training effectiveness from a financial perspective using the LAM as the basis.

Some studies claim that investing in internal training will positively impact business variables such as turnover, costs, profit growth, quality of work performed and organisational productivity (Aguinis & Kraiger, 2009; Lacerenza et al., 2017). Hence, organisations that strategically invest in training obtain a high grade of competitiveness in the marketplace because firm-specific knowledge is developed by employees (Sahay et al., 2018; Van Iddekinge et al., 2009). For example, new employees are trained to implement best practices in services or products to foster productivity and innovation in the workplace. In this way, the organisation develops unique and valuable principles in its employees (Van Iddekinge et al., 2009). The International Atomic Energy Authority (2003) claims that these variables should be measured quantitatively to obtain the effectiveness of training programmes.

The main characteristic of these components is that they are quantitative. D. L. Kirkpatrick (2006) recommends implementing a survey to collect data before and after the course is performed. In this way, business variables are calculated easily. For example, to identify the variation in the sales change, the LAM should collect the turnover values before and after the training finishes.

4.2.4.1 Tangible components

Profitability, revenue and expenses

The financial department is responsible for giving the business variables to the LAM. Precisely, profitability, revenue and expenses are calculated before and during the programme execution (Buganza et al., 2013b). Revenue determines the total income generated from services or goods sold during a specific period. Profitability is the difference between sales and expenses (Cano et al., 2017; Kaplan & Norton, 2005). Expenses are costs to produce goods or services, for example, raw materials and shipping. Thus, if profitability or revenue increases after training is given to employees, it is concluded that the training programme positively impacts business objectives. If expenses decrease, the effect is positive because the course has taught how to minimise or optimise creating goods or providing services (Barnett & Mattox, 2010). The formulas to obtain these variables are:

$$Profitability = sales - expenses$$

$$Revenue = price\ (of\ product\ or\ service)\ X\ Quantity\ sold$$

Return on investment (ROI)

The Return on Investment (ROI) component is considered to obtain the benefits of the training programme compared to the cost of investment (Barnett & Mattox, 2010). Before the course starts, the ROI must be calculated to ensure the investment is worth it (Phillips, 2011b). In other words, behaviours are monetised to provide the value of a benefit (Barnett & Mattox, 2010; Bell et al., 2017; Philips, 1996). However, some studies found that most organisations do not calculate this indicator due to its complexity and great effort to obtain the value (Reio et al., 2017). In this case, the LAM plays a fundamental role because one of its tasks is to facilitate the extraction, computation and presentation of financial components. In addition, other studies claim that this indicator is unsuitable for all courses (Barnett & Mattox, 2010), and it should be used to measure only the first year of benefit.

The ROI model is based on Kirkpatrick's model (J. J. Phillips, 2011b) since it adapts the reaction, learning, application and business impact levels. The novelty in this model is the return on investment as the fifth level, which establishes four steps. The first is the evaluation plan to determine the programme's purpose, feasibility, and objectives—the second step consists of gathering data related to trainees' reactions, acquired knowledge and behaviours. The third step comprises gathering data linked to data analysis and programme costs. In addition, this step converts data into monetary values and calculates the ROI. The last step involves communicating the results through reports to the stakeholders (Philips, 1996; Phillips, 2011b). The author Phillips (2011) recommends isolating the programme during the evaluation. In this way, the results would be more accurate. Otherwise, ROI results may be affected by other factors unrelated to the training. The ROI formula is defined as:

$$ROI\ (\%) = \frac{Net\ programme\ benefits}{Programme\ costs} \text{ X } 100$$

To obtain the ROI, there is a requirement to monetise the benefits, converting data into money. The model proposes sorting out hard data and soft data. Hard data refers to standard measures across all organisations that are required to assess organisational performance (Phillips, 2012). For example, the number of products sold and the time needed to perform an activity before and after the programme was delivered. Soft data refers to measures that evaluate employees' soft skills. These measures are difficult to convert into monetary benefits because they involve assessing participants' behaviours—for example, job satisfaction and increased confidence. It is worth noting that the LAM is designed to support soft and hard data. Therefore, the unique condition is that the programme's objectives should define the metrics to be considered in the LAM.

The model (Phillips, 2012; Phillips, 2011b) suggests four categories to classify hard data as part of a process to obtain monetary benefits: output, time, cost, and quality. The result comprises measures such as units produced, products sold, applications processed and services delivered. Time involves measures like time to process a task, time to finish a job, cycle time, equipment downtime, overtime, lost time days, and efficiency (Barnett & Mattox, 2010). Measures related to costs are budget variances, unit cost, variable cost, fixed cost, overhead cost and operating cost. The measures that are part of the last category comprise error rates, rework, shortages, rejects, defects, product failures, inventory adjustments and the number of accidents (Franklin et al., 2014).

Similarly, the model (Bell et al., 2017; Phillips, 2012) suggests the following six categories for soft data - work habits, customer service, work climate, development, job attitudes and initiative. Work habits include absenteeism, tardiness, excessive breaks, and safety rules violations. Customer service comprises customer satisfaction, customer loyalty and customer complaints. Work climate refers to internal processes' measures, for instance, the number of grievances or complaints against the organisation, job satisfaction and employee turnover. The development category involves employees' advancements in the organisation. Thus, the proposed LAM should include measures like the number of promotions, pay increases and job effectiveness. Job attitudes measures such as organisational commitment and employee loyalty. The initiative category evaluates the innovation capacity of employees, for instance, the implementation of new ideas, the number of projects finished, and the number of suggestions implemented.

In addition to the monetary benefits, the programme cost is another fundamental variable to obtaining the ROI. Thus, programme cost should incorporate the cost to plan, design, implement and deliver the programme (e.g., face-to-face or remote) (Barnett & Mattox, 2010; Phillips, 2012). For example, the cost of designing the programme syllabus, its learning objectives, and the payments related to the trainers. Other costs related to the training programme are people that support the programme's logistics, for instance, people that manage processes associated with attendance records, snacks, beverages, user privileges to access online material or any additional investment in equipment or services needed for the programme development.

Another programme cost involves the time invested by employees to attend sessions and develop exercises at home. Hence, calculating this cost is paramount to consider the following variables, employees' salary and time required to participate in the programme.

Some authors found limitations in the ROI model (Anderson et al., 1994; Phillips, 2012). The model should not be applied for short-duration programmes, for instance, 1 hour, because it is difficult to improve and impact processes in a reduced time frame. The ROI is unsuitable when high investment costs and the returns are not perceived during the next 12 months. The last limitation applies when the programme is delivered by regulation, as positive benefits are difficult to calculate. In this case, it is suggested to use the net present value as a model.

Net Present Value (NPV)

Another well-known and widely used indicator that a LAM should consider is the net present value (NPV), namely when the ROI benefits of the first year do not exceed the initial costs, leading to a negative ROI (Pasqual et al., 2013). NPV is adopted to appraise programme profitability in organisations. This measure is defined as the result of a multiyear investment expressed in today's dollars, from which it is determined whether the programme investment is profitable or not (Anderson et al., 1994). The formula is defined as:

$$NPV = \sum \frac{Cash\ flow\ in\ period\ n}{(1 + discount\ rate)^n} - N_0\ (cash\ outflow\ in\ time\ 0)$$

Equation 4.1 NPV equation

The numerator represents the cash flow over a specific period. The variable *n* represents the time of the cash flow. The variable N_0 indicates the investment cost in the first year or initial investment. The denominator refers to the required return or discount rate. Hence, the programme investment is profitable if the result is positive because the benefits exceed the initial costs. On the contrary, the organisation should not invest in the programme.

4.2.4.2 Intangible components

Phillips proposes intangible variables as part of the programme evaluation (Phillips, 2012). Intangible variables are neither visible nor easy to quantify. They are intentionally identified not to be measured and converted to money because they are more relevant soft skills than monetary benefits or simply cannot be easily monetised. For instance, soft skills variables include organisational commitment, leadership, teamwork, cooperation and effective communication. Another example comprises variables representing a competitive advantage in the marketplace, such as reputation and innovation. According to Phillips (2011b), intangible variables are unlimited. They vary depending on the organisation.

Organisational commitment is the extent to which employees are identified with organisational values, goals, mission, policies and practices. A positive impact on employees' productivities is evidenced if the commitment grade is high. If this measure is included in the LAM, it is recommended to apply an attitude survey using five or seven scales (Thi et al., 2014).

Leadership is the most difficult measure to evaluate (Phillips, 2012). This soft skill may lead organisations to fail or succeed. Leadership is the way to reach business goals by taking advantage of resources and inspiring others during the journey during a specific period (Aguinis & Kraiger, 2009; Thi et al., 2014). If the LAM is required to incorporate this measure, the 360-degree feedback method is typically used. It consists of gathering perceptions about a person's leadership from immediate managers, customers, colleagues and employees. Furthermore, the assessment includes a self-assessment. Then, the overall leadership behaviour is calculated.

Teamwork measures how well teams are working on a project or typical process. A positive result leads to positive productivity thanks to the team's synergy. In case this measure is incorporated into the LAM, it is recommended to evaluate the perception of every team member before and after the training (Thi et al., 2014).

Cooperation refers to the action or spirit of working together to reach a common goal, for example, an organisational project or task. The perception scale is suggested if the organisation requires incorporating this measure into the LAM (Thi et al., 2014).

Effective communication measures how well employees listen and speak effectively with superiors, colleagues and customers. It involves nonverbal communication, clarity, friendliness, respect and choosing a suitable medium to express ideas. Similarly to cooperation and teamwork measures, it is recommended to apply a perception survey at different moments, before and after the training finishes, to update the LAM (Phillips, 2011a).

Reputation and innovation reflect the competitiveness and performance of companies in the marketplace. These measures are relevant to customers and providers because they represent the quality and continuum evolution of products and services, including financial consequences (Aguinis & Kraiger, 2009; Phillips, 2012).

4.2.4.3 Relationships

Aguinis and Kraiger (2009) identify a relationship between an organisation's reputation, training and the impact on financial variables. Training to foster quality, innovation, and the acceptable use of new products is a fundamental factor in guaranteeing an excellent reputation, which has a positive financial impact due to the credibility and reputation developed by organisations. Van Iddekinge et al. (2009) also identified a direct contribution of training in sales and profits evidenced by applying the reciprocal causality model from which a strong influence was found between training and organisational performance, namely profitable growth. This research study (Choudhury & Vedna Sharma, 2019) encourages organisations to define and implement a programme strategy to train employees across all organisational units to reach positive business objectives.

A study by Aguinis and Kraiger (2009) found that soft-skills programmes positively impact financial performance because training is operationalised on bottom-line processes. It results from applying acquired knowledge to manage and engage employees adequately based on their motivations and organisational goals. In this way, products and services are delivered with high quality making the organisation more profitable and competitive.

4.2.5 Customer

This domain aims to identify the components a LAM should incorporate to evaluate the impact of training on products and services delivered to customers. The following components are the proposed components: time to market, market share, quality of service or products, service, cost, customer acquisition, customer satisfaction, customer loyalty, and customer retention.

Some authors propose another group of variables to address marketing and sales measures related to the customer domain, revenue and marketplace participation.

According to Kaplan and Norton, the following components should be considered during customer interactions: time to market, quality of service or products, and cost of products (Kaplan & Norton, 2005). Hence, the proposed components are market share, customer retention, customer acquisition, customer satisfaction and customer loyalty (Alsufyani & Gill, 2022; Edeling & Himme, 2018; Gupta & Zeithaml, 2006; Olson & Slater, 2002). Training becomes essential when organisations desire to improve these components by qualifying their workforce to strengthen the indicators related to customer relationships. In this way, the LAM may help organisations measure and evaluate the impact of training in these scenarios.

New products refer to the time to release the product or service into the marketplace, also known as the time to market. It is the time required to deliver the product or service to the customer for existing products. Quality measures the defects perceived by the customers. The services element measures how products and services create value for their customers. The cost component involves manufacturing or providing services like raw materials, employee wages, and shipping.

Market share is the percentage of an organisation's total industry revenue from selling services or products. This measure determines the organisation's position in the industry (Edeling & Himme, 2018). For example, Google has a market share of 92% in the search engine industry, which means it has a dominant position in the marketplace. Market share is a quantitative measure calculated during a specific period, i.e., yearly or monthly, depending on the business needs. It is determined by dividing the organisation's revenue by the total industry revenue multiplied by 100 (Edeling & Himme, 2018). To incorporate this result into the LAM, the financial department should provide this number before and after the training.

Buchanan and Gillies (n.d.) define customer retention as the percentage of customers at the beginning of the year that remains at the end of the year. The marketing department is responsible for providing this number annually. It is recommended to evaluate this measure before and after the training is performed. In this way, the impact of training is measured. Programmes that teach employees the importance of providing excellent service and the financial consequences will guarantee that customers return to buy. That is, high customer retention is reached. Another effect of these sorts of programmes is that organisations will not share their market share because satisfied customers will refer new customers at no cost, and some are willing to pay premium prices.

Customer acquisition measures the cost required to obtain a new customer (Alsufyani & Gill, 2022; Edeling & Himme, 2018). It results from a business strategy to increase revenue and evaluate what the marketplace requests. For example, marketing and sales strategies should invest in social media campaigns, pay-per-click ads and magazine ads to acquire potential customers. Then the ROI is calculated to evaluate the effectiveness of the training and the relationship with customer acquisition (Alsufyani & Gill, 2022; Gupta & Zeithaml, 2006). The marketing department is responsible for providing this measure periodically, i.e., monthly or quarterly. The calculation consists of dividing the resources needed to bring new customers by the number of new customers. This measure should be provided to the LAM before and after the training is delivered.

Customer satisfaction measures whether a service or product meets or exceeds customers' expectations (Gupta & Zeithaml, 2006). This measure is performed through a survey that collects the customers' feedback regarding the overall experience based on the total purchase and consumption of a product or service. It is a one to five scale survey, from which one is very unsatisfied and five is very satisfied. Thus, the results lead to a quantitative score measure provided by the marketing department to incorporate the change in the LAM. It is also recommended to apply this measure before and after the training to evaluate the impact of training. To calculate this measure is the division between the number of satisfied customers and the number of survey responses multiplied by 100 (Zaki et al., 2016).

Customer loyalty measures the desire to have a long-term relationship with the product or service provider due to the current customer's positive satisfaction. It is translated into the likelihood of the renewal of contracts or services. Loyal customers will refer the organisation or services to potential customers like the customer retention measure. Net Promoter Score (NPS) is the mechanism to measure whether the customers will purchase again and refer the service to another person. The unique question presented to customers is, "How likely is it that you would recommend company X to a friend or colleague?" After that, the customers are grouped into three groups, promoters, passives and detractors (Reichheld, 2003). Those who are in the promoter's group are considered loyal.

Relationships

This investigation (Buchanan & Gillies, 1990) found a direct relationship between customer retention and profitability. They found that if the customer retention rate increases from 90% to 95%, the profitability may vary between 30% and 125%. The justification is that regular and satisfied customers will refer to other customers, which means sales and profitability will rise, and the investment to bring new customers will decrease.

Reichheld (2003) also claims that NPS is used to predict an organisation's financial growth because this measure allows identifying those customers willing to rebuy and recommend the organisation, leading to increased revenue (Zaki et al., 2016). However, other research studies claim that measures such as net satisfied, net delighter, and net committed are fundamental to determining organisational growth. The reason is that NPS is not the only customer feedback associated with loyalty index and financial performance. It is corroborated by other studies claiming that there is not enough evidence demonstrating that NPS correlates to the financial domain (Fisher & Kordupleski, 2019). Reichheld (2003), in his further studies, state that the author of NPS proposes that it should be applied as a model because it must incorporate more measures into the process to determine financial growth (Fisher & Kordupleski, 2019).

According to the authors Gupta & Zeithaml (2006), more than 12 studies in different timelines found a proportional relationship between customer satisfaction and financial performance. It is evidenced in the same study performed by Gupta & Zeithaml (2006) using 200 of the Fortune 500 firms, from which he concludes that a 1% improvement in satisfaction will lead to a $240 million increase in the market value of a firm. Other studies found that net operational cash flow will increase if customer satisfaction measures increase (Gupta & Zeithaml, 2006). The authors Gupta and Zeithaml (2006) also found a 2.37% increase in ROI when at least a 1% improvement in satisfaction. In conclusion, a positive customer satisfaction index growth will positively affect financial performance.

A quantitative research study carried out by Edeling and Himme (2018) states an inverse relationship between market share and customer satisfaction. It is the result of analysing 77 firms from different industries using the time series method to find the correlation between variables. They argue that when the market share is significant, companies should provide services, products or support to a diverse and heterogeneous set of customers, which leads to decreasing customer satisfaction. By contrast, companies with a small market share will provide a tailored and excellent service. This argument is corroborated by Fisher and Kordupleski (2019).

Market share directly relates to financial performance (Edeling & Himme, 2018). Specifically, in the scenarios where organisations grow precipitously because of the novelty or quality of products, it automatically increases the position in the market share, which in turn, means that variables such as revenue and ROI will increase.

Customer acquisition is related to financial performance because it directly impacts revenue growth. Thus, if the marketing campaign is successful, new customers become part of the client's portfolio, and at the same time, the revenue will increase. By contrast, the revenue is negative in scenarios where the number of new customers is zero.

4.3 Theme 3: Reporting

This theme addresses three analytical models to manage data, descriptive, predictive and prescriptive. They collect, transform, track, store and present data to make informed decisions based on the outcomes provided by software (Gasevic, 2018; Mohammed, 2019). Each of these models presents data depending on the scope required in the organisation. Thus, the LAM should define which of them is included in the graphical reporting interface or may be part of the LAM's scope. Furthermore, this section presents different categories of visualisations that should align with the business message in reports and dashboards.

4.3.1 Descriptive analytics

The descriptive models provide insights focusing on the past using queries, reports and descriptive statistics (Mauro, 2021). It is the most widely used and easy to implement because it does not require complex calculations (Raghupathi & Raghupathi, 2021). It consists of tracking and storing historical data to determine behaviours and outcomes in terms of summaries. After that, data consumers analyse data through reports able to segment data and drill down into different levels.

This model responds to the question, What has happened? (Frazzetto et al., 2019a; Lepenioti et al., 2020; Raghupathi & Raghupathi, 2021). For example, it should comprise the number of trainees that have been part of training programmes, total investment in training, number of courses performed and the percentage of training effectiveness in the organisation. After that, organisations make decisions regarding these data. An extension of this model called diagnostic analysis answers the question, Why did it happen?, which helps organisations to discover the events that originated the current data (Lepenioti et al., 2020).

Descriptive analytics variables that may be part of the LAM include summary statistics, aggregations, visualisations and KPIs. Statistics variables encompass average, median, mode, standard deviation, correlation matrix, and variance, which are typical calculations to observe the behaviour of historical data (Mauro, 2021; Raghupathi & Raghupathi, 2021). For instance, the average is used in training reports to present the employees' dropouts.

Aggregation attributes comprise indices, counts, sums, minimum and maximum. These variables are basic arithmetic operations. They are used for consolidating data. For example, sums present the number of training programmes delivered for employees; the minimum and the maximum variables consolidate the trainees that attended courses during a specific time frame. On the other hand, indices represent a unique identifier for every record, and the counts variable calculates the number of records in a data set (Mauro, 2021; Raghupathi & Raghupathi, 2021).

Visualisations' attributes are filters, selectors, buttons, and visuals such as maps, tables, pie charts, treemaps, and other charts to present descriptive data. These variables comprise the elements of a report which may vary according to the business needs (Mauro, 2021; Raghupathi & Raghupathi, 2021).

KPIs are the mechanism to control the performance of organisations to facilitate goal achievement. KPIs are metrics that compare the desired outcome with the current situation. In this way, managers control organisational processes and make decisions interpreting the KPIs results. The KPIs should be measurable, reliable, and few to ease the periodic monitoring (Jay & Liebowitz, 2013). KPIs considered in training and development programmes are defined in organisations to measure the impact of training on different aspects of the organisation, such as employees, processes, customers and finance (Bersin, 2008). Although the list of KPIs is endless and varies among organisations, the following are the standard KPIs' definitions: time to proficiency, examination pass rate, increased quality rate, skill retention, productivity, ROI, employee engagement, training completion percentage rate and sales turnover (Cano et al., 2017). The unique condition to applying KPIs is that they should be measured before and after the training to obtain the desired benefit.

4.3.2 Predictive analytics

Predictive analytics uses forecasting models to predict the future (Gasevic, 2018). It combines the descriptive analytics outcomes with machine learning algorithms and data mining techniques to predict with a specific grade of accuracy the future events and a combination of them, in this case, events related to training processes (Gasevic, 2018; Soltanpoor, 2016). The accuracy depends on the amount of data collected by predictive models. Hence, it is essential to collect as much data as the organisation can to increase the probability of the occurrence of the model's prediction. This model responds to the questions: What will happen? and Why will it happen? in the future (Frazzetto et al., 2019a; Lepenioti et al., 2020). For example, a predictive analytics model may determine the training effectiveness indicator for the next year based on historical data and the application of some algorithms (Szabó, 2020). Simultaneously, it can discover future opportunities like increased market share participation because of the high probability of process optimisation and new innovative products thanks to the new skills acquired by employees in training programmes (Greller & Drachsler, 2012b).

Predictive analytics models are determined to be part of the LAM variables because they are the basis of the prediction process. Thus, according to Baesens (2014), two models' categories are defined according to data nature, regression and classification. Regression involves the analysis of continuous variables, i.e., numeric values or quantitative variables that are possible to measure, for instance, course cost, number of students attending an organisational course and profits (Gasevic, 2018; Mohammed, 2019). Regression models are commonly applied when it is required to predict missing numerical data values, e.g., the likelihood of using the acquired knowledge in their job (Chatti et al., 2012). Additionally, date-time variables are considered continuous.

