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MMALA: Developing and Evaluating a Maturity Model for Adopting Learning Analytics

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Abstract

Learning analytics (LA) adoption is a challenging task for higher education institutions (HEIs) since it involves different aspects of the academic environment, such as information technology infrastructure, human resource management, ethics, and pedagogical issues. Therefore, it is necessary to provide institutions with supporting instruments to deal with these challenges. Although there has been much research on factors that are associated with the adoption of LA in HEIs, there has been much less research on specific models that can be used to guide actual adoption. In this sense, we developed MMALA, a Maturity Model for Adopting Learning Analytics. It is a guide that describes the necessary practices for taking the first steps in this area and enables institutions to reach higher levels of maturity in LA use, culminating in an organized and systematic adoption. In this paper, we describe the development process of MMALA, focusing on the model evaluation, which used both the questionnaire and the expert opinion method. MMALA can also give institutions an overview of their current situation regarding LA adoption. In this sense, we present the results of the maturity evaluation of three Brazilian HEIs using MMALA.

Notes for Practice

- Researchers can understand how to explore the knowledge of experts to evaluate a proposed model using the expert opinion methodology.
- Higher education institutions (HEIs) can understand the necessary activities for adopting learning analytics (LA), covering different areas, such as data management, data analysis, pedagogy, ethics, and privacy.
- HEIs can have a roadmap to guide them to a more mature adoption of LA.
- HEIs can assess their maturity level in LA use.

Keywords

Maturity model, processes, policy development, learning analytics, higher education

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1. Introduction

Learning analytics (LA) aims to analyze educational data in order to both assess and improve the teaching and learning process (del Blanco et al., 2013; Siemens & Baker, 2012; Govindarajan et al., 2015). These analyses occur, for example, based on data resulting from the interactions of students and instructors with each other and with the resources available in learning management systems, such as videos, exams, and learning objects. Greller and Drachsler (2012) point out that LA allows instructors to plan interventions and adjust pedagogical strategies (i.e., if they identify students at dropout risk or students who have knowledge gaps). LA can also give students information about their learning process, allowing them to reflect on and improve their own learning (Charleer et al., 2016).

Although a wide variety of LA solutions has been proposed, enabling the use of these tools at an institutional level (to reach all students and instructors) remains a challenging task (Pérez-Sanagustín et al., 2022). As Siemens and colleagues (2013) state, LA is not merely a technical matter; it encompasses technical, cultural, and social aspects (Alzahrani, Tsai, Aljohani, et al., 2023; Alzahrani, Tsai, Iqbal, et al., 2023). In this regard, many studies highlight the difficulties of adopting LA at scale (Dawson et al., 2019; Gašević et al., 2019; Tsai & Gašević, 2017b).

Some of the challenges involved in LA adoption are related to the institution's management and leadership, the required skills to explore data, the relationship between LA and pedagogical theories, and ethical and legal issues (Greller & Drachsler, 2012; Tsai & Gašević, 2017a; Tsai et al., 2021). Furthermore, one of the main issues is how to start; that is, educators, managers, administrators, and researchers are not clear on the approach their institution should take to begin using LA (Gašević et al., 2019).

Given the extent and diversity of challenges, which unfold across different knowledge areas, it is important and useful for higher education institutions (HEIs) to have a guide that identifies the areas that require attention for the adoption of LA. Broos and colleagues (2020) reinforce this statement by explaining that an institution with limited resources and experience may be hesitant to start an LA project without guidance. Also, Arroway and colleagues (2016) argue that a high-level LA strategy (with comprehensive and well-defined planning) can increase the likelihood of success.

A maturity model (MM) can guide HEIs in understanding their current situation, and then planning and executing a strategy for LA institutional adoption. An MM describes the development of an entity, such as an organizational function, over time (Klimko, 2001). According to Al-Sai and colleagues (2019), an MM can be applied to assess the "as-is" situation of organizations regarding specific key areas. That is, an MM works as a roadmap that can support institutions to both understand their level of maturity in a particular domain and identify the activities they should perform to gradually achieve higher levels of maturity in this specific field (Freitas, Fonseca, Garcia, Ferreira Mello, & Gašević, 2020).

MMs do not define specific processes but are a guide for organizations to define their own processes and then improve them over time (Hanaei & Rashid, 2014). They have been successfully employed in different fields, such as software development, data management, and project management. Caralli and colleagues (2012) explain that organizations that use MMs can determine where they are in their improvement journey and set targets for future investments in performance improvement. The authors also add that MMs can be used as the basis for developing action plans to close performance gaps and improve maturity.

In a complementary way, Khalil and colleagues (2022, p. 153) indicate that a model "presents a defined and set scope and sequence of operations to realise the phenomenon in question." On the other hand, frameworks "present a set of essential elements or parts of a particular phenomenon, noting the interrelationships and interdependencies between these different elements that the framework envisions to see realised or implemented." In this context, this paper proposes the MMALA, a Maturity Model for Adopting Learning Analytics. An MM can help an HEI coordinate toward LA adoption. The goal is to guide the adoption from the most basic scenario to the application of more complex techniques of analysis, without neglecting the planning of the organizational aspects required when adopting new technologies. Moreover, the goal of MMALA is to direct the institution so that it can benefit from important data for student learning, emphasizing aspects necessary to facilitate the adoption of LA (Freitas, Fonseca, Garcia, Falcão, et al., 2020). Since MMALA provides a sequence of operations (functional practices) to reach institutional adoption of LA, it is, by definition, a model (Khalil et al., 2022). MMALA can support institutions with great or no experience in adopting and using LA, covering 16 key areas and four levels of maturity. The assessment of MMALA used expert opinion, defined by Li and Smidts (2003, p. 813) as "a series of scientific endeavors which are employed to interpret data, predict system's behavior, and assess uncertainties." The assessment results suggest that 90% of the experts consider MMALA comprehensive, consistent, and adequate to support HEIs in LA adoption. Although MMALA was defined and validated in Latin America, it can be used by any institution worldwide.

This paper describes MMALA's development toward its evaluation from the perspective of experts in LA. Also, we provide a study using one of the possible applications of MMALA—the definition of the maturity level of HEIs—applied to three Brazilian institutions. Although the adoption of LA in Brazilian institutions has previously been studied, especially from the point of view of the stakeholders' expectations in specific institutions (S. Garcia et al., 2021; Pontual Falcão et al., 2022; Kelvin et al., 2021), the only study that investigated the adoption of LA in a holistic manner was Sheneider and colleagues (2022), which studied the level of maturity in Brazilian institutions using our MM (published in Brazilian Portuguese as a doctoral thesis).

2. Related Work

A significant amount of previous research has supported the development of the MMALA proposed in the current paper. Some of the previous studies focus purely on LA adoption. For example, Colvin and colleagues (2017) review the existing models so far for LA adoption, indicate their limitations, and detail the dimensions commonly found in these models; the studies by Tsai and Gašević (2017b) and Tsai and colleagues (2020, 2021) detailed the state of LA adoption in Europe and the existing expectations and challenges to advance in this adoption; and the review conducted by Viberg and colleagues (2018) identified the almost complete absence of evidence that LA has been adopted institutionally so far.

Other research focuses on leadership, such as Dawson and colleagues (2018, p. 236), which proposed a leadership model for LA adoption based on the Complexity Leadership Theory. Also, the authors identified that institutions could be divided into two classes of leadership: (i) those who adopt LA in a top-down manner ("large scale project with high technology focus yet demonstrating limited staff uptake") and (ii) those who adopt LA in a bottom-up way ("strong consultation process, but with subsequent challenges in communicating and scaling up innovations"); in turn, Tsai and colleagues (2019), building upon the work by Dawson and colleagues (2018) and after extensive research in the United Kingdom, identified the challenges related to leadership and LA adoption; lastly, Hilliger and colleagues (2020) identified the importance of leadership processes and organizational maturity to facilitate the adoption and use of LA.