The classification category aims to analyse categorical variables, which are a finite number of groups with no logical order, for instance, trainees' gender and course category (remote or face-to-face). Some models, such as decision trees, are adaptable to classification or regression categories. Table 4.1 presents a list of predictive models classified by type.

Category	Predictive Model	Objective
Regression	Linear regression	It is the most used model to predict numeric values. This model predicts outcomes considering one dependent variable and one or more independent variables. E.g., in the case of predicting the course completion rate, the independent variables may be the trainees' ages (Gasevic, 2018; Klimberg & McCullough, 2017).
Classification	Logistic regression	It is typically customed to predict binary values using the standard logistic distribution. For example, whether an email is spam (1) or not (0), thus the output could be 0 or 1, depending on the model's analysis (Baesens, 2014; Gasevic, 2018).
	Support vector machines	This model classifies features by plotting them in the n-dimensional space; a line is proposed to differentiate two classes. The line is named a classifier (Baesens, 2014; Gasevic, 2018).
	Naive Bayes	It classifies data considering that every feature of an object is a class. For example, orange with characteristics such as yellow and rounded will be part of two independent classes contributing to the probability of being an orange (Baesens, 2014; Gasevic, 2018).
	Neuronal networks	It is called the black-box model because the income is known but the process to obtain the outcome is unknown. The network is built upon

Category	Predictive Model	Objective
		layers and neurons. The first layer contains neurons that provide the income data, and then subsequent layers process and combine neurons to generate results (Gasevic, 2018; Klimberg & McCullough, 2017).
REGRESSION OR CLASSIFICATION	Decision trees	This model classifies data according to the decisions or conditions evaluated in hierarchical steps. The top node is the testing condition; the outcome is placed in the branch, and the terminal nodes provide the classification (Baesens, 2014; Gasevic, 2018).

Table 4.1 Predictive models used as variables in LAM

Valle et al. (2021) developed a predictive analytics dashboard to validate the influence on learners' motivation using historical data and the Naïve Bayes Model, a standard machine learning method to predict patterns.

4.3.3 Prescriptive analytics

Prescriptive analytics aim to answer the question, What should be the optimal outcome? employing prescriptive models (Frazzetto et al., 2019a). Hence, this answer is addressed by evaluating the effects of the possible decisions and providing the best alternative for a decision considering business requirements and constraints (Frazzetto et al., 2019a). Compared to descriptive and predictive models, prescriptive models incorporate business knowledge into their calculations and suggest executing actions (Raghupathi & Raghupathi, 2021). These models are used in organisations when descriptive and predictive models offer many alternatives and choices. Lepenioti et al. (2020) conclude in the investigation that predictive models are also viable for prescriptive models, for instance, probabilistic models and machine learning techniques. However, prescription models are exclusive to logic-based models and methods such as simulation, evolutionary computation and mathematical programming.

The following conditions are required before prescriptive models come into action: historical data are understood using descriptive models, and predictive models define foreseen scenarios. Then, the model prescribes the best alternative combining human recommendations, artificial intelligence and optimisation techniques in a probabilistic environment (Lepenioti et al., 2020). Finally, decision-makers shape the plans, define business goals and execute actions considering the prescription (Raghupathi & Raghupathi, 2021).

4.3.4 Visualisations

Visualisation is considered one of the pillars of analytics (Raghupathi & Raghupathi, 2021). It involves presenting data through reports and dashboards through various visual objects such as pie charts, scatterplots, line charts, tables and metrics (Jay & Liebowitz, 2013; Raghupathi & Raghupathi, 2021). These objects are built upon variables, dimensions, correlations and business rules. Visual objects are grouped to present data as information using business analytics software. These tools incorporate descriptive, predictive and prescriptive analytics to provide the insights, recommendations and indicators required by organisations to make informed decisions at the right time. However, these studies (Frazzetto et al., 2019a; Raghupathi & Raghupathi, 2021) found that business analytics tools are specialised in one of the models, forcing organisations to purchase several tools to support all three models. Hence, these studies recommend further research in this area.

The variables that may be part of the LAM are the visuals associated with the training reports, though the list of visuals is unlimited. Nevertheless, Mauro (2021) proposes three categories to group visuals according to their nature and type of business message: evolution, size and relation.

Evolution comprises charts that provide growth, decline, increase, decrease, lag, overtake or trend information. These charts are the most used visuals to determine the evolution of business performance (Mauro, 2021). Line charts are examples of visuals that respond to questions such as, is there any increment in the process's efficiency after the training programme started? Is there any growth in sales after the marketing team took the training programme? KPIs visuals are part of this category since they provide the increase or decrease of a measure in terms of percentage; for instance, the revenue growth compared to the previous year when training courses were not offered to employees.

Size category refers to visuals that compare proportions or quantities to a whole. The most common visuals are pie charts, doughnut charts, treemaps and bar charts, designed to contrast items and make informed decisions based on the most or least relevant element. These visuals respond to the questions: what is the percentage of men attending a training programme?, what is the proportion of trainees by departments in an organisation? or What courses are driving sales growth (Mauro, 2021).

The relation category includes visuals that show how one variable changes concerning another. Subsequently, data analysis is performed to identify the cause-effect relationship. Typical questions are what is the relationship between customer satisfaction and the training course attended by the customer service team? The visuals that conform to this category are scatterplots, quadrant charts and geospatial maps (Mauro, 2021).

4.3.5 Relationships

Raghupathi and Raghupathi (2021) present in their investigation a relationship matrix from which visualisation objects are associated with analytic models according to their nature. Thus, descriptive analytics is directly associated with reports that involve charts that present historical data, dimensions and measures, such as pie charts, charting and visual storytelling. Then, patterns and trends are understood to make decisions. Another relationship is between predictive analytics and visuals such as line charts and scatterplot charts, whose function is to forecast by plotting trend lines using historical data. There is no evidence of a relationship between prescriptive models and visual models because prescriptive analytics is oriented to define a path to follow.

4.4 Theme 4: Data preparation

This theme covers all organisational prerequisites before data are presented in a report. The manner to guarantee a reliable pre-processing procedure includes data cleaning and transformation (Singhal, 2007; Chatti et al., 2012; Gasevic, 2018).

4.4.1 Data cleaning

According to Gasevic (2018), data cleaning is the process of correcting data based on cleaning rules to guarantee a high-quality standard. Hence, cleaning rules aim to detect and correct incomplete, duplicated, inconsistent, mis-labelled and misformatted data. This process is executed once data are extracted from data sources such as a LMS, training request forms and Human Resources Systems. The main benefit of data cleaning is that upcoming processes will be built upon high-quality standards. Therefore, decision-makers may interpret and analyse data with high certainty and reliability. The LAM should adopt this process as part of its scope to meet data quality standards. Thus, it should correct errors from the original data that may lead to wrong interpretations; for instance, removing trainees who have left the organisation because they are no longer part of the training process (Siemens, 2013a).

4.4.2 Data transformation

Data transformation is the process of converting data into desired content. In this way, data quality is ensured (Chatti et al., 2012; Gasevic, 2018). Then, data are sent as income to any of the following analytical models: descriptive, predictive and prescriptive models (Greller & Drachsler, 2012b). During this process, data may be experimented on with different quality rules and transformations depending on the business needs. The most salient types of data transformation are aggregation, generalisation, normalisation and data reduction (Singhal, 2007).

According to Anoop Singhal (2007), aggregation refers to adding more attributes or columns into the data set due to summarising data. Subsequently, data are consolidated and presented in reports or dashboards in a simplified manner to make informed decisions. For example, the LAM should aggregate data regarding the investment cost in training programmes. Thus, the LAM should sum up the cost of every programme and present the total expenses through reports.

Generalisation is similar to aggregation in adding more attributes or columns to the original dataset (Singhal, 2007). The difference stemmed from creating hierarchies based on the data values; for instance, the human resources department requires a report with an age classification according to a specific range: young, middle age, and senior. Therefore, the LAM should generalise the trainees' age to satisfy the business need.

The normalisation process involves placing values into standardised categories so that reports present homogenous data (Singhal, 2007). For example, headquarters settled in the United Kingdom (UK) with offices in different countries require the total global investment in training to measure the effectiveness. Therefore, local investment in training programmes is converted into pounds currency to present data uniquely, avoiding misunderstanding during the interpretation and data analysis processes.

Contrary to aggregation and generalisation, data reduction removes or hides attributes from the original dataset because it is too complex to process and analyse, leading to an impractical and infeasible data interpretation (Singhal, 2007). For example, if it is required to analyse the academic performance of trainees, financial data such as investment and expenses should not be part of the required report.

4.4.3 Relationships

Frazzetto et al. (2019b) and Raghupathi and Raghupathi (2021) propose a workflow case study that presents a clear relationship between data preparation and data sources because the first step is to identify data sources that may participate in the process, for instance, LMS. Then, data are extracted and sent to be cleaned and transformed. The workflow's last phase incorporates data presentation through visuals that support descriptive, predictive and prescriptive models. In this case, it is essential to highlight that data should be prepared before further phases are performed. In addition, Raghupathi and Raghupathi (2021) suggest defining whether data flow from data sources and data preparation phases will be in real-time since it has technological implications which should be solved according to the organisational needs. Siemens (2013b) suggests another relationship in the way that is fundamental to add data quality before data are transformed, so data cleaning activity should be executed once data are extracted from LMS or any other information system.

4.5 Chapter summary

This chapter presents the outcomes of this thesis through four themes and their potential relationships that should be part of the proposed LAM. The first theme is defined as inputs. This theme comprises the elements acting as data sources, such as software systems (LMS, HRTS and Request Forms). Other data sources are internal and external factors that obligate organisations to perform training programmes, for instance, regulations designed by governmental entities or simply because customers and market share require products or services with some degree of innovation. The second theme is business impact, which refers to the elements that impact business goals—namely, trainee and learning, internal processes, financial aspects, and customers. Measures, indicators and metrics are the means to validate whether training programmes are effective according to internal and external requirements. For example, in scenarios where organisations require to automate processes to reduce the time to execute them, human resources departments may design training programmes to develop technical skills in employees to manipulate software tools or technologies. In this manner, productivity indicators will be impacted positively. The third theme is reporting, which involves the analytical models as mechanisms to consolidate and present data to make informed decisions about the training process. Descriptive, predictive and prescriptive models are the means to support the analysis of data. In addition, visualisations are presented in categories according to their nature because it is crucial to incorporate them in reports adequately. The fourth theme is called data processing; this involves data cleaning and data transformation elements to guarantee a certain degree of quality in the proposed LAM. For example, removing null values or changing data types. These four themes are considered the cornerstone to define the LAM in the discussion section (see detail in chapter 5), including the elements and relationships presented in this chapter.

5 Discussion

This chapter presents the key findings to answer the overarching question: *How can a learning analytics model provide relevant data to evaluate and measure the impact of training programmes in organisations?* The thematic analysis method was the mechanism to identify the variables, relationships and assumptions that compose the model by identifying themes that cluster data according to its nature. The following sub-questions guided this method:

- What elements are required to build a LAM that measures and evaluates the impact of training programmes in organisations?
- What are the relationships among elements that define the interactions within the LAM?
- What are the required assumptions and boundaries of the LAM that guarantee a successful application in organisational settings?

Hence, this chapter discusses the results in light of the *Theory Development Process* proposed by Rivard (2021) and Whetten (1989). This methodology comprises three building blocks to define a solid and consistent model or theory. Therefore, each building block is mapped to one of the research questions in this research study. The first building block comprises the set of factors that compose the model, for instance, elements or variables. The first research question addresses this building block. The second building block involves the relationships among factors, e.g., rules or causality. In this case, the second research question responds to the aim of this building block. The last building block encompasses the underlying assumptions and conditions associated with the model. The last research question is related to this building block. In addition, the proposed LAM is presented in a diagram to consolidate and facilitate its understanding and future implementations. Hence, the model is presented in two different versions to evidence the model's construction. The first version presents the set of variables grouped by themes, domains, and categories, and the second version shows the relationships incorporated into the model.

5.1 The underlying elements

This section answers the question: “What elements are required to build a LAM that measures and evaluates the impact of training programmes in organisations?” Hence, this question is addressed by adopting the guidelines proposed by Whetten (1989) to select the elements that comprise the LAM. Then, the elements found in the results section are detailed to understand their objective, importance, contribution, limitations and how they fit in the proposed LAM.

According to Ardichvili et al. (2003) and Whetten (1989), variables or elements are the building blocks of a model. They are concepts that represent attributes or essential characteristics of a model. In this research, concepts emerged from the thematic analysis method as units of meaning that belong to a specific domain with a unifying purpose.

Hence, the results show that the fundamental elements that compose the LAM should be interpreted by grouping them according to their nature into five themes, data sources, external and internal factors, data preparation, MIMs (measures, metrics and indicators) and reporting (see Figure 5.1).

Data sources act as data providers to the LAM during the training process. External and internal factors are the variables that trigger or modify the training process’s execution. Data preparation incorporates variables that ensure data quality by cleaning and transforming. MIMs consolidate strategic variables required to measure and evaluate the effectiveness of training programmes through the LAM. They are classified as strategic because they impact the business goals from different dimensions: employees and learning, internal process, financial and customer. The last theme is reporting, which includes variables related to the analytical models and how they are presented using visuals.

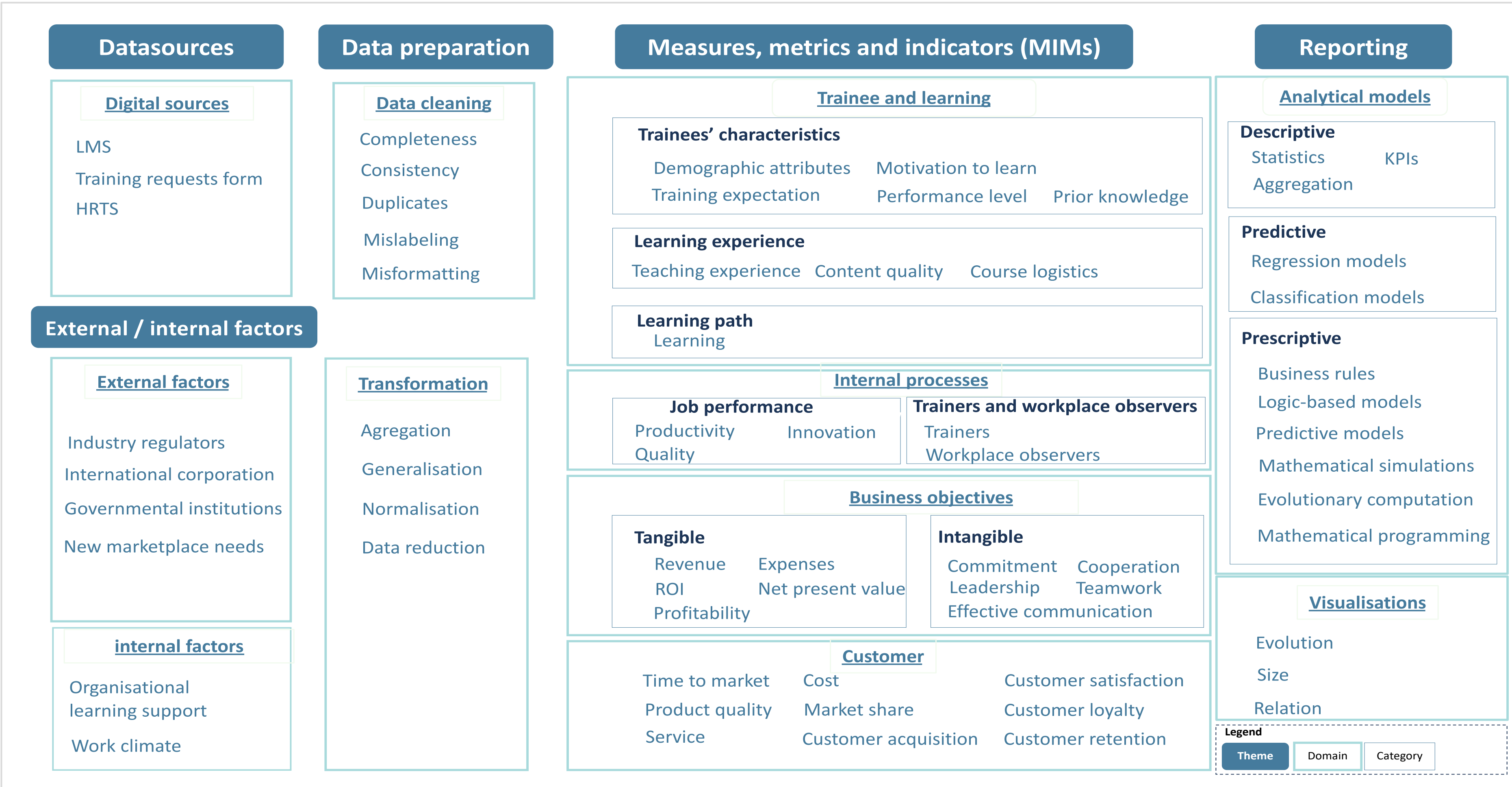

Figure 5.1 The LAM's elements

5.1.1 **Data sources**

The results section supports that LMS, training request forms and HRST are elements that aim to provide data to the proposed LAM. They provide data before, during and after the training is given to the trainees. These three elements are evidenced when trainees or internal areas ask for a course by filling out a digital form known as a training request form containing the course's reasons, objectives and benefits. Then, the human resources department analyses and approves the requirement. Before the programme starts, the human resources area defines in the HRST a budget for a specific course and the employees that will take the course. Then, trainees' performances, course experiences and some other metrics are measured in the LMS. In summary, the proposed LAM considers these three elements as the primary data sources and the starting point of learning analytics. Then, other elements and processes related to the LAM will use, reuse or transform these data into information.

5.1.1.1 Data sources and conditions

In this case, the LAM should evaluate the data sources that act as raw material for the entire model. It is suggested to include data from LMS, training request form and HRST. However, it depends on the business needs and the nature of the learning processes because it may be the case that organisations do not use one or more of these elements. Therefore, the LAM should be flexible to compute calculations considering at least one of the proposed data sources, including the data formats, e.g., PDF or MS Excel. It is also relevant to define the frequency of synchronisation between the LAM and data sources, for instance, every hour, every week or every minute. The LAM should define the data fields to be imported. For example, grades, number of trainees attending the programme, course duration, and other data required by the organisation. Then, these data are transformed and presented using visual reports.

Other studies concur that data sources are essential for collecting data required for performing activities such as discovering patterns, transforming data and presenting the information on reports. Chatti et al. (2012) and Siemens (2013b) propose two categories of tools to ease the identification of potential data sources, centralised educational systems and distributed learning environments. Centralised systems involve digital tools that trace educational data, for instance, attendance time, social interaction among trainees, exercises, results and quizzes (Verbert et al., 2013). LMSs are an example of data sources that store this sort of data. Commercial and open-source tools are available to support face-to-face and distance learning, e.g., Blackboard and Moodle (Verbert et al., 2013). On the other hand, distributed learning environments are those sources that go beyond a LMS, for instance, HRTS, digital forms, and blogs. Chatti et al. (2012) claim that collecting data from these sources will ensure solid and precise results. Notwithstanding, Chatti et al. (2012), Duan and Da Xu (2021), Dyckhoff et al. (2013), Sciarrone and Temperini (2019) and Siemens (2013b) concur that it is also essential to define the conditions for gathering data to guarantee a reliable dataflow. Therefore, the proposed LAM should consider the multiple sources and heterogeneous data to be imported. Namely, the type of format, e.g., MS Excel, PDF or plain text and the frequency for collecting the data. Siemens (2013b) outlines that distributed data are a challenge for analytics because it represents gathering vast amounts of data with different meanings and formats to provide a coherent whole through reports.

In practice, the proposed LAM will contribute to the identification of multiple sources and heterogenous formats before data are gathered. Hence, the LAM collects data from educational data systems and distributed learning environments considering business conditions such as data types and frequency of importing data from other digital tools. Conditions vary depending on the maturity of the training process and the technological tools available to support this process.

5.1.1.2 The type of data required to add value to organisations

The sort of data stored in the LAM may vary with organisations because it depends on the software systems available to collect and provide training data, that is, LMS, HRST and other digital tools immersed in the process. However, financial and educational data are always present to make informed decisions. For example, the cost of designing and delivering the course, the number of employees attending the course, salaries, expected monetary benefits, employees' performances and class format (face-to-face or remote). In this way, the proposed LAM ensures an alignment between the business goals and the training process. Notwithstanding, it is worth noting that educational data are insufficient to interpret and execute strategic actions when financial data are missing. Namely, decision-makers expect to measure the monetary benefits versus the investment, not just trainees' performances and satisfaction metrics. Jülicher (2018) and Nalchigar et al. (2016) outline that business strategies, decision processes and organisational performance are fundamental in the analytical model to add business value using data-driven decisions. Nonetheless, they recognise that this alignment is critical and challenging to define because it requires discovering the business needs and then translating them into analytics to gain new insights regarding profits, competitiveness and internal efficiencies.

Hence, the contribution of these results ensures that any organisation that adapts the proposed LAM should identify data sources that provide educational and financial data to facilitate the analysis and interpretation of the monetary benefits that the training brings to the organisation. For example, decision-makers may determine whether to invest in specific training programmes based on historical data and the measures and metrics provided by the LAM, e.g., ROI and NPV (see section **Error! Reference source not found.**). In this way, strategic and business goals are aligned with the training process using the LAM since its structure can measure and evaluate the impact of training in sales, profits, innovation or internal processes considering the monetary investment and the skills developed in employees. LMS, HRTS, and training request forms are potential sources to provide these sorts of data.

5.1.1.3 Limitations of this finding

The proposed data sources in the LAM are limited to the research studies analysed in this investigation. Hence, in practice, the proposed LAM may expand the number of sources contributing to measuring and evaluating the training process. Even so, it may be the case that organisations must reduce the number of the proposed data sources because the training process is immature or simply there is one data source that centralises data related to training programmes. Another limitation is related to LAM flexibility. It means that this investigation did not address the degree of accuracy when the number and type of data sources are reduced or increased due to organisational restrictions. The reason for these limitations is that it was not included in the scope of this investigation. Hence, further studies may focus on evaluating the impact of changing the number of data sources proposed in this research.

5.1.2 External and internal factors

5.1.2.1 External factors

The results highlight how industry regulators become external factors in the training process by imposing mandatory regulations or laws. Organisations should respond to these requirements by implementing metrics and alerts into the LAM to evidence the programmes designed and delivered to employees. Regulators that are part of the government and private sector are examples of external entities. Another external factor is the need to be competitive in the marketplace. Thus, organisations must adopt strategies to develop new products and services based on customer needs. Consequently, employees should upskill and reskill to guarantee business continuity and success. The name proposed for this external factor is *new marketplace needs.*

In contrast to the results found in this thesis, some studies (Ognjenović, 2015a; Singh et al., 2016; Sung & Choi, 2021) propose technology as another external and crucial factor that obligates organisations to deliver training programmes. The justification is that implementing technology into the business processes will impact the customers positively during the production or delivery of products. Hence, organisations will gain unique capabilities and processes reflected in creating patents and innovative services and products. Differences between previous studies and this investigation are mainly because the technology factor is considered within the factor "*new marketplace needs"* as one of the means to fulfil new customers' expectations and needs. However, this difference does not affect the LAM's definition, given that the most relevant is to identify the marketplace need that should be included in the LAM to generate the training plan that will develop organisational capabilities through its employees, processes and technology. Other approaches that propose learning analytics models lack internal and external factors that impact and trigger the training process (Chatti et al., 2012; Pineda, 2010).

On the other hand, other studies (Ognjenović, 2015b; Rozhkova, 2020) agree that being competitive in the marketplace is the manner to retain and attract new customers and deliver a new volume of products. Consequently, sales and revenue indicators will increase year by year. It becomes true if organisations enhance the quality of processes through training programmes (Pattinson et al., 2020). This way, current conditions and forms of customer service delivery are incorporated into the business processes. These similarities are aligned with this study because the labour force is the only means to transform organisations to respond to competitiveness. For example, organisations whose business objective is to be competitive and innovative in this digital age should invest in training programmes that help develop digital skills for data manipulation and create compelling data content to make informed decisions. Another example is evidenced when there is an improvement in service quality thanks to the soft skills acquired in courses attended by employees.

In this case, the novelty of the proposed LAM is evidenced during the course design and when it finishes. Therefore, during the design phase, the LAM should collect and characterise the external factor that originates the training programme, e.g., industry regulator, international corporation, governmental institution or new market needs. This characterisation is the basis for the upcoming phase since it allows the appropriate metrics to measure and evaluate the effectiveness of training programmes to be defined. Specifically, the LAM should provide analytics in the following form:

- External entities: the LAM may provide the number and type of programmes delivered to employees. In addition, it gives the results of the assessments that validate the level of knowledge and skills developed by the employees in particular processes. Hence, organisations may demonstrate that employees are able to manipulate or execute certain elements or tasks with a specific grade of knowledge without affecting or injuring others.
- New market needs: The LAM may impact the training in the marketplace by measuring and evaluating the competitiveness. It is evidenced if new products or services are launched from knowledge or skills developed in training programmes in response to customers' needs. Other metrics the LAM provides are the change in sales, the number of new customers or the number of retained customers thanks to the training process.

5.1.2.2 Internal factors

Results from this research indicate that organisational learning support and work climate are internal factors that impact the transfer of training in the workplace. Organisational learning support focuses on providing the means to develop skills in employees. For instance, time is a fundamental means to support the training route in organisations, which is reflected in employees' satisfaction. On the other hand, work climate evaluates whether the organisation supports the training process and whether peers and managers are committed to encouraging trainees to incorporate concepts and developed skills into the workplace. Hence, these two factors should be measured and evaluated within the LAM because they can be a hindrance during the training process in cases where trainees' satisfaction is negative or individuals hinder initiatives generated from a training programme. As a consequence, metrics and indicators will show undesirable results.

Other studies (Jehanzeb & Ahmed Bashir, 2013; Martins et al., 2019; Richter & Kauffeld, 2020) agree that employee satisfaction is the manner to measure whether organisations have defined a clear and successful development plan for employees. It means that they support the training process to achieve positive results in terms of organisational performance, employee performance, low employee turnover, employee commitment and better retention of employees. In addition to the current results, Jehanzeb and Ahmed Bashir (2013) propose that facilities are another fundamental variable that should be considered in the LAM to compute employee satisfaction. This variable refers to the place and conditions where the training is carried out. Thus, rooms or auditoriums should satisfy requirements such as being adaptable, safe, comfortable, accessible and fully equipped to guarantee a high grade of attention and excellent task performance. They may become obstacles during learning processes when they are not considered or simply deficient (Long-Sutehall et al., 2011).

Some studies found no difference from the results of this thesis. Namely, they pose that supervisor and peer support is crucial in ensuring the effectiveness of training programmes (Botke et al., 2018; Burke, 2017; Hughes et al., 2020; Tian et al., 2016). They concur that the trainees' performances will improve when managers and peers give opportunities to innovate and incorporate the knowledge gained, and skills developed. In conclusion, managers and peers should be part of the training process to maximise the benefits of the training development programme. Ignoring these two stakeholders will inhibit the transfer of training in the workplace because they do not recognise the importance of supporting trainees and the benefits of the possible changes that training brings.

Hence, in line with the results and the literature, the contribution of the proposed LAM is reflected as follows:

- Given that organisational support is essential for training programmes, the proposed LAM should measure and evaluate the level of employee satisfaction, reflecting the kind of support the organisation provides. The proposed LAM considers surveys as a source of data to compute the employees' satisfaction and to collect variables such as facilities, overall satisfaction and employees' attitude. The survey may collect data during or after the programme ends. Hence, if the employees' satisfaction indicator is positive, it is concluded that there is support from the organisation. It leads to an increase in the performance of either the organisation or the employee. Other metrics may be included in the LAM to measure the benefits that the training process brings to the organisation, for instance, level of commitment, employee retention, and reduction of employee turnover. Nevertheless, there is no standard definition or guide to establishing the grade of the relationship between these benefits and employees' satisfaction. Therefore, they are the subject of study in the learning field.
- There must be an agreement between trainees, managers and peers before the programme starts. These individuals should set the expected goals, the benefits and the plan to incorporate the competencies gained in the workplace. Then, the proposed LAM should be configured with the quantitative benefits, metrics and those responsible, that is, trainee, peer and supervisor, to facilitate the evaluation and measurement of the programme's effectiveness. For example, the benefit may be reducing the time to 5 minutes to execute a particular task. Thus, after the programme ends, the supervisor should give the time, space and support to incorporate the new manner of performing the task. Co-workers also participate actively in the new process by providing feedback

on how the changes should be included. Finally, the old and new time required to perform the procedure is stored in the LAM to determine the process optimisation. In this way, the LAM can present the programme's effectiveness.

5.1.2.3 Limitation

The results of this study did not reveal if there is an impact on the training process when competitors are considered as external factors. Therefore, further studies should explore scenarios where competitors lead organisations to design development programmes to increase employees' skills and competencies and become more competitive in the marketplace.

No quantitative measure indicates the level of relationship between organisational support and performance in organisations. Thus, other studies are suggested to address this gap by considering employee satisfaction as the independent variable and benefits as the dependent variable.

5.1.3 Measures, metrics and indicators (MIMs)

According to the results section, the effectiveness measurement (EM) comprises the essential part of the LAM because it proposes variables, metrics, indicators and metrics to measure and evaluate the impact of the training process in organisations. It is worth noting that a measure refers to a single number or data point, for example, total employees. A metric is composite of different measures over time and an indicator is the comparison between a current value and expected value. The following domains are proposed to analyse the effect of training in the entire organisation: people and learning, internal processes, finance and customer.

5.1.3.1 Trainee and learning

Trainees' characterisation

The results demonstrate that the LAM may provide a trainee's characterisation to determine the driving forces that affect the trainee and their effects. The characterisation comprises the following components: demographic attributes, motivation, training expectations, performance level and prior experience. These data are collected through a survey that stores data in an LMS before, during and after the programme has been taught. Then data are sent to the LAM.

Demographic attributes

The demographic data component addresses variables that allow the LAM to compute statistical operations such as the average age, counting the number of participants according to their age, and the number of trainees participating in the training process according to their tenure, department, and country or position. All these data are helpful for trainers to design or adjust the course in terms of pedagogy, didactics and methodology. Consequently, the course's success is ensured to a great extent because the programme is adapted to the audience.

The results also demonstrate that the LAM should incorporate components that cover trainees' emotions and behaviours to predict the programme's success. Hence, this study proposes the following components: trainee's motivation, training expectation, performance level and prior experience. The LAM should measure these components through metrics before and during the execution of the programme to identify and classify those trainees with low motivation, poor grades of interest and negative perceptions to establish a strategy to convert these metrics into positive results. Some mechanisms are available in the literature to obtain excellent results. They are:

Motivation to learn

This presents the benefits of training, showing the positive impact on personal development and workplace activities since training brings new ways of doing the job, the best practices to perform certain professional activities and, in some cases, incentives. Consequently, trainee enthusiasm and attention increase during the training reflected in trainees' attendance and commitment to performing academic activities with excellent results. It means that trainees are unfazed by possible distractions, e.g., demotivation.

Hughes et al. (2020) and Shen and Tang (2018) also agree with classifying motivation to learn as part of a trainee's characteristics because it is part of the individual beliefs, personality and emotions from which trainees determine the relevance and importance of training in the organisation. In addition, the authors found that there is a direct relationship between work performance and motivation to learn. In line with the results of this thesis, Bauer et al. (2016) pose that it is fundamental to establish a measure to assess the motivation to learn because it maximises the desired outcomes. Although the study does not specify a particular metric or formula to measure motivation, the author suggests that organisations should implement an adequate measurement depending on the situation. However, D. L. Kirkpatrick (2006) proposes a short-term metric named trainee engagement which acts as a leading indicator to assess whether trainees are involved in the training actively by asking questions, developing workshops and attending the training sessions. The author suggests computing this metric through a survey focusing on the programme content, content relevance and the trainer experience. Hence, if the metric is positive, trainees are interested in the programme and have a great training experience reflected in the trainees' performances. In the opposite case, immediate actions should be implemented to improve this metric.

Training expectations

This measures the grade of trainees' interests before the training programme starts. This component is also important because if the expectation is negative, the trainees' performances will have the same result. The variables that determine the grade of trainees' interests are training reputation, instructor's experience, programme content and quality. Therefore, it is fundamental that trainees recognise in advance whether trainers have enough experience in the topic to generate confidence in participants before the programme initiates. The interest is also measured once the content is delivered. Trainees may evaluate the content quality and whether it is accessible anytime, anywhere, and from any device, e.g., computer and mobile. Other criteria to assess the content are its simplicity, effectiveness and interactivity. However, remote or face-to-face expectations may vary depending on the programme format.

Hughes et al. (2020) concurs with these results proposing trainees' interests as crucial metrics to determine the reaction and encouragement to transfer knowledge on the job. Therefore, if the interest is positive, trainees will experience positive reactions and motivation to apply knowledge to their daily activities. In contrast to the findings of my study, Hughes et al. (2020) suggest establishing a notification strategy for employees to set high expectations before the training programme starts, for instance, communicating the benefits of training, describing the training programme as an opportunity to improve the professional career and explaining the importance of training for the organisation. As a consequence, readiness and interest in learning will increase.

Performance level

This component gathers data related to trainees' performances in the organisation. These data are collected and stored in the HRMS. Then it is sent to the LAM. Three common levels are evident, high, medium and low. These levels allow organisations to determine employees' results and behaviours, which in turn are reflected in the training programme; for instance, if the trainee has a high performance, s/he will reflect a positive perception and active behaviour during the execution of the training. On the contrary, negative perception is perceived in cases where the performance level is low.

Similar studies (Blanco et al., 2013; Elnaga & Imran, 2013; Guan & Frenkel, 2019; Khan, 2012) agree that organisations should classify the employees' performance. In this way, a human resources department could establish strategies to help employees with low performance. Training programmes are one of the essential methods to enhance skills, attitude, competencies and behaviour because it provides the opportunity to learn while employees are working and applying the knowledge acquired in the training programme, which in turn, means that performance is increased. The authors Blanco et al. (2013) and Elnaga and Imran (2013) propose other elements to measure employees' performance: planning, monitoring, developing, rating and rewarding. However, they will not be considered in the scope of this study since they are phases that make up part of the HRMS. In addition, the authors Guan and Frenkel (2019) and Khan (2012) reveal that factors that affect employees' performances are technology, working environment, management behaviour, motivation and training. However, according to its statistical (Khan, 2012) analysis, the more influential factor is training, which should be measured to obtain tangible, verifiable and timely results aligned with the proposed LAM.

Hence, according to previous studies and the findings, the contribution of the LAM consists of gathering, transforming and presenting data that comes from HRMS before the training programme initiates. Namely, the LAM should provide a performance level scale per employee or group of employees. The scale comprises three sorts of values, low, medium and high. The novelty encompasses alerts and notifications generated by the LAM to inform decision-makers regarding the importance of monitoring and controlling trainees that may be at risk during the training programme because they are assessed at a low-level scale. Omitting performance level metrics in the LAM will lead to a negative attitude and perception by trainees, which in turn means the programme's effectiveness will be affected negatively. In addition, decision-makers may identify those employees that require an urgent training plan to increase their performance.

Limitations

Although the LAM will measure the performance level using a specific scale, i.e., low, medium and high. In practice, organisations may incorporate other metrics that widen the spectrum of employees' performances. It means that the scale proposed by the LAM is flexible and may be adapted or transformed according to organisational needs and settings. It is worth noting that the employee's performance is essential in the learning analytics process. For example, the scale may change to the percentage of reduced errors in a business process or decrease products with defects.

Prior knowledge

This component provides metrics through the LAM to determine whether the trainee has previous experience and knowledge related to the programme's content. If this is the case, trainees may feel discouraged or demotivated because they feel that the programme does not contribute to their work or professional skills. Hence, it is fundamental that the LAM provides this information in advance to make decisions before or during the programme's execution. For example, the organisation may suggest changing the programme content or excluding the trainee from the training process and giving the place to another employee to obtain better results.

Other research studies are in line with the findings presented in this thesis. They all agree with adapting the learner-centred approach and the importance of determining the grade of trainees' knowledge before the programme starts (Pattinson et al., 2020; Sternschein et al., 2021). In this way, previous experience is a worthy metric to tailor programmes’ content and ensure business objective alignment (Dover et al., 2018; Pattinson et al., 2020). Pattinson et al. (2020) suggest computing this metric by gathering data using an appraisal that collects data associated with trainees’ skills and knowledge. However, Dover et al. (2018) argue that some organisations may claim that generic learning helps to deliver programmes rapidly and at a low cost because the content is generic. The implication is that these sorts of programmes may not be relevant for employees.

The LAM contributes to the current body of knowledge in two respects, preventing potential demotivation of trainees and evaluating the content pertinence. The process to assess these aspects consists of collecting data related to trainees’ knowledge and skills using an assessment instrument, i.e., a survey. Then, the LAM evaluates and selects trainees whose knowledge and skills are low, that is, potential candidates that will be part of the training programme. At the same time, the LAM also notifies decision-makers regarding employees that do not require the programme. Suppose the organisation decides to include this group of employees in the training programme. In that case, there is a high risk of demotivation because they have already developed the competencies, leading to an adverse affectation on the dropout rate and the effectiveness of training. In case the majority of employees are overqualified, the LAM should suggest adapting or changing the programme content because its pertinence is low, which means that the programme may not contribute to the business objectives, and the programme effectiveness could be zero.

Limitations

The findings related to this study and the literature do not define how to compute or measure the trainee’s experiences and knowledge levels. The rationale consists of tailored needs that the programme should fulfil, which is not replicable in organisations, for instance, in cases where employees should develop skills regarding a software tool to make their daily activities more efficient. However, defining a scale, i.e., from 1 to 5, and a minimum threshold may be enough to determine whether the trainee’s experience is low, medium or high. Thus, further studies may delve deeper into defining the sorts of scales and conditions required to establish the appropriate computation of trainees’ experiences.

Learning experience

According to the results, the LAM consolidates data related to trainees' experiences defined by the training programme in which trainees participate. Then, the LAM is responsible for presenting metrics associated with the quality that evaluates three topics: instructor, content and course logistics. In this way, decision-makers may identify whether motivation exists during the learning path. If demotivation is identified, immediate action should be taken to guarantee the programme's effectiveness. The author D. L. Kirkpatrick (2006) argues that this component is a fundamental part of the cognitive process because it is the only manner to assess internal customer satisfaction.

Teaching experience

This component evaluates the trainee's perception regarding the trainer, that is, her/his level of experience, grade of knowledge and clarity to express and convey ideas. The LAM collects these data using a survey or evaluation that computes data provided by trainees. This component is essential in scenarios when negative results are identified during the cognitive process because the LAM may inform regarding the potential affectation of the programme.

Other authors (Kirkpatrick, 2006; Kirkpatrick, 2008; Ulum, 2015) agree that gathering data to evaluate the teaching experience is through happy sheets or reaction sheets which are feedback forms based on trainees' reactions to the training experience. Unlike the results obtained in this thesis, the author Kirkpatrick (2006) delved into the questions that are fundamental to ask. The questions are classified into four categories: programme objectives, facilitator knowledge, facilitator delivery and facilitator style (Ulum, 2015; Yaghi & Bates, 2020). Programme objectives ask whether the trainer covered the learning objectives of the programme. The second category is facilitator knowledge, which intends to address whether the trainer demonstrated good knowledge regarding the content and whether he shared his professional and personal experiences related to the content. The third category is named trainer delivery. This category focuses on the effectiveness of conveying ideas, the accuracy related to the methods used for teaching, the grade of trainees' interactions during the sessions and the pace to address the entire content. The last category is the trainer's style which addresses the ease of managing the programme and the pertinence of adapting activities and exercises during the sessions.

In summary, these categories provide results that may help trainers change their behaviours or methods if the results are negative (Reio et al., 2017). In that way, they increase their motivation (Piryani et al., 2018). In addition, Reio et al. (2017) proposed that the teaching experience evaluation should be designed considering the Likert scale; that is, responses are predefined with the options strongly disagree, disagree, agree and strongly agree.

Quality of content

This component evaluates the content quality based on the trainee's perceptions. Like teaching experience, data are collected using a written or digital questionnaire. Then, the LAM extracts data from the questionnaire and presents whether the content is relevant for the audience using the Likert scale. In this way, decision-makers may adjust the content in cases where the results are negative. The trainees evaluate the programme execution, for instance, when a unit or module has finished.

In line with the results, Kirkpatrick (Kirkpatrick, 2006; Reio et al., 2017) suggests evaluating the content's completeness and relevance. Therefore, the trainees should respond to whether the content was presented according to the learning objectives and whether the content is relevant to the activities that employees perform daily at work. It is also essential to ask trainees whether workshops and tests were based on the content presented in the training programme.

Course Logistics

This component aims to present data related to the programme's logistics. Hence, the LAM shows metrics that depend on the programme's format, face-to-face or remote. Programmes delivered face-to-face have metrics such as the quality of the classroom or food. In cases where programmes are taught remotely, the LAM should associate metrics like the opportunity to access content and meeting software quality.

Considering previous research studies (Kirkpatrick, 2006; Kirkpatrick, 2008), they agree that course logistics impact trainees' experiences, although there are variables that have no relationship with the academic setting. However, they play an essential role during the programme execution. For instance, the author Kirkpatrick suggests applying a questionnaire about the programme facilities: the lighting, room temperature, food quality and the breaks required to reduce fatigue. All these variables should be incorporated into the questionnaire, which sends the data to the LAM. Then, data are analysed to make informed decisions, such as changing the room or food in scenarios where negative results are perceived.

The contribution of the LAM to the learning analytics field comprises:

- The LAM acts as a centraliser of trainees' experiences. It gathers data from questionnaires that evaluate trainees' perceptions regarding the quality of teaching, content and facilities. Thus, decision-makers may find the information in just one place; they do not have to download data from different questionnaires and combine data to analyse the results separately.
- The LAM serves as a notifier when negative results are detected, for instance, when the content is irrelevant or complete according to the Likert scale. In this case, the LAM should send a message to the decision-makers to perform rapid actions to reduce demotivation and maintain the programme's effectiveness. In this case, the LAM can come ahead of time, informing negative experiences in time.

Limitations

The collected studies did not present how prescriptive and predictive analytics may help to predict results according to the satisfaction of the internal client, that is, trainees. Therefore, further studies may evaluate the machine learning models adapted to these settings. In this way, strategies and actions may be performed to ensure that motivation is not affected during the execution of the training programme.