Of high relevance is the work done by Tsai and colleagues (2018, p. 5) and their SHEILA framework, focused on policy and strategy development, which can "assist with strategic planning and policy processes for learning analytics." SHEILA also offers survey instruments and interview protocols that can assist HEIs in understanding stakeholder expectations and needs. The conceptual model proposed by Greller and Drachsler (2012) also identified and described the dimensions that need to be considered to attend to the problem of LA adoption. Finally, it is worth mentioning that the LALA (Learning Analytics for Latin America) Project (Pérez-Sanagustín et al., 2019), which adapted SHEILA's instruments to Latin America, influenced the development of MMALA. This influence is both on the composition of the model's areas and on the effort to expand the use of LA in Latin America since this work presents a pilot study in a country in this region, and it supports the dissemination of LA. LALA, however, does not provide an MM.

Three studies that are highly relevant to our work on MMALA propose approaches to LA adoption as follows:

- The sophistication model proposed by Siemens and colleagues (2013, p. 27): The authors advocate that LA can reshape education. They argue that it requires a coordinated and national strategy. So, this model is concentrated not only within HEIs but also across the higher education sector. It details stages of LA sophistication—moving from "small pockets of innovation and excellence to a transformative force impacting and driving evidence-based decision making across all facets of the education sector." That model, however, has not been empirically developed or tested. It was primarily proposed through the integration of early developments in LA.

- The Learning Analytics Capability Model (LACM) (Knobbout & van der Stappen, 2020): The authors argue that the existing models for LA adoption are focused on specific areas or lack operationalization for successful development. LACM identifies five categories with 34 different capabilities to support LA adoption. Many of these capabilities are also available in MMALA, such as ethics, infrastructure, and stakeholder identification and engagement. This model was later evaluated by Knobbout and colleagues (2023), and the authors concluded that it supported practitioners in the planning phase of LA adoption. Although there is a detailed description of these capabilities, it does not describe the activities that are needed to achieve higher levels of maturity, as is done with MMALA.

- The LA Adoption Maturity Framework (LAAMF): LAAMF was developed "to contribute to a better understanding of success factors and barriers to adopting LA in HE institutions with blended learning environments" (Aničić et al., 2022, p. 711). Although it is also related to maturity, LAAMF is still in the sketch phase. The authors noted that they aim to use a combination of two methodologies for the development of their model (Mettler, 2010; Becker et al., 2009); the latter was also used for the development of MMALA.

Besides the models focused on supporting LA adoption that we just reviewed above, there are also models that address related areas, such as the Maturity Model for Supporting Graduates' Early Careers, by Aničić and Divjak (2020), that support the career development of higher education students. Others are the Data Management Maturity Model (DMM, 2014), Data & Analytics Maturity Model (D&AMM, Keystone Strategy (2016)), and TDWI Analytics Maturity Model (Halper & Stodder, 2014). DMM is a comprehensive guide to supporting organizations in data management. The other two models support data analysis activities. Even though these models encompass some tasks considered necessary for LA adoption, they are not suitable to be used as a unique guide for this matter (Freitas, Fonseca, Garcia, Ferreira Mello, & Gašević, 2020) because they do not describe the steps required for organizations to move from one level to another.

Considering previous research on LA adoption and the lack of a comprehensive and progressive guide that encompasses the areas of interest and practices necessary for LA adoption, the research question we aimed to address in the current study is, "How can we develop and evaluate a comprehensive MM to support the adoption of LA?"

3. Method

MMALA is intended to be a comprehensive guide for HEIs that identifies the necessary activities to be performed when adopting LA, organized into four levels of maturity and covering several key areas (hereafter: process areas). In this way, institutions can identify the areas concerning LA adoption and the steps toward a planned and systematic use. This paper aims to describe MMALA development and assessment as well as its application in three HEIs in order to identify their level of maturity in LA adoption.

As Aničić and Divjak (2020) explain, it is common to use design science as an approach for the design of MMs. MMALA has been designed following the methodology for MM development proposed by Becker and colleagues (2009). We decided to use this methodology because it is based on concepts of design science, and it was successfully used in the development of other MMs in the information technology area, in addition to being largely used in the literature. Finally, their methodology relies on the study and comparison of 51 previously proposed MMs in the literature. The methodology has the following steps:

- (a) Problem definition—Our problem was related to the setting of a roadmap to support HEIs in adopting LA.
- (b) Comparison of existing MMs—Since we had not found any MMs for LA, we decided to analyze models in related areas (data management and data analysis).
- (c) Determination of development strategy—We included areas resulting from the previously reviewed MMs, such as Data Quality, Leadership, and Funding, as well as new and specific areas for LA, such as the categories of Pedagogical Support and Legislation Privacy and Ethics.
- (d) Iterative MM development—In the first iteration (phase 1), we proposed the process areas for the model and assessed it. In the second iteration (phase 2), we finished the model development.
- (e), (f) Conception of transfer and evaluation; implementation of transfer media—We have disclosed the model for both the LA community and the scientific community.
- (g) Evaluation—After we finished the model, it underwent an expert evaluation. It is worth noting that qualitative methods are commonly used to evaluate MMs. Becker and colleagues (2009) mention some strategies that have already been employed for MMs' evaluation in the literature, such as application of the model in case studies, discussion in workshops, Delphi studies, and interviews. Other studies that evaluate MMs can be cited: Hausladen and Schosser (2020) used interviews, V. C. Garcia (2010) used Expert Opinion, and Aničić and colleagues (2022) intend to use expert evaluations and focus groups to evaluate their model.

In our work, we report on the development of MMALA in two phases. The first (phase 1) refers to the steps toward the definition of the MMALA process areas, including the evaluation (i.e.,, steps (a) to (f)). The second (phase 2) refers to the finalization of MMALA, including the description of its levels as well as the results of the second evaluation the model underwent, in which 13 LA experts participated (steps (d) and (g)). Therefore, this paper summarizes all the main activities performed as well as explaining the results of the MMALA evaluation.

After completing the development of MMALA, we performed a pilot by analyzing three Brazilian HEIs using MMALA. The pilot aimed to show the level of maturity of these institutions.

It is worth noting that phase 1 of MMALA development has already been published by Freitas, Fonseca, Garcia, Falcão, and colleagues (2020). Therefore, Section 4.1 presents a summary of this study as well as including complementary information. Phase 2 (MMALA completion) and the pilot (mapping of three institutions' maturity levels using MMALA) are original contributions of this paper.

4. MMALA Proposal

4.1 Phase 1—Defining the Process Areas of MMALA

We proposed a set of process areas for MMALA (Freitas, Fonseca, Garcia, Falcão, et al., 2020), through both a comprehensive literature review and the analysis of the MMs previously reviewed in the paper (DMM, D&AMM, and TDWI). We also analyzed the DAMA Guide to the Data Management Body of Knowledge (DMBoK, Molsey et al. (2009)), since it is a comprehensive guide to data management, an essential activity for LA. The first version of MMALA had 18 process areas, divided into five categories, as depicted in Table 1. At this time, we were concerned with the definition of areas for the model and only after that would we define the levels of maturity for MMALA. This section describes the process for assessing the level of importance of the proposed categories and process areas.

Table 1. MMALA's first version with five categories, 18 process areas, and its acronyms.

Category	Process areas
Data management	Data acquisition (DA) Data quality (DQ) Data ownership (DO) Infrastructure (Architecture/Data Integration, INF)
Administration and training	Funding (FUN) Leadership (LEA) Stakeholders' identification and involvement (SII) Communication (COM) Stakeholders' training (STR)
Pedagogical support	Pedagogical planning of solutions (PPS) Alignment of the institution's needs to theories and pedagogical evidence (ALI) Support in interpreting results (SIR)
Data analysis	Development of own solutions (DOS) Acquisition of ready-made solutions (ACQ) Evaluating the effectiveness of solutions (EVA)
Legislation, privacy, and ethics	Data Usage Policy (DUP) Permissions (informed consent/opt-out, PER) Compliance with local and national laws and regulations (LAW)

4.1.1 Evaluation

During this first assessment, we were interested in understanding the adequacy of the proposed process areas and categories. The adequacy was measured using an instrument sent to several researchers from the worldwide LA community. The evaluators were asked to assess the level of importance for each area of the proposed model and suggest new areas if they deemed that necessary. Thus, it was possible to identify whether important areas for LA adoption were omitted, allowing the evaluation of MMALA's comprehensiveness as well. The evaluation was performed using a questionnaire[1] with 5-point Likert-type scale questions, in which LA researchers could rate each process area from "not important" to "very important," as well as open questions, asking for new process areas or categories that should be included in the model. A total of 31 participants answered the questionnaire. Participants were recruited by email or through international mailing lists where the topic of LA is discussed (e.g., Learning Analytics Google group). Regarding the participants' characteristics, most of the people had master's and doctoral degrees (90%); they worked as professors or researchers (81%); and they had been working with LA for up to 5 years (81%), between 6 and 10 years (13%), or more than 11 years (6%). The output of this assessment allowed us to complete the proposal of categories and process areas of MMALA.