Learning path

According to the results, the LAM should incorporate learning and behaviour components to present metrics related to the grade average, maximum and minimum, and KPIs that indicate whether developed competencies are applied in the workplace. In summary, the learning path domain aims to measure and evaluate the acquired knowledge and how the developed competencies are applied in the workplace.

Learning

The learning component focuses on measuring and evaluating the grade of knowledge trainees acquire after the training has finished. Evaluation, tests and assessments are typically designed and fulfilled through a questionnaire which should act as a data source for the LAM. Then, data are presented in the LAM as metrics to leverage the analysis and interpretation of information and determine whether trainees achieved the learning objectives and the programmes' effectiveness. In addition, there is no unique design and set of questions that may be reused because it depends on the learning objectives, business objectives and whether hard or soft skills are evaluated. However, the scale, i.e., one to five, and the minimum threshold, should be established and standardised across the organisation to measure and assess the impact of training considering the whole set of programmes given to employees during a specific time.

Several authors (Cho et al., 2009; Razanaufal & Lantu, 2019; Ruiz & Snoeck, 2018) concur with the results of this thesis in the sense that questionnaires are the means to evaluate technical or leadership skills before and after the training is performed. Razanaufal and Lantu (2019) went beyond this point, comparing groups that attended the programme to those that did not participate. In this case, the programme's effectiveness may be computed efficiently. Different models are proposed to design, trace and evaluate the level of cognitive abilities developed in a training programme. Examples of models are Kirkpatrick, Phillips and CIPP (Reio et al., 2017). Notwithstanding, the Kirkpatrick model is the most used worldwide in academic and industry settings (Alsalamah & Callinan, 2021b). The learning component of the proposed LAM is also based on Kirkpatrick. These studies also suggest setting a scale before the training starts since it is essential to establish a quantitative measurement to identify the programme's effectiveness. In addition, a case study (Ruiz & Snoeck, 2018) detailed how to design the initial assessment by adapting a derivative from Bloom's taxonomy. This was the basis for determining trainees' cognitive levels after the programme finished. This taxonomy comprises six levels, recalling, comprehension, application, analysis, evaluation and creation. Although the study only applied the first three levels to evaluate how well trainees remember, explain and identify the correct application of their knowledge, it is worth noting that the proposed

LAM is not able to infer in the assessment design since it depends on the business needs and learning objectives. Thus, the LAM is responsible only for extracting data from the questionnaire, transforming data and presenting the learning results according to the scale defined by the decision-makers.

5.1.3.2 Internal processes

Job performance

This measures and evaluates the extent to which skills, knowledge or competencies acquired by trainees are incorporated into their daily activities and behaviours. For example, the reduction of rate errors or improvements of tasks in terms of time. Digital or written assessments are designed to evaluate the level of behaviour. However, the questions related to the evaluation may vary according to the learning and business objectives. Unlike the learning element defined in the learning path category (see section 5.1.3.1), behaviour is computed considering three roles - trainee, supervisor and peers - since they act as observers to validate and evaluate whether the training has impacted business processes and a trainee’s performance. Hence, the LAM extracts the results from the assessments to present quantitative indicators that allow measuring of the impact of training. For instance, if no changes are identified in the trainee’s workplace or behaviour, the decision-maker should interpret information presented by the LAM and execute actions that enhance the trainee’s productivity.

Other studies (Choudhury & Vedna Sharma, 2019; Razanaufal & Lantu, 2019; Yaghi & Bates, 2020) also agree that workplace changes and habits should be evaluated to measure the impact of training in organisations. Namely, Razanaufal and Lantu (2019) recommend that the evaluation should be applied one month after the training finishes. Yaghi and Bates (2020) claims that to obtain accurate results, it is fundamental to involve during the evaluation, the training participants, the leader of the training participant, subordinates and colleagues. Another study (Choudhury & Vedna Sharma, 2019) affirms that the behaviour should be evaluated several times to measure the participant’s progress. In case negative impact is detected, Botke et al. (2018) indicate that the main reasons are training motivation, trainer, training method and training environment. In summary, the behaviour component represents an important role in the LAM, given that it provides the required information to evaluate whether training is modifying employees’ behaviours or skills that are being applied in the job.

Hence, in practice, the LAM’s contribution is revealed in presenting data that alerts and notifies the positive or negative impact of training in the workplace. Namely, the metrics that measure and evaluate the effect are classified into three categories, efficiency, quality and innovation. Hence, efficiency points to reducing time or cost in a specific process. Efficiency is also known as productivity. For example, an employee took 5 minutes to execute a task. But, after the training programme, the job decreased to 2.5 minutes, so the efficiency provided by the LAM is 50% which in turn means that the training has been effective. The second category of metrics is quality which refers to the metrics’ quality in terms of reduction of errors or accidents. In this scenario, the LAM presents the changes considering the number of errors or accidents before and after the training is delivered to the employees. Then, according to the results, the decision-maker decides whether the programme impacted the workplace. Concerning the innovation category, the LAM computes the degree of innovation by comparing the current manner of delivering a product or service to the previous method. Namely, it can be measured by calculating the number of innovative ideas implemented after the training is provided. However, it is worth noting that this is not the only manner to obtain the degree of innovation, as some frameworks and methodologies suggest metrics according to the nature of the company and the business goals. In addition, the LAM gathers data related to these three categories by extracting data from the initial and final questionnaires setup in the LAM or any other digital application.

Limitation

The metrics defined to measure the efficiency, quality and innovation using the LAM may be used as a reference to determine the effectiveness of the training. However, organisations may adapt or change them according to their needs. Hence, the limitation in this case comprises the reduced number of metrics to compute the efficiency, quality and innovation since they were defined according to the results provided by the TA method. It means that it may be the case that in other bodies of knowledge, such as management, different metrics and variables can be found to expand the number of metrics in the LAM. The impact of this limitation is minimal on the LAM because it is designed to adopt any sort of metrics that allow measuring and evaluating the elements and relationships proposed in this research.

Trainers and workplace observers

The results present the stakeholders and their requirements that arise during a programme's design, delivery and post-training phases. Hence, during the design, managers or supervisors request the programme to develop skills or competencies in their employees. Another stakeholder is the human resources department in charge of facilitating the budget and resources to make the programme happen. The last stakeholder in this phase is educational institutions such as HEIs (higher education institutions) or institutes whose responsibility is to provide trainers to satisfy the organisational needs. However, this last stakeholder is optional because there are some scenarios where organisations assume the role of educational institutions. In the training phase, trainers and trainees are the primary stakeholders. Trainers have the function of defining pedagogical strategies and adapting the academic content according to the organisational needs and teaching. On the other hand, trainees are responsible for developing skills and competencies defined in the learning objectives. The post-training phase involves the trainee's supervisor and colleagues, whose role is to observe whether trainees are applying their acquired knowledge in the workplace. All these stakeholders are essential for the LAM because they act as the input of data at different levels. For example, the human resources department provides the costs of investment in the training and the return of investment (ROI); trainees give the initial and final time values to determine their productivity or similar metrics.

Some authors (Erina et al., 2015b; Guerci & Vinante, 2011) agree with the current study since these studies consider that stakeholders involved in the training process are participants, managers and training specialists, i.e., trainers. The stakeholder depends on the training phase, that is, design, delivery or post-training. The authors (Erina et al., 2015b; Guerci & Vinante, 2011) pose that depending on the stakeholders, the training programme has different aims. For example, trainees consider that building skills and professional development are fundamental. However, managers believe that it is a priority to apply the acquired knowledge in the workplace and change the trainees' behaviours. One study (Guerci & Vinante, 2011) focuses on gathering data from multiple stakeholders using questionnaires, surveys or focus groups to provide different information and facilitate interpretation. In conclusion, the proposed LAM aligns with the literature because it considers the stakeholders involved in the training process as a source of data collected through digital or written instruments that measure the learning, application of acquired knowledge and trainees' behaviours.

In summary, the LAM contributes to the training field by identifying the importance and role of trainers, managers, colleagues, collaborators and a human resources department during the training process. In this way, metrics and indicators presented by the LAM are impacted directly because these stakeholders act as the data input along the training phases. In detail:

- Trainers evaluate the trainee's performances during the workshops or exercises defined and performed during the programme execution. The LAM collects the data. Then, the results are computed and presented using reports.
- Managers provide data through questionnaires according to the change in trainees' attitudes or behaviours in their workplace. In addition, they evaluate whether optimisations are implemented in processes or tasks to reduce costs or time, thanks to the skills developed in the programme. In this case, the LAM presents the impact of training on reducing costs or money. However, there may be scenarios where new processes, products or services are created. In this case, the innovation metrics are impacted.
- Colleagues and collaborators complete a questionnaire regarding the trainees' performances in the workplace. Like the managers' analyses, the LAM extracts data stored in the questionnaires to compute and present data in the form of information to analyse and interpret the results. Thus, if indicators or metrics reach adverse effects, the LAM should highlight and notify the human resources department regarding the poor results after the programme finishes.
- A human resources department has the role of providing the initial costs and time of processes that are due to improve. This information is collected before the training programme starts. After that, this department should set the desired threshold that trainees should achieve. Finally, the LAM collects the initial values and compares them to new values provided by managers, colleagues and collaborators. In this way, results are presented considering a 360º view of

the process, which means that results are more accurate given that different observers evaluate the impact of training on the workplace.

Limitations

The metrics presented may be adapted or varied according to the organisational context because every organisation is unique in its culture, customers and processes. Thus, future implementations of the LAM could expand or decrease the number of metrics to evaluate the impact of training in the workplace.

5.1.3.3 Business objectives

The results propose two categories that the LAM should present in the form of metrics. The first category is named tangible, which refers to quantitative metrics that directly affect the business objectives according to the benefits of the training. The second category is intangible, whose restriction is that benefits cannot be calculated using statistical operations such as sum or average. However, they represent an impact on business objectives.

Tangible components

This category aims to present metrics through the LAM to translate benefits into monetary values aligned with the business objectives. Thus, the LAM encompasses the following essential components: revenue, ROI, profitability, expenses and NPV. Similar to other components, revenue profitability and costs should be measured before and after the programme finishes. In this way, the LAM computes the changes and impact on sales indicators thanks to the training. On the other hand, ROI and NPV are components that focus on monetising trainees' behaviours, reactions and skills acquired during the programme. In this case, an assessment is performed to measure the benefits using variables such as output, time savings, cost and quality. Then, the LAM evaluates the monetary benefits versus the cost of the programme investment related to the phases required to build it, that is, design, delivery and the cost of having the trainees in the programme, which is calculated according to their salaries.

Studies developed by Bukhari et al. (2017), Matthews and Jackson (2021) and Subramanian et al. (2012) are in line with the results obtained in this study in the sense that elements such as time savings and reduction of errors are identified as benefits to calculate the ROI and NPV metrics. Questionnaires are designed to gather data and perform calculations using MS Excel software. In contrast to this study, Bukhari et al. (2017) add employee satisfaction and organisational reputation as intangible components. Matthews and Jackson (2021) and Subramanian et al. (2012) also suggest the internal rate of return (IRR) as another financial component to prioritise. At the same time, NVP, benefit-cost ratio (BCR) and payback period are proposed to determine whether the programme is profitable. However, it is worth noting that the tangible and intangible components may increase or decrease depending on the organisational needs. Therefore, the LAM should support and calculate metrics related to additional components in any case. In addition, all these authors concur that running simulations using the Phillips model (J. Phillips & Phillips, 2012) before the organisations invest in training programmes using programme costs and potential benefits.

In practice, the LAM contributes to the field of learning analytics applied to organisations in the following manner:

- Computing tangible benefits: the LAM condenses tangible and intangible benefits of training programmes. Benefits are expressed in monetary indicators such as ROI, NPV, revenue, profitability, and expenses. Although, in reality, it may increase or decrease the indicators list, the LAM may adapt itself to the organisational needs. It is paramount to mention that ROI is the most widely used in organisations. Hence, regardless of the financial indicator, the LAM is designed to gather data related to the cost of programmes stored in digital tools such as ERP or LMS. Then, the LAM collects the benefits calculated in terms of time savings, sales growth or reduction of errors, depending on the programme scope. These data are provided by a human resources department and stored in a digital tool. The last part of the process consists of computing the investment versus the benefits. Depending on the indicator, the calculation process may vary according to variables such as time or thresholds.
- Accurate data: the LAM provides precise data to be analysed and interpreted by decision-makers such as managers or supervisors. In this way, they may decide whether to invest in training programmes in the future. In addition, they also may use the LAM to simulate the benefits of the programme by introducing

expected values. Therefore, organisations have a powerful tool that forecasts the profits of training. It is worth noting that programmes delivered to employees due to external regulators or law will have negative indicators because they are not oriented to increase sales or make processes efficient.

Intangible components

The intangible components aim to present the benefits of training and set monetary variables aside. These components are intentionally measured and established in organisations because they help to reach business objectives by taking advantage of soft skills in employees, for instance, teamwork, effective communication, organisational commitment and leadership. Before and after the training is delivered to trainees, it is paramount to perform a perception survey and 360-degree feedback assessment based on observation and interviews involving people that interact with the trainee, for example, the trainee's supervisor and colleagues. In this way, the LAM may extract, measure and evaluate the changes in soft-skills based on the data from surveys and assessments.

Comparing the results of this study to the literature, some studies (J. J. Phillips, 2011b; Schueler & Loveder, 2020) agree on adapting intangible variables as the basis to measure the impact on training regardless of the monetary value. In contrast to my study, P. P. Phillips (n.d.) includes variables such as stress reduction, job satisfaction, fewer conflicts and improved image in the company. Ferguson et al. (2019) and Schueler & Loveder (2020) argue that intangible variables may vary according to organisational needs. Hence, there is no unique set of variables that the LAM may adapt. In addition, this study poses that depending on the intangible variables, they may be converted to tangible variables. For example, in employee retention, some organisations compute the cost of recruitment, that is, time for induction and interviews, and then these variables are transformed into financial indicators. However, in other organisations, recruitment costs are not estimated, which leads to defining the retention indicator as intangible since it is difficult to measure.

The LAM's contribution consists of gathering, consolidating, computing and presenting intangible data to measure the impact of training using metrics unrelated to calculating the monetary value. Hence, the LAM extracts data from assessments and computes the changes considering the initial and final values of the defined components, i.e., teamwork and leadership. Although there is no standard manner to present the intangible benefits, the LAM should support custom metrics. The only condition is to apply assessments before and after the training is delivered to identify the changes.

Limitations

Although the proposed LAM computes and presents intangible components in the form of metrics, this study did not consider the importance of defining thresholds for every metric. In this way, decision-makers may determine how far the results are from the expected goal. Consequently, they may initiate strategical and tactical actions when the threshold is reached. For example, in the scenario where the teamwork indicator exceeds the expected goals, the LAM should trigger messages or alerts informing stakeholders about this achievement to congratulate employees because they have developed skills to work with others collaboratively to reach a common goal.

5.1.3.4 Customer

The customer domain aims to measure and evaluate the impact on customer relationship indicators when the training process is involved in response to the strategy of improving processes that affect customers' interactions. Therefore, the LAM is responsible for facilitating the analysis of the training impact when a programme is performed to reduce the time of delivering a product, increase sales or enhance the quality of a product. Thus, to cover this objective, the LAM's elements comprise time to market, product quality, service, cost of producing a product or service, market share, customer acquisition, customer satisfaction, customer loyalty, and customer retention. These elements are fundamental because they impact the achievement of business objectives directly. For example, providing a training programme to develop customer service skills in this way, the customer experience and loyalty are affected positively. These sorts of programmes are designed to influence indicators such as customer service, customer satisfaction, customer loyalty, and customer retention because they change the manner to elaborate products. In any case, it is crucial to define the learning objectives and the expected results to contrast them at the end of the programme.

In line with this study, Pettijohn et al. (2002), Román et al. (2002) and Vadi and Suuroja (2006) confirm in their studies that training is vital to raise customer experience indicators. For example, Vadi and Suuroja (2006) concluded that awareness and attitude were part of the learning objectives to improve customer interactions and communication. Consequently, it positively impacted pattern behaviours, namely in verbal and non-verbal communication with customers. Román et al. (2002) also present positive results in sales performance thanks to a training programme. Pettijohn et al. (2002) claims that up-skilling employees are a critical determinant to enriching indicators such as customer orientation. V. L. Singh et al. (2015) pose that it is mandatory to evaluate the effectiveness of programmes using analytics. In this manner, organisations can identify and eliminate sales training programmes that do not contribute to sales growth. My study also suggests that programmes with content related to soft skills may enhance indicators such as customer orientation.

The novelty of the LAM in this domain consists of grouping elements that measure and evaluate the impact of training on customer relationship indicators. In this case, the LAM should gather the initial values related to these indicators. Then, it collects the values after the training programme finishes. Finally, the LAM computes the variations and presents the information to validate whether the contribution of training was positive or negative. The information provided by the LAM in this domain is relevant because it directly impacts customer interactions and business goals, i.e., sales and customer experience. Therefore, training programmes should be aligned with the organisational balanced scorecard to articulate how employees should behave, interact, communicate and support customers thanks to the developed skills and behaviours during a programme. For example, suppose a training programme is designed to strengthen the process of delivering services with the objective of exceeding customer expectations. In that case, it is a likelihood that indicators such as customer satisfaction and loyalty will be affected positively. In this case, it is crucial to measure the initial indicators to determine the changes once the programme finishes.

Limitations

The proposed LAM assumes that the initial and final values related to customer relationship indicators come from the human resources department as a source of information. However, in practice, the source of information may vary according to the element that the organisation desires to evaluate. For example, to validate the improvement of customer loyalty, product quality or quality of service, one potential source may be a CRM (Customer Relationship Management) because it consolidates data from different perspectives, such as claims, complaints, requirements, sales and invoices. Even the indicators may be calculated using more than one source. For instance, data may come from sales systems, CRM and social media. Although this limitation has no impact on the findings because the LAM is designed to receive data from multiple data sources, it is relevant that further investigations address what data sources are ideal for performing the calculations for each element. Consequently, the reports provided by the LAM become more accurate.

5.1.4 **Data preparation**

Data preparation is the process of cleaning and transforming data originating from digital organisational tools such as LMS, ERP, HRMS, questionnaires and other similar sources. This process aims to ensure high data quality in the LAM. Therefore, before the LAM computes and presents information through reports, this process executes business rules that are fundamental to making informed decisions with high accuracy, consistency and completeness. For example, if the costs of delivering a programme are not defined, the data preparation process would not allow computing and presenting information regarding ROI, because these data are essential to calculate the benefits of the investment. Thus, considering the results of this study, data cleaning and transformation are categories that guarantee the LAM's data quality. They are presented here in detail.

5.1.4.1 Data cleaning

This category aims to correct data from digital organisational tools such as LMS, ERP, HRMS or other similar tools defined by the organisation to provide learning data. The components used by the LAM to perform the cleaning tasks are completeness, consistency, duplicates, mislabelling, and mis-formatting. Therefore, each component evaluates whether data entering into the LAM satisfies the rules to correct errors. For example, typographical errors, missing values or mixed formats.

Berti-Equille (2019) and Chu et al. (2016) also claim that data cleaning is fundamental to avoid misinterpretation and unreliable analysis. Unlike the current results, the author poses two phases for cleaning: error detection, which consists of automatically identifying anomalies, and error repairing, which encompasses data ready to be used. Chu et al. (2016) argue that although these phases are widely used to ensure high data quality, in reality, there are challenges to be coped with by data cleaning, that is, processing vast amounts of data and processing unstructured data, for instance, documents. However, these challenges do not impact the proposed LAM because it focuses on processing learning data different from audio or text files since they were not found in this study. Berti-Equille (2019) presents a framework for data cleaning using automatised tasks based on artificial intelligence. However, Berti-Equille (2019) found that rules and restrictions for cleaning should be customised for every situation; the LAM should adopt rules that vary according to organisational nature.

The contribution of the LAM in this respect consists of applying a data cleaning process to detect and correct errors included in the data that come from sources such as questionnaires or LMSs. In this way, high data quality is ensured. Consequently, decision-makers may trust the information presented on the LAM because reports are reliable.

In practice, those organisations that decide to adopt the LAM should determine their own rules and constraints depending on their context in the way shown in Figure 5.2.

Component	Rules and constraints (example)
Completeness	The LAM should identify and replace empty fields.
Consistency	The LAM should not consider trainees who are no longer part of the organisation in the calculations.
Duplicates	Detect and remove trainees with the same ID attending the same training programme.
Mislabelling	The trainee’s department has an incorrect name; for instance, it should change mkt by Marketing. In this case, the LAM should allow changing this name.
Misformating	The initial and final date is in the yy/mm/dd format. However, it is required the format dd/mm/yyyy. Thus, the LAM should apply these rules before the data are loaded into the LAM.

Figure 5.2 Data cleaning rules

5.1.4.2 Limitations

Since rules and constraints depend on organisational needs, this study cannot provide specific rules to be applied to the cleaning process. For example, the organisation is not asked to apply rules about removing duplicates because the information systems contain strong restrictions in their processes and graphical interfaces that is impossible to duplicate data. However, the components that are part of the process should be used as guidelines to set the rules and achieve a high data quality standard.

5.1.4.3 Data transformation

According to the results, the data transformation process consists of converting original data into desired content. The LAM incorporates this process by applying the most salient sorts of transformation: aggregation, generalisation, normalisation and data reduction. Hence, aggregation refers to adding new columns or rows based on the original dataset, for instance, calculating the average of trainees attending training programmes. Generalisation consists of adding hierarchies based on the original data. For example, using the dates of beginning and end of a set of programmes, the LAM may add hierarchical columns such as semester or quarter, which help to filter information responding to the question of what was the number of programmes delivered in the first semester? Normalisation refers to standardisation of data categories. For example, the list of areas or departments participating in the training process should be unique. The last sort of data transformation is data reduction which consists of hiding or removing columns that are not required for calculating metrics.

The results of this study are in line with other investigations (Akçapınar et al., 2019; Berti-Equille, 2019; Di Mitri et al., 2018) because data transformation is a fundamental process performed by the LAM to generate new data or convert it into the desired formats to present information into suitable graphical reports. For example, the proposed model by Mitri et al. (2019) includes a numerical transformation phase to get data ready before the artificial intelligent model runs. Akçapınar et al. (2019) propose different techniques to transform data according to the problem nature. For instance, data reduction is proposed to remove characteristics of datasets extracted from a LMS, VLE and personalised learning environment (PLE). This study also establishes that transformation is vital before the model starts its calculations and predictions. In summary, these studies concur that data preparation should be executed before any other phase to guarantee the correct data content and format.

The LAM's contribution during the data transformation process consists of converting data into a desired format and content regardless of the data source, i.e., LMS, VLE and PLE. In this way, the LAM guarantees the correct and required data for further activities, such as presenting information through dashboards. The importance of this process is reflected in scenarios where the LAM collects date formats from different digital tools, with the requirement to filter by a specific date. The decision-makers will be able to do so and obtain the correct information since a previous transformation process was performed. In practice, organisations that desire to implement this process should identify the required data that further phases will use for reporting and measurement. Then, data should be transformed considering the components proposed by the LAM: aggregation, generalisation, normalisation and data reduction. Finally, data may be used by measures, metrics and indicators (see details in section 5.1.3).

Limitations

According to the results and the reviewed literature, the number of scenarios to convert data are endless because they depend on the organisational needs and peculiarities. Therefore, the examples and scenarios discovered in this study are limited concerning the potential cases in organisations. Nevertheless, the components presented in the LAM may cover any case. Hence, analysing the data transformation rules in light of these components is strongly recommended.

5.1.5 Reporting

This theme focuses on how the LAM incorporates the existing analytical models and best practices to visualise reports. Thus, depending on the learning analytical maturity model in the organisation, the LAM should implement any of the analytical models. The following subsections will detail descriptive, predictive and prescriptive models and how their components should be adopted and presented using visualisations to perform deep analysis and interpretations regarding the impact of training in organisations.

5.1.5.1 Analytical models

Descriptive models

These models are included in the LAM to compute and present training programmes' behaviours, patterns and outcomes. These models only process historical data through three components: statistics, aggregations and KPIs. Statistics involves calculations such as sum, average, maximum and minimum. Aggregation comprises the sum of particular variables, for instance, the number of trainees that attend the training process. The last component is KPIs which measure the desired outcome versus the current situation. The main objective is to control the organisational performance to ease the analysis and interpretation of the indicators related to the training process, for instance, the ROI.

Caeiro-Rodríguez et al. (2016), Du et al. (2021), Foung and Chen (2019), Romero and Ventura (2020) and Susnjak et al. (2022) concur with the results of this study in that descriptive analytics is a fundamental tool to answer the question, "what has happened?" Thus, the means to address this question is designing and implementing metrics that allow comparing class averages and patterns to identify the crucial elements affecting the training programme negatively. Susnjak et al. (2022) propose in their investigation a learning analytics dashboard to measure the assessments' scores, participation levels and interaction with academic activities. In addition, this study highlights that it is also essential to measure the instructor's performance. B. T. M. Wong (2017) proposes the following KPIs: trainees' successes and retention rates, which help to make informed decisions and interventions to improve these indicators. Du et al. (2021) and Susnjak et al. (2022) claim that most of the learning analytics reports are implemented using descriptive models. Susnjak et al. (2022) also pose that technological tools are an essential factor in implementing interactive dashboards that ease the implementation of these models and allow setting alerts that notify decision-makers regarding the achievement of specific KPIs.

The LAM's contribution involves the computing and presentation of historical data derived from training programmes. Thus, before decision-makers analyse and interpret data, the process comprises calculating statistical operations and aggregating data to obtain summarised information and KPIs defined for controlling and measuring the desired business objectives. For example, attendance rate and ROI. In addition, the LAM incorporates alerts that notify stakeholders regarding the fulfilment of indicators. In this way, the LAM facilitates the monitoring of indicators. In practice, the adopters of the proposed model should define the data to be analysed. For example, the total of employees attending training programmes, the average age of trainees, maximum assessment score, number of programmes delivered per year, number of employees per month, cost of investment yearly, number of innovations and other variables that may be calculated using statistical operations. It is also paramount to define the KPIs to evaluate whether the desired outcomes are achieved. According to the results, ROI and NPV are common KPIs. In scenarios where the LAM shows negative metrics, decision-makers should perform actions to improve the indicator.

Predictive models

According to the results, the LAM incorporates models that predict future outcomes by combining historical data and algorithms. The aim is to answer the question, "What will happen?" associated with a degree of certainty depending on the applied model. For example, organisations may forecast investments in training for the next year considering the historical results of ROI or the number of innovations implemented in business processes thanks to the training programmes delivered to employees. There are two categories of predictive models that are adopted depending on the nature of the data. The first category is known as regression models. They are implemented for scenarios where variables are quantitative or numerical. The most used model is linear regression. The second category is named classification models. They are considered when variables are categorical with no logical order. The most salient models are logistic regression, naïve Bayes and neuronal networks. However, the decision trees model can be either part of regression or classification models.

According to the current results and the literature reviewed, adopting predictive models in organisations is indisputably essential to make informed decisions in advance (Akçapınar et al., 2019; Foung & Chen, 2019; Mitri et al., 2019). In addition, these models may be used to set early warnings when there is a risk of having negative metrics. For example, the LAM may predict trainees with a low attendance rate. However, models should not be generalised across organisations because variables are specific, and they may vary depending on settings and industry; for instance, one investigation (Akçapınar et al., 2019) had to perform different proofs of concepts to determine the most suitable classification model. The result was the KNN algorithm with an accuracy of 89%, which helped to predict potential trainees with low performance. Thus, early strategies could be designed to obtain positive results.

Similarly, Mitri et al. (2019) propose that predictive models should be adopted to process data depending on the measurement strategy. This investigation differs from this study in the lists of models. Namely, the authors propose an expert-learner comparison model, which consists of training experts and comparing the expected results with the current results. Then, the model determines behaviours in the future. In contrast to these results, Romero and Ventura (2020) proposes that the predictive model should be designed and implemented in a specialised software tool that acts as an engine to run the required model and then provides the results using analytics APIs. However, a drawback compared to the proposed LAM is the high dependency on the external tool. For example, in the scenario where the external tool is required to be flexible and available at any time, but the software tool is not prepared and limited to perform custom changes, the LAM will not be able to predict. Therefore, the proposed LAM is the best alternative for this scenario because it is designed to incorporate data processing using predictive models into its components.

The contribution to the literature and the organisations is that, through the LAM, decision-makers could intervene in a timely way when any predictive models alert negative results concerning patterns, behaviours or outcomes that affect the training process. For example, the LAM analyses variables such as employees with an average age of 25 years with one year career in the organisation. Then, the LAM runs its algorithms and concludes that the drop-out risk is high considering historical data and the trainees' characteristics attending a particular programme. The number of examples in which predictive models may be used is unlimited. However, in practice, organisations must define the indicators and measures that these sorts of models should evaluate to adopt the most suitable one depending on the data nature and the strategic objective.

Prescriptive models

The results revealed that the LAM might suggest actions to execute based on business knowledge and the alternatives provided by descriptive and predictive models. The combination of these three elements is named prescriptive models. These models are designed and adapted into the LAM to answer the question: What should be the optimal outcome? The LAM addresses this question by evaluating the effects of a set of possible decisions. Then, it selects the best alternative. For example, the descriptive model presents that ROI and the assessments were positive when training was delivered in the morning. In contrast, previous training programmes delivered in the evenings had negative results. On the other hand, the predictive model suggests that a current programme will have adverse effects because the probability of success is low by combining the variables ROI, learning rate, time schedule, and average age. In addition, the business knowledge establishes that employees in the evening are when most employees are busy due to meetings with other partners around the world. Thus, the LAM runs the prescriptive model and will suggest suspending or changing the programme's time schedule if the organisations desire a positive impact.

Two investigations (Du et al., 2021; Susnjak et al., 2022) argue that prescriptive analytics can be deployed in dashboards to provide concrete advice to learners. In this way, they have insights to make informed decisions. For example, making rapid changes in the learning strategy. These studies are in line with the proposed LAM because both studies coincide in that prescriptive analytics play a vital role during the training process. However, there is a gap in the literature and industry because these models do not exist. Therefore, the organisations would recognise the worth of the proposed LAM in case they decide to adopt it. In addition, Caeiro-Rodríguez et al. (2016) agree with my study in combining descriptive and prescriptive models using visual reports to support trainers and managers in their decisions.

The contribution of the LAM is that it combines descriptive, prescriptive and predictive models at the same time. It means that managers, trainers, and other stakeholders involved in the training process may interpret information regarding the past, the present and the future, including suggestions to improve the indicators established to measure the impact of training in the organisation. According to the literature, this contribution is a novelty because neither the academic field nor industry has designed or implemented a LAM with these characteristics. In practice, the adaptation of the proposed model requires:

- Defining indicators and learning variables to be measured. The list of indicators varies according to the organisation and its business needs. For example, drop-out rate, learning performance or learning application in the workplace.
- Collecting storing and computing historical data related to the defined indicators. These sorts of data serve to build descriptive models.
- Designing and implementing predictive models. The models can be chosen from two categories, regression or classification. They vary according to the data's nature and organisational needs.
- Defining the business rules and suggestions depending on the possible alternatives from the descriptive and predictive models.

5.1.5.2 Visualisations

According to the results, the visualisations domain plays a vital role in the LAM because it is responsible for presenting visual objects using reports or dashboards to ease the interpretation and analysis of training data. Descriptive, predictive and prescriptive models are incorporated in reports to show their results. Since the number of visual objects is large, the LAM proposes three categories of graphical objects to classify them. Evolution is the first category, which groups visuals that show the variation of data in terms of increasing or decreasing data. For example, the variation of ROI with respect to the current and desired results. Size is the second category; it compares different types of elements, for instance, the types of programme formats delivered to employees, i.e., face-to-face or remote. The last category is relational; it groups visuals that compute how variables change with respect to one another. These visuals also present cause-effect relationships.

Some studies (Caeiro-Rodríguez et al., 2016; Lu et al., 2017; Susnjak et al., 2022; B. T. M. Wong, 2017) concur with this study in the form of having a report or dashboard to present information to initiate interpretation and analysis considering the decision-makers criteria. Reports are customised depending on the organisational settings and business needs. Similar to this study, some studies (Lu et al., 2017; Susnjak et al., 2022) propose using digital tools to take advantage of learning analytics. The first suggestion is to alert and send personalised messages recommending pedagogical activities considering the data collected during the training process (Du et al., 2021). For example, the trainer is informed through email proactively because his trainees are at risk due to low performance. The second suggestion refers to user experience, which is also essential to facilitate data analysis, that is, setting reports with a maximum of three hues and a neutral pastel palate (Caeiro-Rodríguez et al., 2016; Susnjak et al., 2022). The last suggestion is to generate indicators or visuals dynamically, evolving from static to smart dashboards (Susnjak et al., 2022).

The contribution of the LAM to the training process consists of providing visual means to present data through reports and dashboards. In practice, organisations may adapt the LAM's visualisations considering the following conditions:

- Define the groups of visuals that should be adapted to learning analytics decisions. Namely, evolution to compare data changes; size to compare elements; and relation to validating variables' behaviour with respect to others. Therefore, the decision-makers will have the criteria to incorporate an endless list of visuals, for instance, pie charts, tree maps, line charts, bubble charts, table charts, KPIs and many more. It is worth noting that there is no unique report or dashboard that may be used for organisations since every organisation has special business needs and training processes.
- Configure a set of rules to trigger personalised messages and alerts that indicate whether metrics are achieved or not. In any case, information sent to the decision-maker should contain descriptive, predictive or prescriptive data that facilitate the design of strategies and actions that should be performed according to the impact on organisations.
- Define the analytical models that are involved in the LAM. This study's findings suggest implementing the models in the following order: descriptive, predictive and prescriptive. They could be implemented in parallel. However, it depends on the maturity of the training process.
- User experience is a crucial factor that ensures the correct form of presenting data, avoiding overloaded reports because of data saturation, a different palette of colours or disorganisation of visuals. Therefore, it is relevant to make a report design that comprises a classification of data related to a unique

training process. For example, different reports should be designed to measure the impact of training on organisations, that is, learning experience, learning paths, customers or finance.

Limitations

The results did not consider software tools that leverage training processes. However, they are fundamental to consolidating the information generated by the LAM. Hence, future research about learning analytics tools may adopt descriptive, predictive and prescriptive data. Another requirement of these tools may be the flexibility to build or change visualisations depending on the business requirements. For example, adding new KPIs or models should not be inconvenient for the LAM. In practice, two paths are possible: creating a visualisation tool as part of the LAM or adapting an existing tool using a mechanism to integrate the LAM and the software tool. Another limitation identified in the results is related to the user experience feature. Thus, the reports should incorporate methodologies and best practices that enhance the manner of navigating and interacting with visualisations.

5.2 The underlying relationships among variables

This section answers the question: What are the relationships among elements that define the interactions within the LAM? Hence, the first part presents the criteria for selecting sequential relationships among components. After that, four sorts of relationships are proposed and discussed based on the elements involved and the data flow among them. The first relationship comprises interactions between external/internal factors and data sources. The second relationship consists of interactions between data sources and data preparation. The third relationship involves MIMs and reporting. The last relationship is among learning path, job performance, and business objectives.

5.2.1 Selecting the relationships among elements

According to the methodology defined in section **Error! Reference source not found.**, the second research question is answered through the Theory Development Process, which poses that any model should identify how the components interact among themselves by establishing a set of relationships. The authors Storberg-Walker and Chermack (2007) and Whetten (1989) suggest that this critical step should identify sequential interactions between components which follow the condition “A precedes B”. Thus, this condition was applied in the results chapter, from which it is concluded that every theme has its own set of relationships. They are detailed as shown in Figure 5.3.

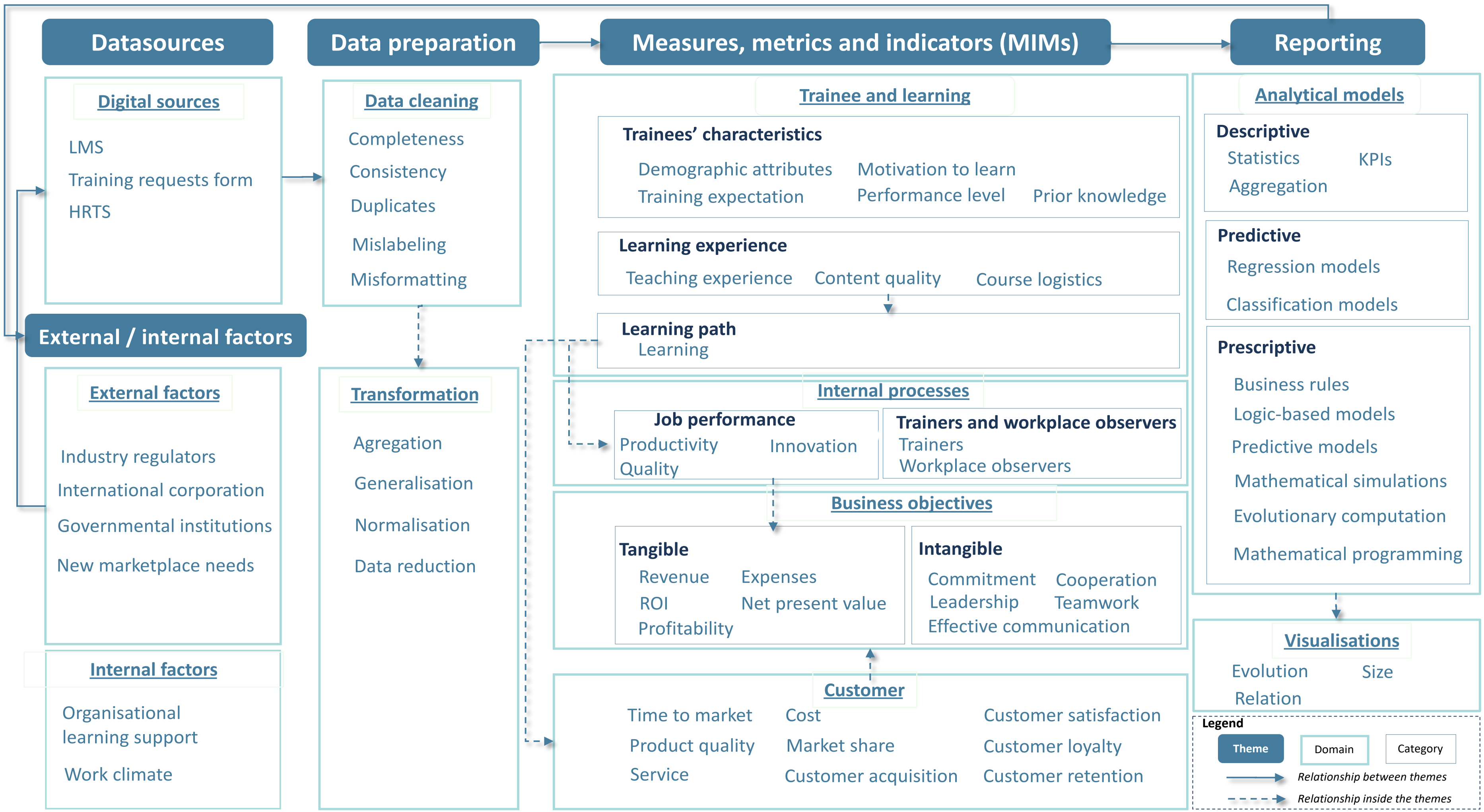

Figure 5.3 LAM's relationships

5.2.2 **External/internal factors and data sources**

This relationship is generated by external entities such as industry regulators, governmental institutions or international corporations to validate that programmes are delivered to employees to meet standards or regulations. This relationship is established when sending and receiving data between the external entity and the organisation. The first scenario is when the external entity asks organisations for evidence of the programmes delivered in a specific period. The second scenario comprises the consolidation and sending of the required information, for instance, the number of programmes delivered, grades obtained by the employees, rate of attendance, number of employees involved in the training and dates of completion.

Verbert et al. (2013) agree with this study on how learning analytics models should provide current and historical data to enable flexible decision-making. In this case, Verbert et al. (2013) propose a dashboard to present data regarding trainees' and trainers' performances, for instance, grades and retention behaviour. The data sources used to consolidate and present data were mainly intelligent tutoring systems and Moodle as LMS. In contrast to this study, Siemens (2013a) did not consider external factors but internal factors such as marketing and administration departments. In this case, these departments may ask for information regarding the training process since they originate the requirement without considering external entities as requester. This relationship was also identified in this study thanks to the thematic analysis method, which indisputably incorporates internal departments into the internal factors domain.

The contribution of the LAM is that it can provide data timely to those entities that require evidence of the training process to meet regulations or standards that guarantee the correct execution of particular business processes, for instance, manipulation of tools, machines or raw materials. In practice, organisations can meet deadlines and provide information in a timely way because the LAM is designed to extract, consolidate, prepare, transform and present data before, during and after the programme finishes. It means that organisations do not have to suffer from collecting and ensuring data quality since the LAM incorporates all these activities. In addition, internal departments may also benefit from using the LAM because it can provide descriptive data such as the number of trainees per programme, the number of programmes delivered to participants or similar aggregations that help internal departments evaluate whether the investment has impacted the organisation. All these data are collected from HRTS, LMS and other digital sources.

Limitation

Comparing the review literature and the results, there is a clear gap regarding the strategy or mechanism to send and receive data between the data sources and the external and internal factors. For example, further research should focus on the frequency of update data between the LAM and the data sources, that is, daily, monthly, or any other period. Another variable is the format to store and retrieve data, for instance, in MS Excel.

5.2.3 **Data source and data preparation**

This relationship is summarised in sending data from data sources such as LMS, HRTS or digital tools to the data preparation theme. The condition to establish this relationship is that data should be extracted from data sources to execute the data preparation operations. The sorts of data flow from one point to another vary according to the data source nature. Thus, LMS sends data such as the number of trainers' interactions, satisfaction, programme performance, number of trainers attending the sessions, hours of training and assessment results. In general, current and past data regarding trainers, trainees and programmes.

On the other hand, HRTS sends data related to trainees' salaries, programme cost, programme budget and expected ROI. The last sort of data source is the Training Request Form which sends data related to the department that requested the programme, indicators aligned with the balanced scorecard, objectives and justification of the programme. Once the data preparation theme receives these data, data cleaning rules are applied to ensure high data quality in the entire LAM. In addition, the type of relationship between data sources and data preparation themes is consequence since one event should be executed before the next one starts.