We performed Friedman's test ($\alpha = 0.05$) to verify the agreement among the participants regarding the importance of each process area of the proposed model. The following hypotheses were formulated:

- H_0: There is no difference in the importance of the process areas.
- H_1: There is a difference between the process areas.

General results about the relevance of each process area have been published in a previous study (Freitas, Fonseca, Garcia, Falcão, et al., 2020). In this paper, we present the results, grouped by category, as shown in Table 2. Furthermore, we provide complementary results to support decision making about the importance of each category to MMALA.

Table 2 presents a comparative synthesis of the categories, where the results were obtained based on the analysis of the 18 process areas. In addition, we performed a complementary analysis, with the Wilcoxon test and Cronbach's alpha (Kloke & Mckean, 2015), to provide more evidence and confirm the reliability of the similarities and differences among the items analyzed.

Table 2 highlights the ratings each category received. Friedman's test ($\alpha = 0.05$) showed a difference in the level of agreement between the respondents' opinions about the importance of each category. The Wilcoxon test grouped the categories into two groups, where DM, PS, and LPE were the most important and AT and DA were the least important.

In addition to the descriptive presentation of these data, we also performed a cluster analysis to present the results using inferential statistics. This analysis provides more information on the relationships between the process areas of MMALA.

[1]This questionnaire is available at https://bit.ly/3pRxHEF.

Table 2. MMALA quantitative evaluation.

<table>
<tr><th>Category</th><th>Mean</th><th>Median</th><th>Standard deviation</th><th>p-value (Friedman)</th><th colspan="2">Homogeneous groups (Wilcoxon)</th><th>Cronbach’s alpha</th><th>Confidence interval</th></tr>
<tr><td>Data Management (DM)</td><td>4.43</td><td>4.50</td><td>0.54</td><td rowspan="5"><0.001</td><td>DM</td><td></td><td rowspan="5">0.846</td><td rowspan="5">0.754 to 0.915</td></tr>
<tr><td>Administration and Training (AT)</td><td>4.20</td><td>4.20</td><td>0.60</td><td></td><td>AT</td></tr>
<tr><td>Pedagogical Support (PS)</td><td>4.56</td><td>5.00</td><td>0.58</td><td>PS</td><td></td></tr>
<tr><td>Data Analysis (DA)</td><td>3.97</td><td>4.00</td><td>0.74</td><td></td><td>DA</td></tr>
<tr><td>Legislation, Privacy and Ethics (LPE)</td><td>4.53</td><td>5.00</td><td>0.65</td><td>LPE</td><td></td></tr>
</table>

We used the responses for each item as input. The responses were dichotomized to enable the use of this method (for values “important” and “very important,” that is, the most concordant values, the answer became 1; and for values “not important,” “slightly important,” and “moderately important,” it became 0). In this way, responses were classified as concordant = 1 and discordant = 0.

Figure 1 shows the hierarchical cluster analysis dendrogram using the binary distance measure with the average linkage method (Hair et al., 2009; Johnson & Wichern, 2008) to the categories DM, AT, PS, DA, and LPE from Table 2. The dendrogram shows that the DA (data analysis) category differed from the other categories, and these other categories formed a single group, G1 = DM, AT, PS, LPE. This result is analogous to that obtained by applying the Wilcoxon tests (Table 2). Therefore, among the five categories, the one with the lowest degree of agreement was DA. In sum, this analysis showed that only the category DA appears with a different prominence because it is the category with the least agreement.

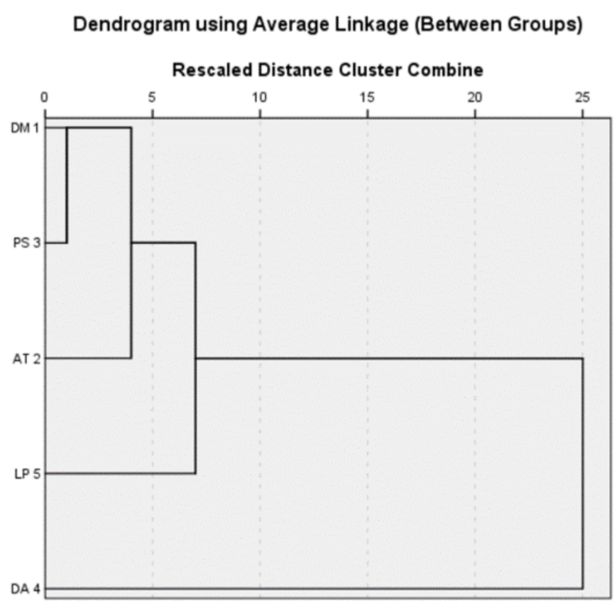

Figure 1. *Dendrogram for cluster analysis aiming at understanding the importance of each category of MMALA.*

Lastly, it is important to point out that the Cronbach’s alpha result is within the confidence interval, as depicted in Table 2. This means that these questions of the instrument were formulated in an appropriate way.

4.1.2 Discussion

The quantitative analysis shows that only the category DA was evaluated with less importance. Since data analysis is an essential activity in LA (Ferguson, 2012), we concluded that the process areas proposed in the model were insufficient. This difference might be caused by the lack of a process area focusing on the use of freely available tools. In this sense, we decided to include this information in the process areas of "acquisition of ready-made solutions."

The open-ended questions were analyzed in a previous study (Freitas, Fonseca, Garcia, Falcão, et al., 2020). Therefore, in this paper, we only briefly summarize the results, which are relevant for the discussion presented. Most of the suggestions from the open-ended questions were included in existing process areas. Also, the analysis resulted in a new process area for MMALA called "result-based intervention" in the pedagogical support category. It is important since, as Purwoningsih and colleagues (2018, p. 3) stated, "effective e-learning does not occur without planned pedagogical action."

It was also possible to identify activities that should be included in the model within the existing process areas. These activities should be part of LA adoption (i.e., standardization of data), although they are not complex enough to become a new process area. In addition to these modifications, MMALA also underwent two changes:

- The process area called "alignment of the institution's needs to theories and pedagogical evidence" became part of the process area called "pedagogical planning of solutions" (see Table 1). This decision was made due to the impediment of defining different levels of alignment with pedagogical theories.
- All process areas in the legislation, privacy, and ethics category were brought together in a single process area, with the same name as the category. This change took place for a reason similar to the previous one: the impossibility of defining different levels of compliance with laws and regulations.

The resulting MMALA, considering all changes made, is shown in Table 3. Changes with respect to Table 1 are marked in bold. In this case, the process area RBI was included in the model, and the LPE brought together all the areas of the legislation, privacy, and ethics category.

Table 3. MMALA categories, its process areas, and acronyms.

Category	Process areas
Data management	Data acquisition (DA) Data quality (DQ) Data ownership (DO) Infrastructure (INF)
Administration and training (subsequently readjusted to Governance and training)	Funding (FUN) Leadership (LEA) Stakeholders' identification and involvement (SII) Communication (COM) Stakeholders' training (STR)
Pedagogical support	Pedagogical planning of solutions (PPS) Support in interpreting results (SIR) **Result-based intervention (RBI)**
Data analysis	Development of own solutions (DOS) Acquisition of ready-made solutions (ACQ) Evaluating the effectiveness of solutions (EVA)
Legislation, privacy, and ethics	**Legislation, privacy, and ethics (LPE)**

4.2 Phase 2—MMALA Completion

In phase 1, we defined the process areas and categories that should compose our MM. In phase 2, we included more details about each process area and its maturity levels. MMALA's structure was based on the DMM (DMM, 2014), so each process area was composed of the following elements, as previously described by Freitas, Fonseca, Garcia, Falcão, and colleagues (2020):

- Purpose: the main focus of the process area;
- Goals: capacities an institution can achieve when deploying the proposed activities in the process area;
- Related process areas: other process areas that have goals or practices related to the current one;
- Functional practices: proposed practices for LA adoption grouped into four levels of maturity;
- Work products: examples of documents resulting from the institutionalization of the respective maturity level.

Therefore, we adopted the structure of DMM, excluding only two items: introductory notes and key questions, aiming not to overextend the model to allow assessment by experts. Moreover, based on the insights extracted from phase 1, we proposed the use of four levels of maturity for MMALA; that is, the number of levels in an MM typically ranges from 3 to 6 (Sen et al., 2012). These levels describe the evolution of LA adoption in the institution. At the first maturity level, ad hoc, projects take place through initiatives of individual stakeholders (e.g., instructors, researchers, or educational designers), involving a small number of students. At level 2, *initial*, the process formalization starts, favouring the expansion of LA use in the institution. LA is also adopted in other institution departments, with greater stakeholder involvement, such as instructors and students, and under the informal leadership of one or more researchers. Level 3, *structured*, is characterized by senior management involvement in the LA adoption processes. Planning of LA projects is in line with the institution's strategic objectives. Finally, at the last maturity level, *systematic*, processes and policies are formally established and followed so that the adoption of LA becomes comprehensive to the entire institution, and it is planned and executed systematically. Figure 2 summarizes these levels, representing a progression of LA adoption when a higher level is reached—from individual initiatives (level 1) to institutional adoption (level 4). It is only possible to proceed to the next level of maturity after performing all the functional practices defined in the current step. This number of levels was considered adequate in order to characterize a field of research that is still immature, while also avoiding adding greater complexity to the proposed model.

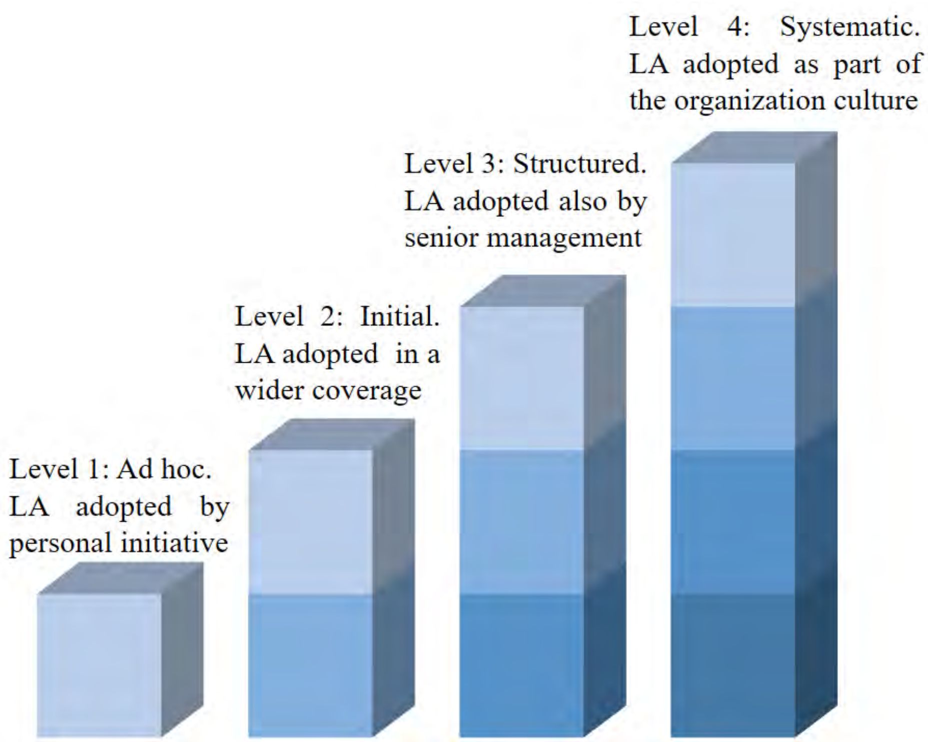

Figure 2. MMALA and its maturity levels (ad hoc, initial, structured, and systematic) (Freitas, Falcão, & Ferreira Mello, 2020).

MMALA was designed to allow two types of applications: (a) to tailor the path toward LA institutional adoption, selecting the process areas or categories in which the HEI has greater knowledge to be a starting point, or (b) to standardize the path, gradually following the defined maturity levels, from 1 to 4, in all the process areas. For instance, in option (a), if an institution has a well-established infrastructure and a team that is able to develop LA solutions, it can select process areas such as infrastructure, data quality, and development of own solutions. However, it is important to analyze related process areas that indicate the areas that should work together. On the other hand, to follow a standardized path (option (b)), institutions may focus on all areas of MMALA, starting from the first level and gradually evolving.

In order to provide a more tangible example of the process area structure, we can cite the data ownership process area, shown in Figure 3 (see the third footnote of this paper to get access to the full MMALA model). To facilitate understanding of the level where each functional practice is located, we adopted a numbering scheme composed of the process area's acronym, followed by two numbers separated by a dot. It works as follows: the first number refers to the maturity level, and the second refers to the functional practice number. For example, DO1.2 refers to the second functional practice of the first maturity level in the data ownership process area (Freitas, Falcão, & Ferreira Mello, 2020). In Figure 3, each column in the model refers to a maturity level, as is also depicted in Figure 2.

Data ownership is concerned with defining ownership criteria, making the data used for LA transparent, and providing owners with access to these data. As in other process areas, functional practices increase their complexity level by level. The

1.3. Process Area: Data Ownership			
Purpose: To specify the ownership of data used in LA projects.			
Goals: 1. To define criteria in order to establish the owners of the data generated by students' and instructors' actions; 2. To provide transparent information on which data about students' and instructors' academic actions are stored and how they are analyzed; and 3. To allow access to data which the participants of the project have ownership over.			
Functional Practices:			
Level 1 **DO1.1.** There are no formally established criteria in LA projects that define ownership over the data. **DO1.2.** Students and instructors are informed of what data on their academic actions are stored and analyzed only upon explicit request.	**Level 2** **DO2.1** The Institution consults students and instructors whether they agree to authorize the use of their data for LA projects or not. **DO2.2** Each project details the kind of data that will be analyzed, in order to obtain the participants' consent. **DO2.3** Participants are aware of all the projects that use their data.	**Level 3** **DO3.1** The Institution defines uniform criteria to classify all the data used in LA projects regarding ownership. Students, the Institution, and other concerned parties, such as government agencies, can own data. **DO3.2** Students and instructors are informed on which data about their actions the Institution stores and what are the purposes for storing and analyzing them. **DO3.3** The way the Institution analyzes data is made clear (that is, how the algorithm used for analysis works). That brings greater transparency to the data analysis process. **DO3.4** Owners are responsible for deciding on matters involving the use of their data. It includes the decision on use within the Institution, as well as on sharing it with third parties. The exception is the data considered essential for the students' basic academic management. All exceptions must be justified.	**Level 4** **DO4.1** Users can access the data they own. **DO4.2** An approved and followed policy defines data ownership, and it is in line with the Institution objectives and it also observes legal and ethical issues. This policy defines the data ownership criteria, and also who has access to the relevant data. It defines the data life cycle (it includes the actions to be taken when the course is over), and rights and liabilities regarding data use.

Figure 3. Data ownership, a process area of MMALA.

first level conveys an environment in which the institution is going through LA's initial experiences, with few participants engaged. Therefore, these practices support the institution to evolve gradually. So, the second level involves a course or department, and then levels 3 and 4 involve the whole institution. In the last level, an institution fully reaches the process area goals. At each level, we have also described examples of documents or files that formalize the execution of the proposed practices (work products).

Also, the related process areas provide information about those that can support the institution to perform the proposed practices effectively. For example, the process area of infrastructure supports reaching a goal defined in the data ownership area (to allow access to data over which the participants of the project have ownership), providing guidelines to arrange the infrastructure to make the data available.