Some studies (Lu et al., 2017; Romero & Ventura, 2020; Slater et al., 2017) agree that there is a clear relationship between data sources and data preparation themes because it is fundamental to convert raw data that come from LMS into suitable formats with high data quality for further activities such as transformation, analysis and interpretation. They also concur in that the data type and frequency of retrieving data vary according to the situation. However, four categories serve to group the type of data that may arise in the LAM: student data, demographic data, trainers' data and organisational data (Romero & Ventura, 2020). In contrast to this thesis, Feldman-Maggor et al. (2021) propose that this relationship should also consider an activity to validate whether data sources are available or not to ensure that the relationship is active. Unlike these results, Slater et al. (2017) proposed 40 software tools that may leverage the analytics process. Specifically, this thesis suggests that raw data generated by LMS should be extracted and cleaned using tools such as Google Sheets, Microsoft Excel, KNIME, EDM workbench or Phyton. In this manner, unusual formats can be processed automatically by the LAM according to the quality rules defined by the decision-makers. Examples of uncommon formats are videos or images, considered unstructured data (Lu et al., 2017).

The importance of the LAM in this relationship consists of the following:

- Guaranteeing a translation of raw data generated by software tools such as LMS or HRTS into desirable data formats will facilitate data manipulation in further activities such as transformation and visualisation. Removing this step from the LAM will lead to wrong decisions because the analysis and interpretation lack completeness, integrity and consistency of data.
- Establishing a list of data sources that will interact with the LAM. It involves defining the schedule to retrieve the required data, data formats and protocols or technologies to connect the set of data sources with the LAM. Moreover, this relationship should establish a data mapping which comprises the extraction of data fields from data sources and matching them into the LAM's data structure

In practice, organisations or practitioners that desire to implement this relationship should list and characterise the software tools that will serve as data sources. For example, defining Moodle as a data source implies the IP (Internet Protocol), credentials, APIs (application programming interfaces), data fields to be imported and their formats, e.g., images, documents or logs. Then, it is essential to define the schedule to extract the required data and validate whether the data sources are available to initiate the extraction. Thus, once the communication is established, data are ready to move from data sources to the data preparation phase.

Limitation

The results obtained in this study did not reveal the mechanisms to process data before data preparation activities are executed. Therefore, further studies should focus on mechanisms such as one-by-one record processing, batch processing or scripting processing. In addition, the software tools that may leverage these mechanisms to make the process efficient and automatic.

5.2.4 **Measures, indicators and metrics (MIMs) and reporting**

According to the results, these two themes are related since reporting cannot exist without a previous definition and computation of MIMs. The results establish that this relationship becomes active when data flow from one theme to another. Specifically, the data that flow from MIMs to the reporting theme are trainees' characteristics, levels of satisfaction experienced by trainees, grades of knowledge acquired during the training and its rate of application in the workplace, tangible and intangible financial variables and variables that measure the impact of training in customer interactions, for instance, time to market, product quality, quality of customer service or customer satisfaction. In this case, defining a data mapping between MIMs and reporting is fundamental. Therefore, MIMs should be matched to the analytical models, that is, descriptive, predictive and prescriptive. In this manner, the LAM could present data adequately according to the business needs and data nature. However, the frequency of synchronisation between these two themes was not defined in the results. It can vary according to each organisation and its requirements. In summary, the relationship type between MIMs and Reporting is known as sequential. Hence, MIMs should be defined before Reporting to guarantee the correct presentation of data using learning analytics models.

In line with these results, some studies (Lu et al., 2017; Sohail et al., 2022) agree with having a causality relationship between MIMs and reporting. However, the name of these two themes changes with the studies. Notwithstanding, the objective remains the same. For example, Lu et al. (2017) refer to feature engineering as the phase of defining measures, conditions, and weights to be considered in the modelling phase, which in turn comprises analytic models and visualisations like 2D scatterplots. In more detail, the case study proposed by Sohail et al. (n.d.) describes the relationship as follows: the first step consists of defining the student's performance indicator; the second step comprises the computing of data using a fuzzy logic algorithm as a predictive model. Then, information is presented as visuals. The last part of the process is designed to warn decision-makers regarding students at risk. As a consequence, strategies are implemented to reduce the drop-out indicator. In addition, M.-S. Lee et al. (2021) focus on a software tool that supports these two themes as a form of phases.

This relationship is extremely important in the LAM because it establishes a logical order before the information is consolidated and presented through reports. It means that the first step consists of setting the MIMs and business requirements before data are passed to the reporting theme. Then, the LAM should map MIMs variables to learning analytical models and visual objects to activate the relationship. Afterwards, information is presented in the form of visuals mapped to descriptive, predictive or prescriptive models. The type of data that may flow in this relationship comprises variables associated with employees, trainers, programme data, employee collaborators, employee supervisors, internal processes data, financial perspective and customer perspective. In summary, all types of data are generated by the training process.

Limitation

Neither the results nor the literature review revealed a frequency of sending and receiving data between MIMs and Reporting themes. It may depend on the business settings. However, further research must recommend an average time to synchronise them and propose a protocol to alert when some themes cannot receive or process data due to technical or external restrictions. In this manner, data quality is ensured.

5.2.5 **Learning path, job performance and business objectives**

According to the results, the LAM should consider relationships between learning path, job performance and business objectives. The first relationship between learning path and job performance can be evidenced when the competencies and knowledge acquired during learning processes are applied in the workplace to improve productivity, innovation, efficiency or quality. In this case, it is paramount to establish the match between learning objectives or competencies and job performance components, e.g., productivity. The second relationship comprises job performance and business objectives (tangible and intangible). In this case, the tangible domain can be activated if job performance components are designed and linked to finance elements for further calculations. For example, the improvement in the profitability indicator could be thanks to a course that developed skills in employees about a specific tool that helps to automate processes. In addition, there is no unique definition regarding the frequency of updates in this relationship. The only condition is that job performance precedes finance elements.

Some authors agree with the results obtained in this study about the relationship between learning path, job performance and finance (Chandrakala & Nijaguna, n.d.; Mdhlalose & Mdhlalose, 2020; Staboulis et al., n.d.). For example, Chandrakala T M and Nijaguna (n.d.), in their case study, claimed that training boosts employees' confidence and their overall performance. Hence, the higher the training quality, the better workplace productivity. In addition, the investigation confirms that ROI is related to productivity and training, which is reflected in the reduction of time performing daily tasks. The authors recommend that to maximise the ROI, it is fundamental to increase employees' productivity. Mdhlalose and Mdhlalose (2020) also discovered the same relationships focusing on the quality of service at the workplace. However, he also found that despite the fact that there must be a relationship between financial objectives and training, in his study, unfortunately, there is a weak or null relationship between them. Staboulis et al. (n.d.) focused on training soft skills to maximise the financial and social benefits since they state that when organisations invest in these sorts of programmes, organisations will have a positive impact at different levels - sales, growth, profitability and quality of products.

In practice, those practitioners or organisations that desire to establish this relationship in the LAM should consider the following process:

- The first step consists of aligning and defining the elements that should be involved in the impact analysis of training in the organisation. It means that decision-makers should plan a data flow among the elements of the learning path, job performance MIMs and business objective domains.

- The second step comprises mapping the learning path, job performance and business objectives, namely, tangible and intangible elements. In this way, computing operations related to revenue, expenses, ROI, NPV and profitability can be performed based on the four elements provided by job performance.
- The third step implies that the learning path domain sends data to the job performance category, which sends data to the finance domain. The frequency of this step depends on organisational needs. However, different authors recommend updating at least twice per programme. At the beginning of the programme, to assess the initial learning level; at the end of the programme, to validate whether a time reduction occurred, and compare the final and initial time to compute the time variation. Then, decision-makers evaluate the impact of training in the organisation by analysing the LAM's results.

Limitations

The type of relationship between job performance and finance is sequential; that is, it is fundamental to execute finance after job performance. However, further investigations could address relationships based on positive or negative correlations. For example, the impact of productivity on revenue, profitability and other financial components.

Other potential relationships

The results of this study discovered other potential relationships. However, they are not considered in the LAM because researchers state a lot of controversies. It means there is not a common agreement in the literature because the conclusions of the investigations vary according to the organisational settings and case studies. For example, some authors agree that motivation to learn directly affects the training process's outcomes. Hence, if the motivation to learn is positive, the same effect is observed in the training programme's expected results. In contrast, other authors propose that it is not valid in all cases because employees may attend a programme and apply the knowledge acquired in the workplace during the training process without being motivated, but they do so if managers obligate them.

The results also found a strong relationship between motivation to learn and transfer because trainees are obligated to learn and apply the knowledge in the workplace as soon as possible, during the training programme or after the training process has finished. The authors Bauer et al. (2016), Khan (2012) and Pettijohn et al.(2002) pose that regulations or other similar factors are examples that obligate trainees to enhance their interest in learning the content. Although, the authors Pettijohn et al.(2002) and Subha & Bhattacharya (2012) also expose that other factors motivate trainees to learn, for instance, a reward for incorporating innovative activities based on the acquired knowledge.

5.3 Assumptions and conditions of the LAM that guarantee a successful application in organisational settings

This section answers the question: What are the required assumptions and boundaries of the LAM that guarantee a successful application in organisational settings? Hence, this question is addressed in light of the literature (Rivard, 2021; Storberg & Chermack, 2007; Whetten, 1989) from which the third step or building block to propose a solid and credible model consists of defining the assumptions and conditions that are related to the model. In this way, empirical research and further investigations will help understand how to test and incorporate the LAM into concrete applications. For example, practitioners could apply the LAM to organisational settings exclusively, setting educational institutions aside due to the model restrictions. The authors Storberg-Walker and Chermack (2007) and Whetten (1989) suggest addressing this building block by separating the analysis into two perspectives: conceptual assumptions and contextual assumptions. Conceptual assumptions refer to the explanation of patterns or processes that are involved in the model. Contextual assumptions respond to the conditions required to successfully apply the model in the learning analytics and training fields. Contextual assumptions should respond to three premises - where, who and when.

5.3.1 Conceptual assumptions

Logical execution of themes

The proposed LAM suggests a logical order of data flow to guarantee high data quality. It means decision-makers could rely on information provided by the LAM because data flow through different phases responsible for extracting, transforming, cleaning, calculating and presenting MIMs as reports are based on descriptive, predictive or prescriptive analysis. In summary, data should stream through the themes in the following order: (1) external factors, (2) data sources, (3) data preparation, (4) MIMs and (5) reporting.

The external factors domain is the first step of the flow. It acts as a data flow trigger, given that training needs originated in this theme. External entities or circumstances are the events that give rise to training programmes. The activities related to this step include identifying business needs due to mandatory regulations or market needs, identifying trainees participating in the programme, designing MIMs to be used in other themes, and the budget definition.

The second step embraces the data source domain, which consists of receiving data from the external theme. This step stores data related to administrative processes and learning processes. HRTS and training request forms store data related to business objectives, budget, cost of delivering training programmes, number of participants and expected benefits. Another source of data is LMSs which store data related to the training process, for instance, assessments.

The third step is named data preparation. It extracts the required data from data sources to clean and transform data to ensure a high data quality standard. In this step, data are generated from statistical operations such as sum, average, maximum or minimum. The condition in this step is that data should be prepared before the following phase (e.g., MIMs) performs any computation.

The fourth step comprises MIMs, which collect the required data to set and compute components of this domain. The condition that should be ensured in this step is that the decision-maker should define the MIMs to be used in measuring and evaluating the training impact because it depends on the alignment with the business objectives and requirements. It means that not all components in this theme should be used in all scenarios. Notwithstanding, all domains should have at least one component configured.

The fifth step encompasses reporting, which presents the information as visuals based on the data collected from the MIMs theme. Data are presented as descriptive, predictive or prescriptive information using visuals that vary depending on the data's nature. This step is fundamental because it is the only manner to analyse and interpret information.

5.3.2 **Contextual assumptions**

Organisational setting (Where)

The LAM is suggested to be applied exclusively in organisational settings that desire to measure and evaluate the impact of training on business objectives. The rationale behind this assumption is that part of the data is conceived in LMSs, and the other amount is generated by HRTS and request training forms. It means that data may pertain to educational, financial, customer and business process domains. For example, the LAM may include variables from different domains such as degree of motivation, knowledge, skill level, cost of training, expected payoff, training budget, number of employees, and sales or profits. Consequently, decision-makers could analyse and interpret data in the form of MIMs that tell decision-makers whether training processes contribute to the organisational strategy and its business goals thanks to the combination of educational and organisational data.

Another justification for this assumption implies the use of organisational MIMs. Hence, the LAM proposes to measure and evaluate indicators such as ROI, NPV, revenue, profitability, and customer satisfaction, among others, which are exclusive components of an organisation. It means that the LAM is not guaranteed to be a success in educational contexts. For example, universities do not measure profitability versus acquired skills or competencies, job performance, behaviour and sales.

Individuals involved (Who)

According to the proposed LAM, some individuals must participate in the measurement and evaluation process. Thus, there are two types of individuals involved in the LAM: those that provide data to the LAM, and consumers who analyse and interpret the information provided by the LAM. Consequently, indispensable contributors are trainees whose primary role is to improve skills or competencies that impact business objectives. They provide different sorts of data related to the training process. For example, trainees' characteristics, learning experiences, learning paths and job performances (see section 4.2.1). These data are the fuel for the entire model because MIMs and analytical models require trainees' variables to perform computational operations. For example, the ROI is calculated using variables like the level of knowledge acquired and the number of innovations or improvements in the workplace compared to the cost of delivering the training programme.

Trainers are considered contributors because they provide the results of assessments that cover variables related to trainees' performances during and after the training programme is delivered. In particular, when trainers design initial and final assessments to compute the ratio of trainers' performances regarding academic and organisational goals. For example, how trainers improve the use of a software tool to be more effective in the job. On the other hand, trainers' performances are also evaluated by trainees in terms of academic and pedagogical quality. Hence, these trainers' results impact computational operations. For example, to calculate trainers' motivations (see section 4.2.1.1).

Another type of contributors are those who evaluate trainees' job performances and behaviours. The significance of these contributors is because they evaluate and provide data through assessments which consolidate information about the changes in the workplace after an individual attends a particular training programme. In this way, MIMs and reports can evaluate the impact of training on the business objectives. Hence, employees generally have positions like managers, supervisors, coordinators or peers.

Consumers comprise employees responsible for analysing and interpreting data provided by the LAM. In practice, managerial positions like managers or supervisors consume data from reports and decide whether the investment in training has been beneficial based on the information presented using descriptive, predictive and prescriptive analytics. The role of consumers in the LAM is fundamental because they can make informed decisions based on the information presented as reports. If consumers do not exist, the whole LAM would not be helpful for the organisation since nobody can establish strategies and actions according to the obtained results, which is the principle of learning analytics.

When to use the LAM

The LAM should be used when it is required to track, measure and evaluate a training programme or set of training programmes in different moments, before, during and after they are delivered to employees. This condition cannot be omitted in any situation; otherwise, MIMs and reporting domains are affected negatively. When data are not collected before the programme starts, decision-makers cannot evaluate the impact of training because the LAM does not have initial values such as levels of knowledge or cost of investment. Consequently, the LAM cannot compute and present indicators such as ROI (see section **Error! Reference source not found.**), productivity (see section 4.2.2) or time reduction (see section 4.2.2). Another negative consequence embraces learning experience and learning path because diagnostic assessments are not performed before the programme starts. The effect is evidenced in demotivation, low training expectations and low results since learning objectives, academic content, workshops, assessments and assignments are not adapted according to the trainees' profiles.

Similarly, the LAM cannot measure and evaluate whether trainees have gained or improved their knowledge, skills or competencies in cases where data are excluded during the execution of a programme. Neither is it possible to measure the learning experience, e.g., content, pedagogical strategy, teaching experience and course logistics.

Excluding data after the programme finishes has a negative effect because the LAM cannot measure the improvements in the workplace. It means that omitting variables such as time required to perform a task, quality of products or sales growth is a grave error because the LAM cannot compare the initial state versus final results to compute the impact of training through MIMs and reports.

5.4 Fictional case study

This section presents a fictional case study that reveals how the model should be used in organisations considering the elements, relationships and assumptions explained in chapter 5. Hence, a general context is given to describe an organisational context. Then, a requirement is detailed to measure and evaluate the impact of training in a specific course whose objective is to upskill employees in a software tool. Finally, it is explained how the LAM behaves when data are collected before, during and after the programme has finished. A report that provides information considering MIMs such as productivity and NPV is also shown.

5.4.1 Context

The fictional case study comprises an oil and gas organisation with more than 3,000 employees worldwide. The human resources department is leading the training process through a structured training programme that delivers courses to employees to strengthen their professional skills. In this manner, the organisation can remain competitive in the long term because employees develop new competencies to change or improve how business processes are executed. For example, some of the courses delivered by the organisation teach how employees should use a software tool to improve the customer service process since this tool provides features that allow downloading certifications and invoices rapidly. In addition, the courses are delivered in face-to-face and online formats through the Moodle platform as a LMS.

5.4.2 The human department concern

The human resources department receives a budget to design new courses and maintain existing ones annually. This time, the CEO (Chief Executive Officer) of this organisation has formulated whether investing in training programmes is valuable for the organisation. Thus, the human resources department is responsible for responding to this question before the CEO approves the budget for the coming year. Hence, the human resources lead has posed a demonstration of the LAM to determine the return on investment of a course and find a systematic manner to replicate how training programmes are assessed. Thus, the data analytics course is chosen to be part of the demonstration because it is delivered frequently due to the high demand in the organisation. In addition, this course has required great effort and investment to be designed and delivered.

5.4.3 The demonstration

This demonstration proposes to validate the potential adoption of the proposed LAM in organisations by presenting the initial requirement, assumptions, elements and relationships involved in the proposed LAM to evaluate the impact on training. In this case, Table 5.1 shows a course requirement form in which the course description is requested from the finance department to the human resources department.

Course name	Data analytics
Level	Basic course
Number of employees	13
Employees departments that participate in the course	Finance department
Duration	40 hours
Format	Face-to-face
Course design cost	100 USD
Cost of having the employees taking the course	150 USD (cost per hour of each employee X course duration)
Responsible	Human Resources Department
Business objective	The course aims to reduce the time required to build reports to make informed decisions. Currently, the Finance Department takes several weeks to construct reports because they lack adequate competencies to use software tools.

Table 5.1 Course requirement form

According to the LAM defined in section 5, it is vital to establish the assumptions before the LAM is used for measuring the impact of training. Hence, the assumptions are defined following the guidelines proposed in section 5.3:

- **Conceptual assumption:** All data used in the LAM should flow considering a strict order of execution of themes, that is, external/internal factors, data sources, data preparation, MIMs and reporting.
- **Contextual assumption:** Contextual assumption: The LAM is used in an organisational setting, and data are gathered before, during and after the training programme is delivered to employees. In addition, the departments and roles involved in the processes are the CEO, the human resources department, the finance department, employees, trainees and trainers.

Next, the dataflow process is shown and explained to understand how each theme is involved in the measurement and assessment performed by the LAM. Figure 5.4 summarises the elements and relationships considered in this fictional case study, from which each element is described and justified. It is worth noting that all elements and relationships proposed by the LAM may be used in any organisational context.

However, in this fictional case study, not all elements were considered because the context and requirements were limited to a specific situation.

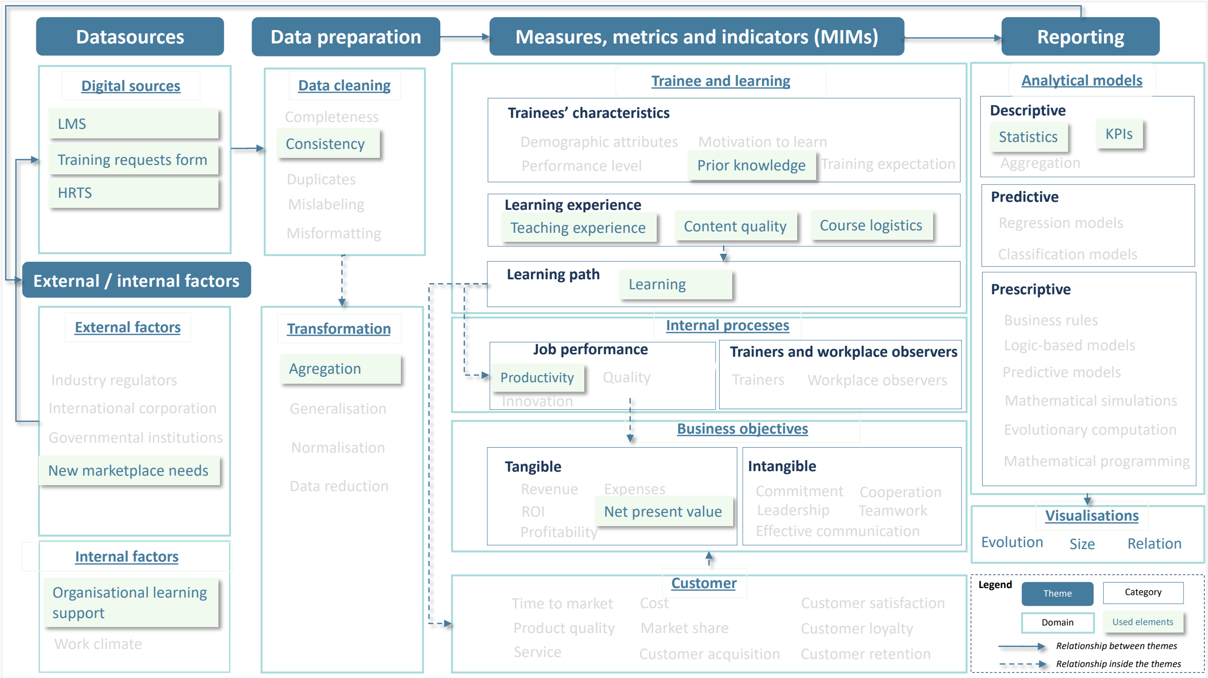

Figure 5.4 Adaptation of the LAM in a fictional case study

5.4.3.1 *External and internal factors*

New marketplace needs

This element is selected from the LAM because a new marketplace need triggers the data flow required by the proposed model. This need is evidenced by the finance department, which has identified that to remain competitive in the marketplace, it is vital to make informed decisions on time by using data as the primary business driver. Namely, data are required to understand the main customers and identify how the consumption patterns are revealed over time. In this manner, marketing and sales departments may set solid strategies and milestones that positively impact the organisation's income.

Hence, the finance department is proposing a training course in data analytics to understand what the fundamentals are and how employees should effectively use an analytical tool to obtain the maximum benefits from it, for example, providing reports in less time with high quality. The requirement should be defined in a training request form. Then, this form should be sent to the human resources department to assess its viability. Table 5.1 shows the details of this requirement.

According to the LAM conditions, the next phase consists of identifying the required data sources that are required by the model to execute the next themes.

5.4.3.2 Data sources

Training request form

This element is used to capture the requirement defined by the finance department to determine the course's scope, objective and cost. The data captured in the requirement form are essential to compare the benefits once the course finishes with the initial investment. Table 5.1 presents the details of the requirement. This element is used before the training course initiates.

Data captured in the training request form are sent to the data preparation theme to ensure the quality of these data.

HRTS

This element is used before the programme initiates to consolidate and track the requests. This data source is also used when the training course finishes to include the tangible and intangible benefits.

The human resources department uses the HRTS to register and approve the course request considering the training request form. In addition, this software consolidates all requirements about the training courses.

LMS

This software tool is Moodle, which is used to store and track data related to the learning processes. In this case, Moodle is used to design and apply an appraisal to the employees who will be part of the course. In this manner, the content of the course is personalised by the trainer to focus on the competencies that genuinely require attention. Moreover, those employees that obtain great results should be identified and excluded from the course. Otherwise, those employees with prior knowledge of the analytical tool will be demotivated. The main consequence is that the drop-out indicator will decrease.

On the other hand, to validate whether the employees require less time to build a report, it is required to design a survey on Moodle as a means of consolidating data related to the process of designing and building reports. The same survey is applied after the course finishes to compare the time variation. The employees involved in this survey are those who will participate in the course and some observers who also can evidence whether there is a reduced time to elaborate reports, such as colleagues.

5.4.3.3 Data preparation

Consistency

As part of the cleaning domain, this element is selected from the LAM to validate that data provided by the finance department are identical in the HRTS and LMS. Hence, in this case, the LAM should execute a task to corroborate that the number of employees taking the course is 10 in both data sources. This validation should be performed considering the remaining variables defined in Table 5.1.

Following the assumptions defined by the proposed LAM, the transformation is the following domain involved in the data flow. In this case, the LAM sends data obtained from the data sources theme to make some statistical operations such as sum and average.

Aggregation

As part of the transformation domain, this element is in charge of adding additional attributes; in this particular case, this element sums the total cost of the course, which the LAM computes by adding the cost of designing the course and the cost of having the employees take the course. The cost of designing comprises the trainer's salary and digital content to upload into the LMS. The cost of having the employees take the course depends on their salaries, which are computed considering the course duration and cost per hour of each employee. In addition, according to the LAM, once data are transformed and cleaned, the next phase consists of calculating measures, metrics and indicators, which is performed by the MIMs theme.

5.4.3.4 Measures, metrics and indicators (MIMs)

Prior knowledge

This element is essential to validate whether employees have prior knowledge about data analytics. Hence, those with previous knowledge in analytics are discarded because the course content is designed for the basic level. In this manner, it is ensured that employees are receiving pertinent content that will impact their level of motivation positively.

In this case, a survey is designed on Moodle to assess employees' prior knowledge of data analytics. The results are sent to the LAM to present the number of students that should take the course. The bar chart in Figure 5.5 presents the outcomes from the assessment as an example. Thus, the LAM should measure the number of participants that should take the course, which is 10 because they do not have previous knowledge of data analytics. In addition, according to the LAM conditions, the next step consists of identifying the data sources required by the model to execute the following themes.

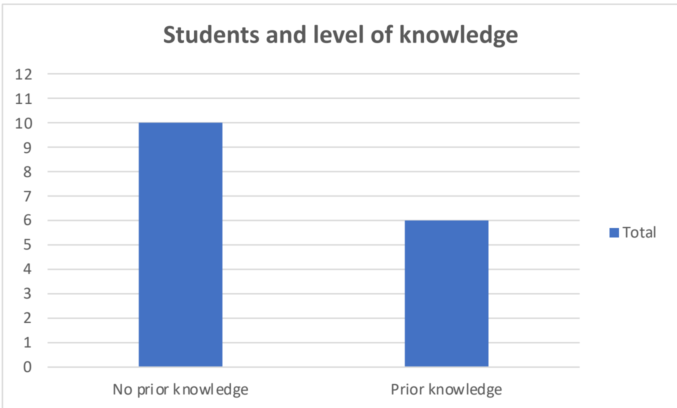

Figure 5.5 Results of prior knowledge in data analytics

Teaching experience, content quality and course logistics

These three elements are vital to be included during the execution of the training programme to validate the learning experience in terms of teaching experience, content quality and course logistics. Hence, an assessment should be performed to address questions related to the trainer's experience and his/her clarity to express and convey ideas, relevance of content and programme facilities (e.g., lighting and room temperature).

Considering this fictional case study, the manner of collecting data about these three elements is through a survey designed in Moodle, from which the bar chart shown as Figure 5.6 summarises the results related to the learning experience from which the content quality and teaching experience are positive results in a range from 0 to 5. On the contrary, the course logistics element is an aspect that should be immediately corrected because there may be external aspects that are affecting the learning processes. It is evidenced in the result, which is 3 of 5.

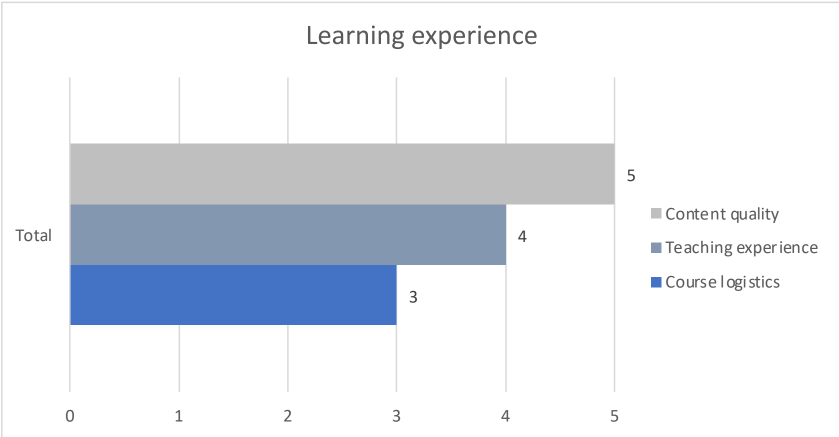

Figure 5.6 Learning experience results from the learning analytics course

In this case, the LAM has established an indicator for each element that composes the learning experience. The indicator consists of dividing the result of each element by 5. In addition, a business rule defines a threshold of 80%, which means all indicators should not be below this limit. Hence, the course logistics indicator is the unique element below the threshold, reported as 60%. As a consequence, the LAM should warn and notify the decision-makers regarding the results obtained during the execution of the training programme in order to evaluate what factors are affecting the learning processes adversely.

Learning

The significance of this element is that the grade of knowledge can be measured and determine results about individuals. Then, decision-makers may validate these results and make some time plans based on these results.

The LAM proposes a digital questionnaire to collect data about the grade of knowledge that employees have gained during the execution of the training programme. The questionnaire is designed in Moodle using a scale from one to five, from which five is the highest grade. The proposed LAM presents the average, maximum and minimum grades as measures. In this manner, decision-makers should identify whether action plans should be designed to improve the current results.

Productivity

The efficiency or productivity element is included in this fictional case study because this is the manner to measure whether employees taking the course are more productive in their workplace thanks to the skills and competencies they have gained during the academic sessions. Hence, to measure productivity, employees should determine a process that the LAM should measure; in this case, employees have agreed that constructing and updating reports is the process that they desire to measure in terms of the time required to perform it.

A questionnaire is designed on Moodle to gather data about the time required to construct and update a specific report. Each employee participating in the course should respond to the questionnaire before and after the programme is delivered. The number of employees that answered the questionnaire was 16.

Once data are collected, the LAM should calculate the efficiency element. Table 5.2 shows the efficiency of each employee. The first column shows the employee's ID, to identify the productivity of each individual. The second column presents the frequency of constructing and updating the report by each employee. The third and fourth columns show the hours required to have the report ready before and after the training course is finished. The fifth column shows the efficiency variation, which is positive in all cases. For example, an employee whose ID is 6 is 98% more efficient after he took the training course. The reason is that he spent 4 hours publishing a report prior to the course, and now he requires 5 minutes. Despite the efficiency being positive, the human resource department desire to monetise the productivity variation obtained at this point which is discussed in the NPV element.

Employee's ID	Process frequency	Time required before the course starts (hours)	Time required after the course finishes (hours)	Productivity (efficiency) (before – after)/before)
1	Montly	5	0,67	87%
2	Biweekly	0,92	0,42	55%
3	Montly	6	2	67%
4	Daily	2	0,25	88%
5	Montly	1	0,25	75%
6	Montly	4	0,08	98%
7	Montly	1	0,25	75%
8	Montly	8	0,08	99%
9	Montly	2	0,5	75%
10	Daily	0,75	0,25	67%
11	Weekly	3	1	67%
12	Montly	1	0,25	75%
13	Montly	1	0,25	75%

Table 5.2 Efficiency for data analytics course

Net present value (NPV)

Considering that productivity is measured in terms of percentage, the LAM is able to convert productivity in terms of monetary benefits. In this case, the NPV element is selected as a metric to compute the training course investment versus the productivity gained after the programme course finishes. The reason for choosing NPV is mainly because the course focuses on developing hard skills and is also required to calculate the tangible benefits over the coming years.

Table 5.3 shows the monetary benefits of the training course employing the NPV concept. Hence, the first column presents the variables required to calculate the NPV, and the second column shows the values related to each variable. The investment variable comprises the course cost (i.e., printed material, trainer cost and software licenses) and the cost of employees attending the course, calculated considering the employees' salaries and the number of hours attending the course (i.e., 40). The currency is given in Colombian pesos. The second variable is named annual savings, calculated by multiplying the time required to create or update a report by the cost of doing so, which varies according to the employee's salary. The third variable is the rate of return, which is equivalent to the expected course profit defined by the organisation, in this case, 10%. The third variable is expected benefits in a specific period, which refers to the number of years the organisation should wait to obtain the entire benefit. In this case, the period is three years. However, from year two, the organisation starts perceiving some profits. The last variable is NPV, which is computed considering the formula defined in Equation 4.1. In this case, the result is positive, and the monetary benefit is $49,919,841.31, from which the proposed LAM concludes that the course in data analytics was a strategic investment in training.

In addition, the investment variable is obtained from the ERP that comprises the organisational financial investments. The annual saving value comes from the productivity variable defined in the LAM. The rate of return and the period expected to have the monetary benefits are defined directly in the LAM by the human resources department. The NPV variable is defined and computed by the proposed LAM.

Variables	Values
Investment	-$ 43.101.190,48 COP
Annual savings	$ 37.405.134 COP
Rate of return	10%
Expected benefits in a specific period	3 (years)
NPV (Expected monetary benefits)	$ 49.919.841,31 COP

Table 5.3 Monetary benefits of the training course

Statistics and KPIs

The proposed LAM indicates that the manner to visualise information and make informed decisions is through the reporting theme, from which descriptive, predictive and prescriptive models are applied to present data. This fictional case study only comprises descriptive analytics because it is only required to evaluate the return on investment of the data analytics course. In other words, the case study is not asking for benefits in the future or recommendations that need to be executed.

Figure 5.7 consolidates information regarding the training course through a report that gathers data from the MIMs theme. Hence, the visuals presented in the report are detailed as follows:

- Number of employees: the number of trainees attending the course. This variable was given before the training programme started and is required to calculate the drop-out indicator. This visual is categorised as a measure.
- Attendance: this visual reveals the percentage of attendance in the course. In this case, 100% indicates that trainees attended all scheduled sessions. This visual is categorised as an indicator since it is computed as considering a

current versus expected value. These two values are collected from an attending format designed in the LMS configured to support the course. In cases where the percentage value is below 80%, the LAM alerts the decision-makers to evaluate the causes behind this value.

- Investment: this visual shows the cost of delivering the course. This value was given before the programme started and stored in the HRTS. In addition, this value is required to compute the monetary benefits of the training course. This visual is categorised as a measure because it is a given value representing the total course investment. The currency is given in Colombian pesos.
- Drop-out: this visual shows the percentage of trainees that complete the training course. In this case, it can be concluded that all employees participated in the course from the beginning to the end. In cases where the drop-out is different from zero, the LAM alerts the decision-makers. Consequently, the human resources department should evaluate the causes of these results. This visual is categorised as an indicator because the result is computed by dividing the current value by the expected value. These two values are gathered from the LMS.
- NPV: this visual reveals the monetary benefits of the training course. In this case, the value obtained was $49,919,841, which means that the training programme positively impacted the organisation and exceeded the investment cost. The details regarding the computation are defined in Table 5.3. In addition, this visual is categorised as a metric since this is a composite of different measures (i.e., investment, rate of return, annual savings and periods) to obtain the result.
- Efficiency variation and annual savings: this chart table was explained using Table 5.2, from which positive productivity was obtained. This chart table is shown again to present data as a single view using a report. Efficiency variation is categorised as a metric, while annual savings is a measure.
- Learning experience and prior knowledge assessment: these two visuals were already explained through Figure 5.5 and Figure 5.6. However, they are presented to present data in a single report. These two visuals are categorised as measures.

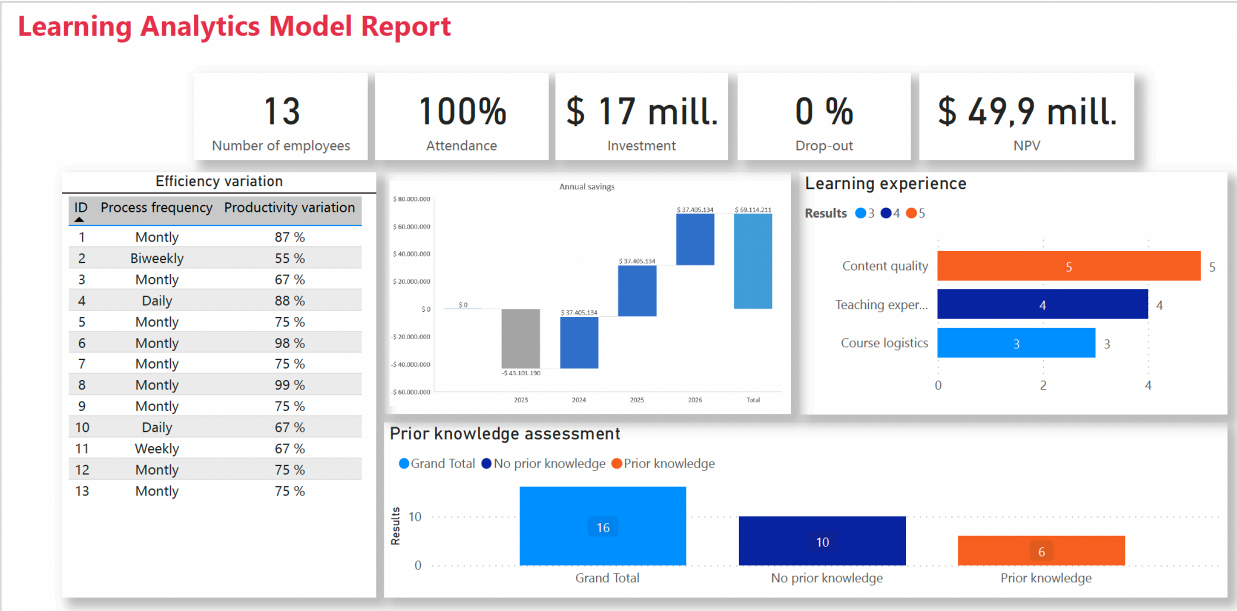

Figure 5.7 LAM report

In summary, it is concluded that the investment by the organisation in the training course had a positive impact on the business objectives because the NPV was positive, and there is an evident monetary benefit of $49,919,841 in terms of reduction of time designing and delivering reports in a software tool. The cause of these positive results is related to the strategy of upskilling employees in an analytical software tool. Furthermore, the LAM was the means to achieve the desired assessment and validate whether the investment in training generated tangible benefits in the organisation.

6 Conclusions and future work

6.1 Summary

This research aimed to develop a LAM that supports informed decisions regarding the training process in organisational settings. The problem behind this objective was the lack of a model to measure and evaluate the training process from different perspectives using learning analytics in organisations. Hence, the proposed model was posed considering a systematic and solid methodology defined by Rivard (2021), Storberg-Walker and Chermack (2007) and Whetten (1989), from which the following three building blocks are the cornerstones to design the model. The first building block includes the factors that compose the model: elements, concepts or inputs. The second building block comprises the relationships among factors. The third building block encompasses the boundaries and conditions that should be considered to apply the model in particular contexts. Hence, based on these building blocks, the following questions were addressed:

How can a learning analytics model provide relevant data to measure and evaluate the impact of training programmes in organisations?

The sub-questions were:

- What elements are required to build a LAM that measures and evaluates the impact of training programmes in organisations?
- What are the relationships among elements that define the interactions within the LAM?
- What are the required assumptions and boundaries of the LAM that guarantee a successful application in organisational settings?

The manner of answering every question is described in the following sections.

6.2 Elements required to build a LAM

The elements required to conform to the LAM were selected based on existing literature, scientific articles and books to answer the research sub-question, “What elements are required to build a LAM that measures and evaluates the impact of training programmes in organisations?” The findings showed an extensive list of elements that organisations should consider if they desire to measure the impact of training by including different dimensions of the training process. Thus, to ease the understanding and implementation of the LAM, the elements were clustered in themes according to their nature, order, and aim. It is worth noting that in educational settings, there are more than 100 models that support the measurement of learning processes. However, there are only 2 LAMs that cover the entire cycle of learning analytics in organisations.

The conclusion is that these existing LAMs are limited compared to the proposed model because they do not consider two perspectives: data quality and relationship among elements. Data quality refers to the transformation and cleaning of data before any operation is performed or information is presented. Omitting this dimension is a high risk in organisations because it means that data can be unreliable, and the consequence is reflected in making wrong informed decisions.

Models ignoring the relationship among the elements is an error found in the literature because dependencies, correlations, and order of execution of some processes are fundamental to computing MIMs. The consequence of this omission is evidenced in reports. Specifically, information is incomplete and inconsistent. For example, the proposed LAM defines that data preparation is executed before MIMs. If this sequential relationship is dismissed, data from data sources may not be cleaned. Consequently, tasks to ensure completeness, consistency, and removing duplicates cannot be performed, leading to scenarios of low data quality.

6.2.1 Theme: data sources

This theme comprises the data sources whose objective is to provide data to the LAM before, during and after programmes are delivered to trainers. The LAM proposes three sources: training request forms, HRTS and LMSs. Thus, before programmes start, the LAM should collect data related to the tangible and intangible benefits, costs, ROI, participants, duration, format (face-to-face or remote), and other aspects related to the programme. Managers provide these data employing a training request form. Then, a human resources department analyses and evaluates the feasibility according to the scope, benefits, and budget. Data collected through the request form are stored in the HRTS to track and monitor the programme status (analysis, ongoing and finished). After that, all these training data are provided to the LAM to evaluate the measure and impact of training programmes.

The second phase is when the programme is delivered to trainees. In this case, the LMS sends training data to the LAM. Namely, data generated from the learning experience, learning assessments, quizzes, trainees' interactions with peers, and educational platforms are considered in this data source. For example, the LMS may send related to the trainees' performance in specific assignments and workshops from which the LAM may compute some calculations to present the individual and collective KPIs based on descriptive, prescriptive and predictive analytics.

The third phase comprises the data generated after the programme finishes. Hence, trainees are measured by managers, supervisors and peers according to criteria such as the degree of application of the skills and concepts in the workplace; the increase of sales from the training; the improvement of efficiencies in internal processes, i.e., a better quality of services. This assessment is collected through different means, such as LMS or online forms. Then, these data are sent to the LAM to perform calculations about the effectiveness of the training.

In conclusion, some studies claim that educational data are insufficient to make decisions about the effectiveness of training programmes because there are also relevant data related to monetary benefits, such as profits, competitiveness and efficiency. Therefore, the approach of the LAM is valid since it combines educational and business data to ease the analysis and interpretation of information that contains MIMs aligned with the training process and business goals.

6.2.2 External and internal factors

This theme refers to the elements that trigger the training programme in organisations. There are two sorts of elements: external factors and internal factors. External factors comprise regulators that obligate organisations to deliver training programmes in order to meet standards or regulations, for example, standards that organisations should incorporate into their processes to manipulate a product adequately. Hence, organisations have found that an efficient and rapid manner to address these sorts of requirements is through a training programme which serves as evidence in case it is required in the future. Regulators may be governmental entities, international entities in charge of defining standards, or industry regulators.