4.2.1 Evaluation

The last development phase of an MM is its evaluation (Becker et al., 2009). At this stage, MMALA was assessed using expert opinion (Beecham et al., 2005; Dybå, 2000). In this work, the expert opinion about LA was applied to evaluate the model, concerning comprehensiveness, consistency, and problem adequacy, as recommended by Becker and colleagues (2009). The guidelines used for the assessment were proposed by Li and Smidts (2003), with the following steps:

- Problem statement—This step includes the definition of the context and problem to be evaluated. The context of MMALA is the adoption of LA and all the challenges previously discussed. The problem consists of the evaluation of the model, concerning, as recommended by Becker and colleagues (2009), (a) comprehensiveness—whether the proposed model can be considered comprehensive to support institutions in the challenges related to the adoption of LA; (b) consistency—whether the description of the model elements (purpose, goals, and functional practices) can be considered coherent in each process area; and (c) problem adequacy—if the model can be considered adequate for its purpose of supporting the adoption of LA.

- Selection of experts—A reasonable number of experts needs to be determined based on a set of criteria, which must include the credibility, knowledge, and reliability of the experts. According to Li and Smidts (2003), a priori, if the expert is perfect (i.e., if they have infinite knowledge on the topic of study and never make a mistake), the number of experts needed for the evaluation is one. However, given the chance that they make mistakes, it is safe to consult more than one expert. Experts can be dependent on each other; for example, they may have similar training, education, or experiences. So, unlike studies that use probabilistic analysis, increasing the number of experts, if they are dependent, does not improve the accuracy of the assessment (Li & Smidts, 2003). For the evaluation of MMALA, we defined the following criteria for the selection: (a) experts who have knowledge in LA, which was demonstrated through their scientific publications or their experience in the execution of projects in the area; (b) experts with diverse educational background (e.g., computer science and education); and (c) experts willing to participate in the assessment, with a duration of approximately 1 hour. Thirty experts were invited based on these criteria. In total, 13 of the experts agreed to participate, with diverse backgrounds, such as software process improvement, education, software architecture, and gamification, in addition to expertise in LA.

- Expert training (or calibration)—This step had the purpose of ensuring that there was a common understanding of the issue being addressed and that the experts would be responding to the same elicitation question (Li & Smidts, 2003). The goal was to minimize the bias of the experts. Li and Smidts (2003, p. 814) explain that "the assessment and compensation of these biases by the analyst is known as expert calibration." In this study, the strategy to minimize bias was to ask experts to include justification for each opinion expressed about the model. Furthermore, we gave respondents a definition of MMs in general and MMALA in particular. Respondents could also contact us in case of any questions. Similarly, we could consult respondents in case of a need for clarification on any responses, similar to the strategy established in Li and Smidts (2003) for calibrating in their study.

- Elicitation of opinions—This step aimed at asking the right question to get expert answers. The questionnaire for eliciting the opinion of experts needs to meet the following criteria, according to Ayyub (2000): (a) properly communicating the statements of the questions of interest to the experts; (b) eliminating any ambiguity or vagueness in the statements of the questions and the anticipated responses; (c) eliminating any ambiguity or vagueness in how the responses should be expressed; and (d) providing an efficient design that is complete, concise, clear and easy to follow.

  To meet the requirements, we prepared a questionnaire based on V. C. Garcia (2010), with the necessary adaptations, since the MM proposed by Garcia had a different structure from MMALA. Key changes can be described as follows: (a) we maintained the questions related to the assessment of the purpose, goals, and process areas; (b) we excluded questions aiming to assess the adequacy of the number of levels and its distribution throughout the model; (c) we excluded questions related to the assessment of the difficulty in achieving each maturity level; and (d) we created three new questions, using the Likert scale, to enable quantitative analysis. All of these changes were made to get the best set of questions while maintaining a reasonable assessment time. Three Ph.D. researchers in computer science evaluated the adapted questionnaire. Additionally, a pilot application was undertaken with two participants, both with master's degrees in computer science, to test and improve the instrument. In the MMALA assessment, we considered all experts with the same weight since they were considered to be of equal importance and credibility for the study.

  We sent the questionnaire[2] to the experts in the period of 25 May 2020 to 8 June 2020. The evaluation lasted approximately 1 hour, and the following items of the model were evaluated: purpose, goals, and functional practices. Regarding MMALA consistency, experts were asked to evaluate each item to identify whether it was described correctly or whether it should be improved or excluded. Regarding comprehensiveness, experts evaluated whether other goals or functional practices should be added to MMALA. They could suggest them for each process area. Experts were also asked to answer questions, using a Likert-type scale, about their view on the adequacy of MMALA to the problem of LA adoption as well as about their evaluation of MMALA's comprehensiveness. Lastly, they could make any other comments on MMALA.

- Aggregation of opinions—The goal of this step was to obtain an aggregate opinion or consensus on which a decision can be based. It is important because, according to Armstrong (1985) and Li and Smidts (2003), aggregate opinions, even if obtained by simple average, are consistently better than the individual opinion of experts. We considered that the experts reached a consensus when the percentage of agreement was higher than 50%, that is, when the majority of the experts agreed that the item was described correctly. Thus, the majority opinion could be preserved, avoiding changes in items that have already been considered correct by that majority. Figure 4 presented these opinions. Each line in Figure 4 refers to a process area of the MMALA, as identified on the left side. The blue fill refers to the percentage of experts who considered the purpose of the referred process area to be described correctly. Similarly, the red fill refers to goals, and the green fill to functional practices.

  Only three items were not deemed to be described correctly (the purpose of data analysis, and the goals of both data quality and communication). These were resolved in the decision-making step described later in the paper. Furthermore, the functional practices of all the process areas were considered to be described correctly. It is important to highlight other results, such as the purpose of legislation, privacy, and ethics, which had full agreement about its correctness. Also,

[2]This questionnaire is available at https://bit.ly/2O4bdCh.

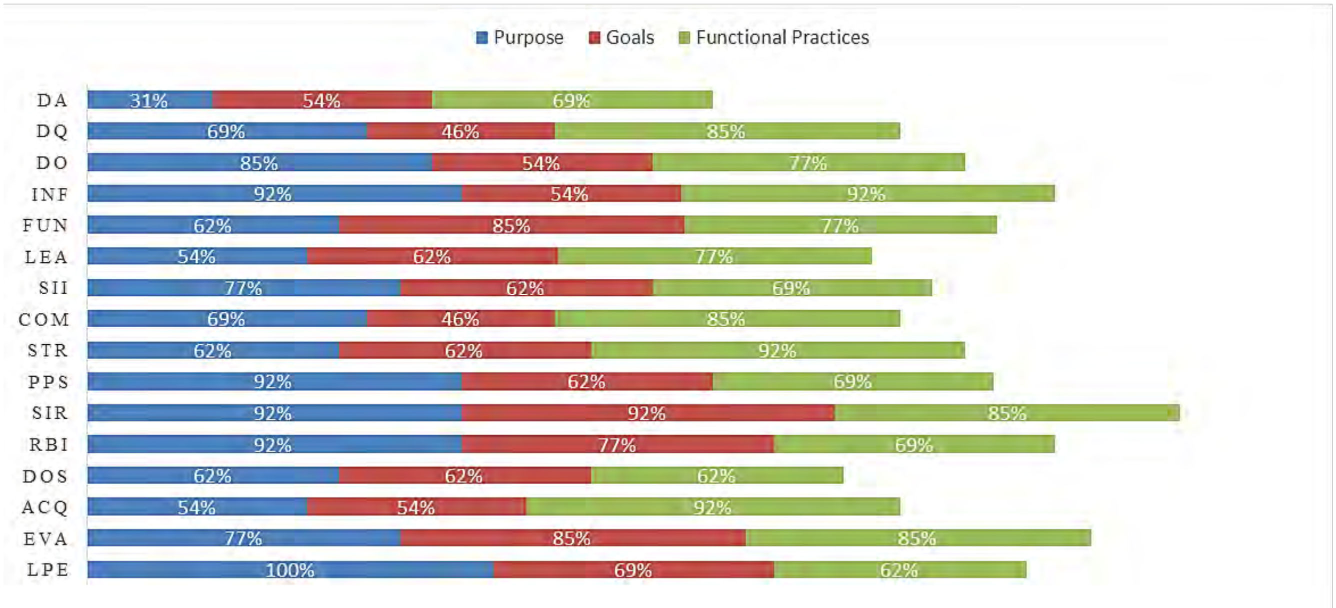

Figure 4. Percentage of experts ($n = 13$) who considered the purpose (blue), goal (red), and functional practices (green) of MMALA to be described correctly. Each item (purpose, goal, and functional practices) was evaluated separately. The full definitions of the abbreviations on the vertical axis are given in Table 3.

the process area of support in interpreting results had the highest agreement for its three items (purpose, goals, and functional practices).

Regarding the inclusion of items in the model, the experts suggested the inclusion of 21 goals and 11 functional practices in the questionnaire, as shown in Figure 5. Each line in Figure 5 refers to a process area of the MMALA, as identified on the left side. The blue fill refers to the number of suggestions for including a new goal in MMALA. Similarly, the red fill refers to the suggestions for including a new functional practice in MMALA. As a result of phase 2, we included new goals and functional practices in MMALA. In the next item, decision making, we give more information about this inclusion.

Regarding the exclusion of items, experts suggested excluding 13 goals and four functional practices. However, in a given process area, at most three experts (23%) considered it necessary to exclude some goals. As for functional practices, at most one expert (7.6%) suggested eliminating some functional practices. Therefore, there was no consensus for the exclusion of MMALA items, and no items were removed.

Lastly, experts were asked to evaluate the following items with a 5-point Likert-type scale (from "strongly disagree" to "strongly agree"): (a) MMALA can support HEIs in LA adoption and guide them to a more mature use of LA, (b) an HEI can obtain benefits using MMALA, and (c) MMALA is a comprehensive guide to supporting LA adoption and its progress. We used statistical analysis to analyze their responses to these items, which are shown below.

The construct validity of this assessment was performed with the measure of Cronbach's alpha reliability, which was equal to 0.865. It is considered good (Pedhazur & Schmelkin, 2013), with a 95% interval from 0.821 to 0.908. This means that these questions were formulated appropriately. The proportions of agreement (i.e., the opinions of the types agree and strongly agree) for each sentence (a), (b), and (c) were 92.3%, 76.9%, and 92.3%, respectively. The Cochran test (Kloke & Mckean, 2015) compares these proportions, which represent dependent samples (since the same individual answers the three questions), and it had a p-value equal to 0.135. This means that there was no significant difference in population proportions (i.e., there is an agreement for all items analyzed). Table 4 summarizes this information.

Table 4. Agreement ratio, Cronbach's alpha and its 75% interval, and Cochran's test.

Sentence	Agreement ratio (agree + strongly agree)	Cronbach's alpha	Confidence interval	Cochran's test (p-value)
(a)	92.3%			
(b)	76.9%	0.865	0.821 to 0.908	0.135
(c)	92.3%			

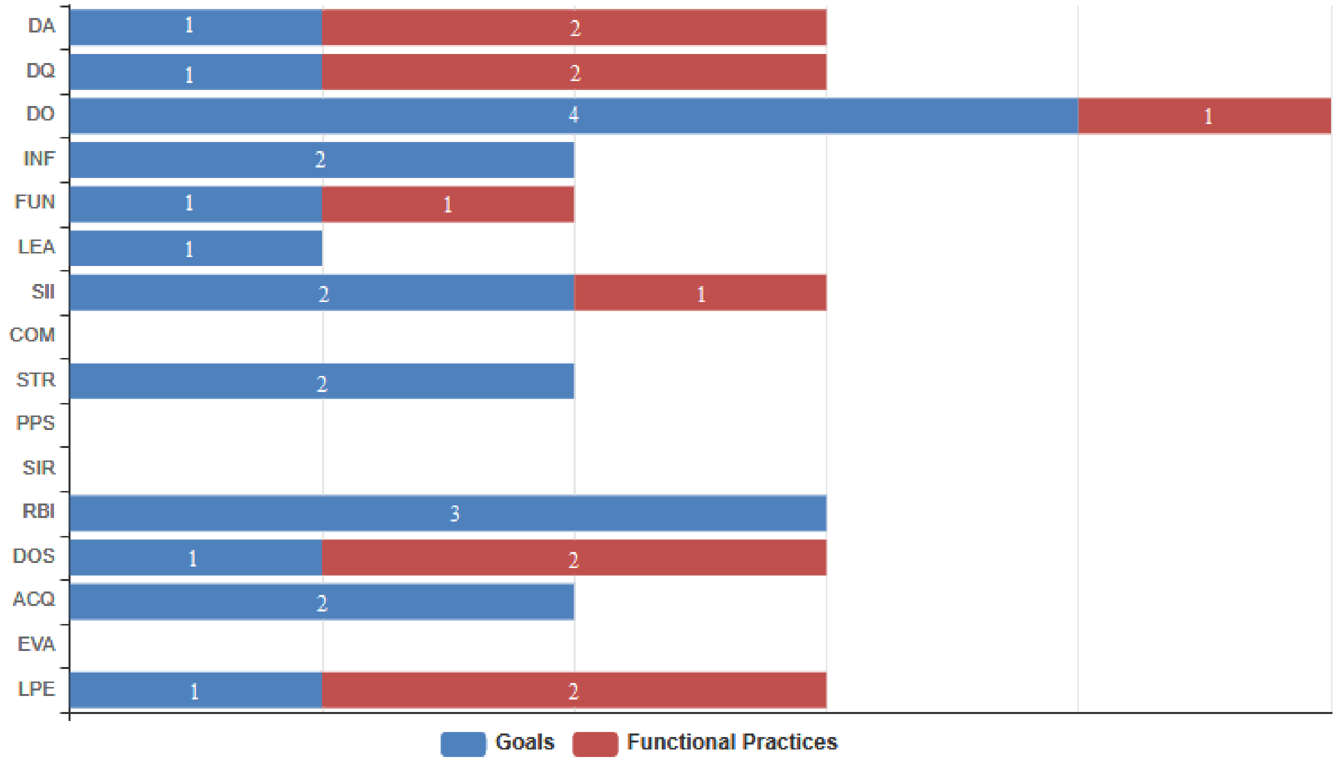

Figure 5. Number of suggestions for inclusion of new goals or functional practices.

Then, we verified in which of the questions the null hypothesis was rejected:

- H_0: Experts do not agree with sentences (a), (b), and (c).
- H_1: Experts agree with sentences (a), (b), and (c).

The agreement with all items was performed with the proportions test. It presented a sample value equal to 87.2%. From the *p*-value (0.7488), it was possible to reject the null hypothesis. So, there was statistical evidence that for every 10 experts, nine agreed with items (a), (b), and (c) about MMALA.

- Decision making—In this step, decisions were made based on the aggregated opinion. MMALA underwent some changes to address the experts' suggestions, that is, updates in the items that did not reach a consensus. In this phase, those items for which the experts had not reached a consensus were analyzed and changed to address the criticisms they made. This process is illustrated in Table 5. For instance, in the first line of Table 5, the purpose of data acquisition (DA) was considered "unclear" and "its second part should be removed." Then, a new version of the item was written to attend to the experts' suggestions.

  The experts also suggested adding other items (goals and functional practices) considered missing in the model. Regarding the goals, suggestions were included in the model by adding a new goal or adapting existing goals. The expert's opinions were addressed if they fit with the purpose and scope of MMALA. Table 6 details the items included in MMALA.

  Some suggestions made by the experts were not addressed, and the reasons were as follows: (a) the suggestion was related to items already available in MMALA (located in other process areas), such as the adoption of data standardization for content interoperability; (b) it was related to specific actions that need to be defined by the institution when carrying out the model, such as practical guidance for educators on how to interpret data; and (c) it referred to topics outside the scope of MMALA, such as other activities related to data management (harmonization, transformation, processing), and it is not within the scope of MMALA to cover all activities related to data management; for data management, it is recommended to consult the DMM.

4.2.2 Discussion

Given the results obtained from the experts' evaluation, it is possible to conclude that MMALA can be considered consistent. That is, the description of the model elements (purpose, objectives, and functional practices) can be regarded as coherent in

Table 5. Suggestions for updating MMALA items.