Internal factors are initiators whose aim is to meet new market needs, that is, new products, new services, or modify the manner of delivering them. As a result, organisations have found that through training, employees may develop skills and competencies that lead to change in the way to execute tasks at work. And the manner of measuring and evaluating whether training has been effective is by implementing the proposed LAM, since it can show how business goals have changed after employees attend training programmes, for example, by presenting KPIs related to innovation, creativity and technology using the LAM.

In summary, these triggers are vital in the proposed LAM because they make the process of LA begin while the LAM monitors, tracks and alerts according to the KPI's behaviour. Thus, designing and implementing MIMs supporting evidence and training compliance is essential. Evidence may be the degree of acquired knowledge or skills during the execution of a training programme which is generated using the LAM.

6.2.3 Measures, metrics and indicators (MIMs)

This theme is an essential part of the LAM because it defines the measures, indicators and metrics required to evaluate the effectiveness of the training process in organisations. In other words, it is the heart of the model. Due to the extensive number of elements found in this theme, the proposed model groups them into four domains: (1) trainee and learning, (2) internal process, (3) finance, and (4) customer. These four domains encompass all perspectives of any organisation regardless of its nature, industry, or size.

6.2.3.1 Trainee and learning

The trainee and learning domain focuses mainly on gathering, measuring, and computing calculations using elements that affect the trainees' learning processes. The first category of elements is defined as trainees' characteristics from which the LAM performs statistical operations such as age average. In addition, the model also considers emotions and behaviours to make an initial trainees' profile. The principal identified emotions are motivation, training expectations, and trainees' performances in the workplace. The advantage of defining an initial trainee's profile is that the programme's content may be adapted and tailored to increase the success probability before the programme starts. Other authors (Hughes et al., 2020) recommend a communication strategy to communicate the importance of training in the organisation. In this manner, trainers will be aware of the benefits that training programmes bring along the way. For instance, professional and personal growth thanks to the competencies and skills acquired during the programme's execution.

The second category of elements is defined as the learning experience. This category aims to measure and evaluate the trainee's experience through elements such as content quality, teaching experience and programme logistics. In addition, some authors (Kirkpatrick, 2006; Kirkpatrick, 2008; Ulum, 2015) propose that trainees' experiences should be evaluated through happy sheets or reaction sheets by incorporating questions associated with the programme objectives, facilitator knowledge, facilitator delivery and facilitator style. In this manner, the evaluation will be accurate. The data are collected using questionnaires during the execution of the programme. Hence, depending on the outcomes, the LAM monitors, tracks and alerts whether trainers are at low, medium or high risks of drop-out. The consequence is that trainers may change the elements that make trainees feel demotivated or with low interest in the training programme. The restriction in this category is that there are no suggestions about how predictive or prescriptive models may be implemented to forecast the learning experience. Therefore, further research should be considered in this regard.

The model defines the third category as the learning path, which measures and evaluates the degree of applying skills and knowledge in the workplace. Thus, two elements are fundamental to understanding in this category; the first one is defined as learning which refers to the degree of acquired knowledge during the programme's execution. The second element is called behaviour, whose aim is to measure and evaluate the degree of expertise that trainees apply in the workplace; for instance, employees took four hours to execute a task, but after the programme finished, employees took 4 minutes. In this example, a straightforward optimisation in the process thanks to the training process is evidenced. There is a common position in the literature (Cho et al., 2009; Razanaufal & Lantu, 2019; Ruiz & Snoeck, 2018) about considering questionnaires to evaluate the degree of knowledge before and after the programme starts in order to compare the results and determine the enhancement of competences and skills. It is also recommended that there is no standard manner of designing the questions that are part of the questionnaires because they depend on the learning objectives and the programme's objective. The role of the LAM in this category consists of performing calculations by importing the results from tests or assessments fulfilled by trainees, a trainee's supervisor, peers or any individual who evaluates the trainee's performance after the programme finishes.

Consequently, the LAM presents the information through reports that determine whether the programme was effective by comparing the thresholds defined before the programme started to the results obtained from the questionnaires after the programme finished. The limitation of the model in this category encompasses the pose defined by some authors (Razanaufal & Lantu, 2019), from which the first part consists of selecting two groups. The first group comprises trainees, and the second group are employees that execute similar tasks in the workplace but do not participate in the training programme. Thereafter, the results should be compared to validate the evolution of both groups. This position was not considered in the LAM because both groups are experiencing different settings and variables. Therefore, it is not considered correct to run a comparison.

6.2.3.2 Internal processes

This domain focuses on measuring and evaluating processes' efficiency, quality, and innovation after trainers finish a training programme. Supervisors, managers, peers, and subordinates are the identified roles that perceive and evaluate whether trainees develop skills and competencies that improve the manner of executing tasks in the workplace. The LAM does not define the moment of evaluation because it depends on the organisational settings. However, some authors recommend assessing one month after the programme finishes.

Efficiency refers to reducing the time or cost of performing a task in the workplace. It is the consequence of attending a training programme from which trainees develop specific skills and competencies applied to their daily tasks. In this case, the LAM calculates the efficiency by comparing the initial time or cost to the final outcomes.

Then, the results are shown as metrics that indicate whether an improvement was found in the process. Hence, if the progress is positive, it can be concluded that the training process was effective.

Quality in training settings refers to the reduction of errors during the execution of a particular task. It is a consequence of developing skills or competencies related to improving the method of performing the job in the workplace within a training programme. The LAM measures and evaluates the quality by comparing the number of errors before and after the training programme is delivered. Then, the metrics present the quality improvement in services, products or processes. If metrics are positive, it means that the training was effective.

Innovation indicates the number of new ideas implemented to deliver products or services differently based on the competencies developed in a training programme. The LAM measures and evaluates this metric by collecting data about the initiatives implemented after the programme finishes. Since metrics can change from one organisation to another, other metrics can be adapted to evaluate the degree of innovation. Therefore, the significance of the LAM is that it incorporates innovation as an essential element with high flexibility to adjust metrics regardless of the frameworks or body of knowledge behind them.

6.2.3.3 Business objectives

This domain refers to the tangible and intangible elements required to reach the business objectives. Hence, the tangible category comprises the elements related to monetary benefits, that is, quantitative variables that are used to compute metrics, indicators, and measures that are calculated comparing the cost of investment to the financial benefits. Specifically, the tangible elements proposed by the LAM are ROI, profitability, NPV, and expenses. The most used element in organisations is ROI. It consists of monetising the skills, competencies and behaviours developed during a training programme. Table 6.1 explains how to obtain the ROI.

Cost of investment	Monetary benefits	Formula
Programme design	Time-saving	$ROI\ (\%) = \frac{Net\ programme\ benefits}{Programme\ costs}$ X 100
Programme delivery	Increase of sales	
Trainer Salary	Reduction of errors	
Academic material		
Other costs (e.g., food)		
Total investment	**Net program benefits**	

Table 6.1 Computing the ROI of a training programme

The main benefit of this category is that through the LAM, organisations may calculate the monetary benefits after investing and spending money in training programmes. Some authors claim that this measurement is not performed in organisations because it is difficult to collect, compute and present information. In this case, the LAM eases all these tasks since it is responsible for collecting data before and after the programme is delivered using digital forms. It makes it easy to gather data from stakeholders such as managers, peers, subordinates, trainees and the human resources department. Therefore, the process becomes automatic and easy to collect and present the programme's effectiveness by presenting individuals and groups to analyse the financial performance and how it is reflected in the business objectives. It is how the LAM generates added value to the organisations when decisions about training should be made.

The second category comprises the intangible elements aligned with the accomplishment of business objectives. The LAM proposes the following qualitative elements: commitment, cooperation, leadership, teamwork and effective communication. These elements traverse the organisation, impacting soft skills at different levels. For instance, the LAM should measure the commitment level after employees attend a training programme. Like tangible elements, intangible elements also should be measured before and after the training is delivered to evaluate the enhancement and the added value of training. Thus, according to the results presented through reports published by the LAM, alerts and notifications are sent to the stakeholders interested in the behaviour of the intangible and tangible elements.

6.2.3.4 Customer

The LAM incorporates, in this category, the elements required to measure and evaluate the impact of a training programme on customer processes: sales, service and support. Thus, the customer category involves the following elements, time to market, product quality, market share, customer satisfaction, customer loyalty, customer retention, customer acquisition, cost, and service. These elements facilitate the analysis of training programmes' benefits to the customers. Specifically, decision-makers could compare the improvement of customer experience after a training programme is delivered with the objective of developing skills or competencies in employees to impact any interaction with customers positively. This category solves the difficulty of measuring the ROI of a training programme focused on bringing benefits to customers because there are no means to gather, transform, calculate and present data applying descriptive, prescriptive, and predictive models, which are part of the proposed LAM.

6.2.4 Reporting

The last theme is named reporting, and it aims to present information related to the effectiveness of training programmes using reports or dashboards. Thus, this theme comprises two domains: analytical models and visualisations. The first category is defined as analytical models from which descriptive, predictive and prescriptive models are proposed. The visualisations domain defines the elements required to present data through visuals such as charts, tables and others. The LAM proposes this theme to ensure information is graphically delivered to decision-makers to facilitate information analysis.

The LAM adopts descriptive models because they consolidate historical data to answer the question what did happen? Thus, the question responds using KPIs, aggregations and basic statistical operations, i.e., average, maximum, minimum and standard deviation. For example, the LAM may provide the ROI of a specific programme by summing the monetary benefits versus the cost of investment. Consolidating the number of trainers is another example of summarising historical data. The novelty of the LAM is that it proposes to notify decision-makers when any indicator reaches its boundaries. This means that the organisation should validate why this behaviour is obtained and establish a strategy to mitigate the impact of the outcomes presented through KPIs and visuals.

Predictive models answer the question of what will happen with the training process. In this case, the LAM should predict the future using regression and classification models based on artificial intelligence. To predict the future, the main income is provided with the descriptive model. Then the specific models run algorithms and present the information using visuals, for instance, line charts with trend lines. The novelty, in this case, is evidenced when the LAM alerts decision-makers about events or situations that may happen in the future. For example, the LAM presents an alert in the report indicating that there are unmotivated trainers, and the consequence is that there is a high probability of drop-out, which has a negative repercussion on the overall course performance and the business objectives.

Prescriptive models address the question of what optimal outcomes should be. Thus, the LAM combines descriptive models, predictive models and business knowledge to suggest alternatives. Then, it determines the optimal one and the corresponding actions. Thus, continuing with the previous example, the LAM identifies and alerts the high probability of drop-out and prescribes what the following actions are by presenting the expectation of the organisations, showing the potential benefits of the programme and performing an assessment about learning processes, which includes variables such as trainers, content and logistics. The consequence is that the drop-out indicators decrease thanks to the actions suggested by the LAM.

6.3 The underlying relationships among variables

To answer the second research question: “What are the relationships among elements that define the interactions within the LAM?” the LAM proposes a set of relationships among its elements to find dependencies and determine whether an order of execution of the proposed themes exists. The first conclusion is that the proposed themes have sequential relationships which are presented as follows:

- **External/internal factors and data sources:** this is a sequential relationship. It means that external factors should be executed before data sources. The LAM establishes that regulators, governmental entities, external entities, customers or industry competitors are those motivators that encourage or obligate organisations to deliver training programmes to their employees to develop organisational competencies that contribute to their processes, products and services. Hence, once the motivators are identified, the organisation registers the training needs in the HRTS, LMS or training request form to initiate the corresponding approvals and training process, that is, designing and delivering the programmes.

In addition, the external factors appear after the programme finishes to ask for evidence about the training process and validate whether employees developed the required skills and competencies. In this manner, the LAM is in charge of providing the required evidence through reports that indicate information related to the number of programmes delivered, the number of trainees that attend training programmes, the number of trainees that pass the assessments and other information that allow organisations to demonstrate that they are following the corresponding standards and they are being competitive.

- **Data sources and data preparation:** this is a sequential relationship. This relationship defines the data sources required to perform further calculations associated with KPIs, metrics and measures. It is also responsible for setting the frequency of extracting data from data sources, that is, weekly, monthly, etc.; the type of data formats, i.e., images, videos or text; and the authentication mechanism, for instance, user and password. The LAM proposes three different moments to extract data from data sources. The first moment is before the training starts. Thus, data are extracted from the HRTS and training request forms for the data preparation phase. The sorts of data are the monetary and intangible benefits, programme cost, programme budget and expected KPIs such as ROI and NPV. The second moment comprises the execution of the programme phase. Hence, the data extracted at this moment are associated with assessment outcomes, attendance rates or programme satisfaction surveys. The third moment involves data collected after the training programme has finished, that is, tangible and intangible outcomes that depend on the real impact on internal processes, customers, innovation or business goals. In addition, omitting this relationship will lead to dismissing data sources that are fundamental to obtaining accurate information.
- **MIMs and reporting:** sequential is the type of relationship between these two themes. Hence, tasks derived from MIMs should be executed before any

analytical model and report are performed to guarantee data consistency. The data that may flow from MIMs to reporting involve trainees' characteristics, the level of training satisfaction, the level of knowledge and skills acquired during a training programme, the degree of skills applied in the workplace, financial elements and intangible elements that impact the business goals directly and customer elements. If this relationship is absent, reports and the analytic learning models are affected negatively because they will not have enough data to perform their calculations. Therefore, decision-makers could make wrong decisions. The LAM does not define the frequency of passing data from one theme to another since there is no evidence in the literature regarding ideal data synchronisation. In addition, it obeys the business needs.

- **Learning path, job performance and business objectives:** The LAM establishes this sequential relationship to guarantee a successful implementation of training programmes. Hence, the LAM suggests practitioners define the training expectations before learning processes start. In this manner, the decision-makers focus their attention on objectives and results. It even allows anticipating problems that may arise during the different phases that comprise the training programme. Therefore, the LAM proposes an alignment among learning path, job performance and business objectives. The best alternative to ensure a correct alignment is through the definition of learning objectives and an assessment to validate which skills and competencies are being applied in the workplace, for instance, the increase in productivity, efficiency in processes, innovative processes and an improvement in the quality of products or services. Finally, tangible (financial) and intangible MIMs should be computed according to the job performance outcomes. In this manner, decision-makers may determine the effectiveness of a training programme.

6.4 Assumptions and conditions to design and implement the proposed LAM adequately

The third building block defines and responds to the third research question with a solid and consistent model that comprises the assumptions and conditions that should be considered to successfully understand and implement the model by organisations or further investigation. Hence, conceptual assumptions and contextual assumptions were defined to guarantee a complete set of requirements before practitioners implement the model in organisational scenarios.

Conceptual assumptions refer to the process or patterns required to make the model work. Thus, the LAM proposes a logical approach to be executed. Therefore, data should flow through the themes in the following order: (1) external factors, (2) data sources, (3) data preparation, (4) MIMs, and (5) reporting. The rationale behind this order consists of:

1. External factors: this theme initiates the entire process by defining external or internal factors. They act as triggers that often obligate organisations to deliver programmes to their employees. For instance, to meet regulations or standards required by the government or simply because the marketplace is demanding organisations to be more competitive by delivering products or services with different features and better quality which should be addressed by developing internal competencies in employees.
2. Data sources: the second phase of the process consists of defining the data sources that provide raw data for performing data analytics. The data type varies according to the nature of the data source nature. For example, LMS provides data related to the training programme, that is, programme experiences, trainers' and trainees' performances. HRTS provides data on programme cost, programme budget, trainers' salaries or expected benefits. Digital request forms provide data such as objectives, benefits, justification, potential stakeholders, and tangible and intangible benefits.
3. Data preparation: this is the third phase of the process. It consists of defining and extracting data from the data sources. Then, data are transformed into desired formats and cleaned to remove unnecessary data, for instance, nulls or duplicates. The consequence of having this phase is that high data quality is ensured. Then, data are sent to the next phase, named MIMs, for further calculations.
4. MIMs: this is the fourth phase of the process. It is considered the heart of the LAM because it performs the required calculations to obtain the desired measures, indicators and metrics, which are the basis for evaluating the

effectiveness of training programmes. In this phase, raw data are converted into information to make informed decisions by combining different perspectives such as learning outcomes, behaviour, productivity, time reduction in certain business processes, innovation, quality, ROI, revenue, and customer experience. Then, all these MIMs are used by the last phase, named reporting.

5. Reporting: This phase consolidates the entire set of MIMs and presents them in reports or dashboards. In this phase, the graphical user interface and user experiences are the cornerstones to ease the analysis and interpretation of information. The LAM proposes a group of visuals that should be used according to the data nature. For instance, evolution visuals should be used in scenarios where decision-makers desire to evaluate data changes over time. In addition, reports should be built by adapting or combining descriptive, predictive or prescriptive models.

In summary, the proposed LAM poses this logical process to ensure a successful implementation in organisations or other scenarios where it may be suitable. Omitting one of the phases will lead to inconsistency of data. The consequence is that the proposed LAM will also be unreliable.

On the other hand, the contextual assumption responds to the questions of where, who and when. Where refers to the suitable settings where the model is suggested to be implemented. In this case, organisational settings are the best scenario to implement the LAM because it was designed with the purpose of providing an analytical means to make decisions considering elements related to business objectives. For instance, sales, revenue, ROI, NPV, processes efficiency, employees and some others explained in the discussion chapter 5. The second question responds to whom is involved in the LAM. Thus, employees play the central role. Notwithstanding, managers, peers, supervisors and trainers act as observers of the training process to evaluate the trainees' performance during and after the programme finishes. In this manner, the LAM calculates and determines whether the programme is effective. The third question is when. This refers to the moment or phases in which the LAM should be applied or implemented. Therefore, the LAM is designed to support activities before, during and after the programme finishes. For example, data generated before the programme starts are related to the budget, cost, monetary benefits, number of employees that should attend the programme, and some other elements defined in the discussion chapter 5. Data generated during the programme's execution comprise programme satisfaction assessment, learning outcomes, attendance rates or trainer's assessment. Lastly, data generated after the programme finishes encompasses the extent of application of concepts in the workplace by increasing the productivity, quality of products and efficiency to perform specific tasks.

6.5 Future work and limitations

Although the limitations and further research were posed in the discussion chapter 5, this chapter presents a summary as follows:

- *Data sources*: there is a need to measure the degree of flexibility of the LAM in terms of reducing or expanding the number of data sources without affecting the accuracy of the data presented to make informed decisions. For example, it may be the case that the organisation would need information systems such as CRMs or ERPs that provide essential data to perform calculations that determine the accomplishment of KPIs. In this scenario, the LAM should not be affected. However, it is necessary to validate this hypothesis (details in section 5.1.1.3).
- *External and internal factors:* the data collected in this research did not reveal factors or relationships related to competitors that lead organisations to implement training programmes to be more competitive. Hence, it is proposed to explore cases in which competitors become an external factor that affects the measurement and evaluation of training programmes. It is evidenced in cases where competitors deliver services in less time with more quality. Therefore, organisations should invest in training programmes to improve employees' skills and competencies (see details in section 5.1.2.3).
- *Metrics, indicators and measures:* this research proposes a set of elements required to measure and evaluate the impact of training in an organisation from different perspectives, namely, trainee and learning, internal processes optimisation, business objectives and customer. Likewise, a set of elements compose these perspectives adopting scales to categorise and interpret data

adequately. However, the model identified that scales and intervals should be adapted according to the business needs and organisational context. Hence, despite the model proposing general scales, these are not mandatory to implement, but organisations should validate whether they should be changed, for example, changing currency units from millions to billions. By doing this change in the scale, the reports will change drastically. Therefore, it is fundamental that further research delves into the criteria required to implement the correct scales in the LAM.

- *Data preparation:* the LAM proposes general rules that should be considered in organisational settings for cleaning data; that is, completeness, consistency, duplicates, mislabelling and mis-formatting. However, depending on the degree of data quality, organisations may select and adapt those that fit their processes. Thus, further research should focus on discovering and defining criteria to adapt the rules and their peculiarities which should be incorporated into the data preparation theme (further details are shown in section 5.1.4.2).
- *Reporting:* during the literature review, no software tool has been developed or tested to support learning analytics in organisations. Therefore, further research is required in this theme to implement the proposed model through a software tool with high flexibility. In this manner, the whole set of elements, relationships and conditions may be implemented successfully, leading to informed decisions in real-time or near real-time. It is also recommended to investigate best practices and criteria to guarantee a great user experience during the interactions between decision-makers and the software tool.
- *Relationship among elements:* the LAM proposes ten sorts of relationships among the elements. All these relationships are based on sequential relationship type. However, this research did not find correlational relationships between the literature review and thematic analysis activities. Therefore, to expand the number of relationships, it is proposed to explore which other variables may be correlated with others. For instance, a potential correlation may be between productivity and revenue elements. In addition, this research also encourages researchers to validate whether other relationships may exist in the LAM.

- Limitation in the research methodology: considering that my study is based on desk-based research it was difficult to find data related to organisational settings. The reason is because organisations are not willing to publish training strategies, costs of investment, turnover indicators, sales volume and efficiencies that training should impact positively. However, it was decided that the manner to deal with this limitation during the data collection was to include non-peer-reviewed studies, namely reliable information collected from projects and consultancies performed by well-recognised firms worldwide. In addition, a fictional case study was presented in section 5.4 to validate how the LAM should be applied in organisations regardless of their nature, that is, size, sector, industry and structure.
- Limitation in the research method: since my study used secondary data as the primary data source, the limitations in this case are associated with finding studies with a low-quality content and low author biases. Thus, the manner to overcome these limitations was through saturation and triangulation standard methods which provide reliable, valid and objective outcomes during the data gathering process. Thus, the challenge was to gather sufficient data from multiple sources with the aim of comparing different studies according to their results, methods, theories and authors. Then, the point of saturation was reached when no new codes, themes and categories arose.

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