Item/ process area	Item description	Synthesis of expert opinion	The definitive version of the item
Purpose/ DA	• To obtain data about students' and instructors' actions, supporting the expansion of the data sources available for analysis	• The second part of this purpose was not clear, and it should be removed. Also, data acquisition should not be limited to students' and instructors' actions.	• To obtain useful data about students' and instructors' actions
Goal/DQ	• 2nd goal: To define people responsible for data quality • 4th goal: To perform actions aimed at improving the quality of stored data in order to minimize analysis accuracy problems	• This goal was not clear. And the task which people are responsible for should be better defined. • This goal was not clear. Besides that, data quality should be verified in all the phases (not only in storage).	• To define people responsible for data quality processes • To perform actions aimed at improving the quality of data in order to minimize accuracy problems
Goal/COM	• 2nd goal: To present the LA institutional program, emphasizing its objectives and results • 3rd goal: To give and receive feedback in order to improve both the projects and policies related to ethics and privacy	• This goal should include the communication of objectives, implications, and limitations of LA projects. • This goal should identify to whom feedback will be given and from whom it will be received.	• To continuously present the LA institutional program to stakeholders by emphasizing its objectives, implications, limitations, and results • To give and receive feedback from the institution in order to improve both the projects and policies related to ethics and privacy

each process area. Only a few updates were necessary, such as the update on the purpose of the data acquisition process area, and even in some goals of the data quality and communication process areas. We also included three new goals and four new functional practices, as well as adapting three goals to meet the specialists' suggestions.

Furthermore, there were suggestions for the inclusion of goals and functional practices in the model. In this case, there were several suggestions for including items that already existed in the model (in related process areas). This difficulty may have been caused by the lack of information on related process areas in the model received by the experts. Therefore, this section is considered necessary for the understanding of the model. Finally, regarding the exclusion of items from the model, the experts also agreed that it would be unnecessary to remove any items from the model, reinforcing the importance of the items already defined for the model.

Previous results of MMALA's comprehensiveness were reinforced by the results obtained from the experts' evaluation, allowing us to conclude that MMALA can be considered comprehensive to support institutions in the challenges related to the adoption of LA. This information was also reinforced by the 92.3% agreement rate of the experts on the comprehensiveness of MMALA.

Regarding problem adequacy, MMALA was also positively evaluated by experts. A total of 92.3% agreed that MMALA could support HEIs in adopting LA and guide them toward more mature use of LA, and 76.9% agreed that an HEI could benefit from using MMALA. Thus, we can conclude that MMALA can be considered adequate to address the problem of adopting LA.

Finally, a significant change was made to the model to meet the experts' suggestion for changing the category's name from "Administration and Training" to "Governance and Training." This decision was taken since the functional practices aim to

Table 6. Accepted suggestions for including items in MMALA.

Item/ process area	Type	Synthesis of expert opinion
Goal/ INF	Inclusion	To include the establishment of a protocol for interconnecting systems
Goal/ LEA	Inclusion	To include the preparation of strategic planning
Goal/ SII	Inclusion	To define stakeholders' roles
Goal/ STR	Adaptation	To include training for the development and maintenance of tools
Goal/ RBI	Adaptation	To include the monitoring of pedagogical interventions
Goal/ ACQ	Adaptation	To include the identification and execution of pedagogical adaptations in the institution when acquiring tools for LA
F. Practice/ INF	Inclusion	To include practices to recommend the use of APIs for data use and the monitoring of this use
F. Practice/ SII	Inclusion	To include the definition of stakeholders' roles and responsibilities
F. Practice/ STR	Inclusion	To include practices to guide the training of researchers and the information technology team to develop LA solutions
F. Practice/ DOS	Inclusion	To include practices of maintaining and retirement of LA tools

create general guidance, which is more related to governance than administration (ABNT NBR ISO/IEC 38500, 2009). After going through the mentioned changes, we were able to obtain the final version of MMALA[3].

It is important to highlight that this evaluation faces some threats to validity. They are listed as follows, along with measures taken to minimize them:

- Absence of related processes areas and work products—As mentioned previously, to make the evaluation process possible by the experts in a viable period of time (in this case, lasting approximately 1 hour), the model sent to experts did not have the related process areas or work products. The absence of this information may have made it difficult for the experts to understand the model, and thus possibly interfered with the evaluation result.
- Duration of the evaluation—Despite efforts to shorten the evaluation time, the duration of the process was around 1 hour, so participants could feel tired or bored during the assessment. To minimize the problem, we made available the option to "finish later" in the questionnaire, which allowed the evaluators to complete the procedure when they considered it most convenient.

5. Pilot—Maturity Level of Brazilian HEIs Using MMALA

The last study reported in this paper aimed to identify the level of maturity of three Brazilian HEIs. To reach this goal, we developed a questionnaire[4] and administered it using Google Forms. This questionnaire was based on MMALA's goals[5], which defined a set of activities to support LA adoption in each process area. To illustrate how we turned MMALA goals into a questionnaire, we can use the example of the data acquisition process area, as follows. The first goal of this area is "to identify and to provide access to data sources that can be used for data analysis in LA, expanding the range of possible analysis." In the questionnaire, this activity was reported as "Identify and provide access to data sources," and respondents could mark one of the following options about it: (a) their institution does not perform the activity in LA projects; (b) it is performed in few projects and mainly by personal initiative of researchers; (c) it is performed by each project in different ways; (d) it is performed uniformly by all the projects at the institution; and (e) their institution has defined policies and/or processes to perform the activity. Each response refers to a level of MMALA, from level 0 (which means that the institution does not perform the activity) to level 4 (i.e.,, the fourth level of maturity of MMALA). These activities were supposed to support institutions in reaching these goals.

[3]MMALA is available at https://bit.ly/3DRRP0J.
[4]This questionnaire is available at https://bit.ly/3KclMN5.
[5]See MMALA, available at https://bit.ly/3DRRP0J.

5.1 Evaluation

We sent the questionnaire to three individuals with leadership positions in Brazilian universities. All three institutions are located in the state of Pernambuco, Brazil. Institution (a) is a public institution, founded in 1912, and currently with 17,000 students and 1,200 faculty members in different locations across the state; (b) is also a public institution, founded 58 years ago, and currently with 15,000 students and 1,066 faculty members, distributed in different locations across the state; and (c) is a private institution that became an HEI just 5 years ago. This institution is located only in the capital (Recife), and it has 1,600 students. The results presented here represent a self-evaluation of these institutions. The sample size is reduced since it is an initial study about the application of MMALA. We intend to expand it in the future. Figure 6 shows the results of this evaluation, which reports three different scenarios in the maturity assessment.

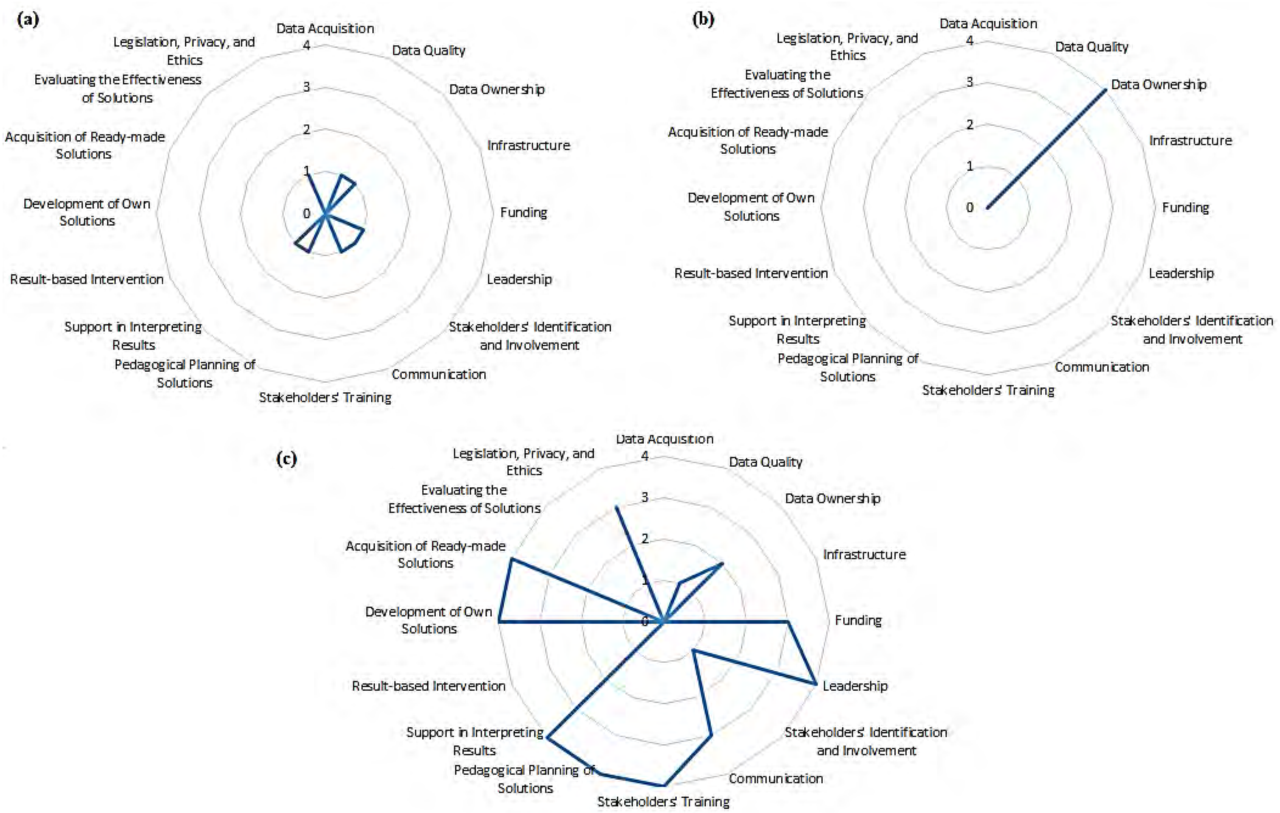

Figure 6. Results for the maturity level assessment of three Brazilian HEIs.

Each chart in Figure 6 includes all 16 process areas of MMALA. The blue line indicates the maturity level of the institution in this specific area (from 0 to 4). The first institution (a) reached the first level of maturity in LA in eight process areas: legislation, privacy, and ethics; data quality; data ownership; leadership; stakeholders' identification and involvement; communication; pedagogical planning of solutions; and support in interpreting results. In all the other process areas, the institution had not reached any level of maturity. The second HEI (b) had reached the fourth level of maturity in the process area of data ownership. However, in all the other process areas, it had not reached any level of maturity. The last institution (c) demonstrated a higher level of maturity than the others. For example, in areas such as support in interpreting results, pedagogical planning of solutions, development of own solutions, and acquisition of ready-made solutions, it had reached the highest level of maturity. However, in areas such as data acquisition, result-based intervention, and evaluating the effectiveness of solutions, it had not reached the first level of maturity.

5.2 Discussion

The results obtained from the evaluation of the maturity in LA in three Brazilian HEIs showed a considerable difference in their institutional contexts of LA adoption. It is possible to conclude that institution (a) was most advanced in the adoption of LA. The institution was working in important areas for LA adoption; however, all these activities were performed mainly through individual initiatives. Therefore, it is important to involve other stakeholders in the adoption of LA, aiming to expand the results. Furthermore, with that same objective, it is important to consider other areas, such as funding and infrastructure.

Institution (b), in turn, did not demonstrate much maturity in LA adoption. The high level of maturity in data ownership could be a result of the General Law for the Protection of Personal Data (LGPD—Law No. 13.853, of 8 July 2019), which recently came into force in Brazil. However, that may not be related to LA initiatives, even though it could be a very important enabler for adoption.

Lastly, institution (c) had an entirely different scenario. It was working in many areas of LA adoption. It defined processes and/or policies in many of them and, therefore, reached the highest maturity level in these areas. Some other areas required further attention if they wanted to attain institutional adoption of LA, such as stakeholders' identification and involvement and result-based intervention.

The results of this self-evaluation can support institutions in identifying the areas that need more attention and investment to reach a successful adoption of LA. Therefore, institutions can draw up a plan to improve their level of maturity using MMALA. MMALA can also support them in identifying areas that are supposed to work together in the section called "Related Process Areas."

Since this sample is limited to three HEIs, it is not possible to generalize the results and provide an overview about Brazilian institutions. However, these results show that it is possible to assess and classify institutions concerning the maturity level in LA adoption using MMALA. Then, it will be possible to suggest to them a path to evolve in this adoption.

It is worth mentioning as a limitation of this research that the respondents may not have been fully aware of all the initiatives (mainly individual) related to LA in the institution. To minimize this limitation, the respondents were instructed to look for people from other areas of the institution in order to provide the most accurate information. In institution (a) the respondent was an advisor responsible for the analysis of educational data; in (b), a deputy coordinator of the post-graduate degree in computer engineering who works on the analysis of educational data; and in (c) a professor and researcher in educational technologies.

6. Conclusions and Future Work

This paper presents the development and assessment of MMALA, an MM to support HEIs in reaching higher maturity levels in LA, aiming at an institutional, planned, and systematic adoption. The development of MMALA followed a rigorous methodology by Becker and colleagues (2009). This work summarizes all the main activities performed to develop MMALA, describes the model in detail, and explains MMALA's evaluation results and its application in three Brazilian HEIs. The results of MMALA's evaluation showed that MMALA is comprehensive, consistent, and adequate to support LA adoption.

The use of MMALA can help institutions understand the areas on which they should focus when adopting LA—even those institutions that have already started using LA. Furthermore, they can assess their own maturity level and use MMALA as a guide to plan the next steps and reach higher levels of maturity in LA. As a result, LA initiatives can reach a more significant number of students, instructors, and professionals. In addition, the use of LA can be more lasting, and the benefits of its use can be extended to the entire institution.

It is worth noting that, since an MM does not define processes or policies (Hanaei & Rashid, 2014), these artifacts could be developed using the SHEILA framework (Tsai et al., 2018), as recommended in the fourth level of maturity of MMALA. Similarly, MMALA can be used together with the instruments of LALA (Pérez-Sanagustín et al., 2019) to identify an institution's current and desired state, support it in the adoption of tools and the ethical considerations in this process, and share the results of adoption with the community. The use of LALA could happen at different levels of maturity, encompassing any number of students and teachers. It is also important to highlight that reaching the fourth level of maturity is not mandatory or the best scenario for all institutions. Each institution should set its goals and define the most suitable maturity level to be achieved, considering its own scenario. The fourth level of maturity can be too costly or unnecessary in some cases.

Despite the contributions achieved with the development of this work, it is necessary to highlight that the study has some limitations. First, the literature review brought several benefits to this research, from deepening the understanding of LA to the identification of critical areas for the adoption of LA, which were the basis for the initial composition of the MMALA. However, the results of this literature review can be considered limited, since only two sources of information were used (ACM Digital Library and IEEEXplore). The decision to use only two sources was due to the limitation of results found, since the articles included discussed the practical application of LA and its results. However, discussions of the challenges encountered by these researchers in the implementation of LA were insufficient or non-existent in most of the primary studies included. Therefore, it was understood that there would be greater effectiveness in acquiring information about these challenges by manually searching for articles on the adoption of LA, starting from those produced by the LALA and SHEILA projects (and not expanding the sources of information for the search of this literature review). This change in strategy proved to be effective, since the model was considered comprehensive after carrying out two evaluations. Second, the application of the proposed model in a real environment could provide important information for its evaluation, especially with regard to the adequacy of MMALA to the problem. Therefore, the absence of the mentioned study can be considered a limitation of this work. To minimize this problem, we sought to evaluate the model in two stages, the last with the participation of renowned experts in LA.

As future work, we intend to apply the proposed MM in HEIs. For this, it is necessary to develop an implementation guide for MMALA. In addition, a diagnostic process can be used to select the process areas most suitable for the implementation of the model in each institution. The application of MMALA will make it possible to identify possible omissions in the model and difficulties in its use. Also, it will allow for reporting the benefits and progress that the institutions observe by using it. It is necessary to apply MMALA in different institutions, with varied scenarios, in order to identify the contexts in which MMALA can bring more significant benefits and, as a consequence of its use, improve the model in order to make it increasingly useful for the purpose of supporting HEIs in adopting LA.

Finally, to improve MMALA, it is also recommended to create an evaluation method that supports a more accurate identification of the maturity level of HEIs that helps in monitoring the evolution of these institutions. Also, we intend to include the metrics that support the institution to quantify whether the objectives for the execution of each practice were reached. The existence of work products is an indication that the institution has carried out the practices properly; however, the presence of metrics allows the assessment of this issue in a quantitative way and with greater precision.

Declaration of Conflicting Interest

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