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Intelligent Prioritization Applied in Asset Management: A Systematic Literature Review

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Abstract: There is increasing interest in using approaches that combine multi-criteria decision analysis methods with artificial intelligence technologies to improve the analysis of alternatives and decision-making. The literature presents many studies that apply these approaches in several different areas. However, there are still many gaps in understanding how intelligent prioritization is applied in asset management. Therefore, the objective of this study is to investigate and improve the understanding of this research field. Thus, we conducted a Systematic Literature Review (SLR) to examine the state of the art of intelligent prioritizationin asset management. A predefined protocol guided this review. It was searched for studies in 5 electronic databases and defined 10 research questions. The databases returned 7.843 studies. To data extraction and analysis were included 82 studies. An overview showed the year of publication, application context, development location, source and type of publication of the included studies. We answered the 10 questions of this SLR and their results were analyzed and discussed. Thus, this work presents some promising, relevant and little explored research opportunities in the study area.

INTRODUCTION

Over the years, the need to evolve asset maintenance has been established because this is no longer just a task to repair what has broken; it has become an important activity within anorganization's asset management process[1]. Consequently, asset management has been gaining more and more attention worldwide due to its various coordinated activities that involve managers, assets and generate benefits for institutions.

However, what can be understood by asset? According to the technical standard, ISO-55000[2], something with addedvalue for an organization is considered an asset. For example, actions, patents, industrial machines, furniture, vehicles, office supplies and products. The International Organizationfor Standardization (ISO) states that it is difficult to standardize the added value of an asset because it changes according to the organization's context and the interests of the stakeholders.

Physical assets are the so-called tangible, concrete; that is, they are those that can be touched which is perceived by touch[3]. The challenges associated with managing these assets go beyond cost reduction, repairs and replacements[4]. Therefore, the management of physical assets needs tobe directed in an organized, planned and systematic way to preserve the assets, extend their useful life, predict possible operational failures, control their life cycle, estimate their costs and so on[5].

Organizations realized the need to make decisions with characteristics more directed towards strategic planning. These actions have a significant influence on the success or failure of institutions[1]. For[6], there is a lack of structured and systematic approaches that support the decision-making process, facilitating the planning and execution of asset management.

Spitzer[7] states that it is prevalent for leaders and managers to make wrong decisions that are likely to harm the business; this occurs because most decisions are based only on theleader's or manager's intuition, experiences and opinions. Moreover, they do not understand the problem in many situations due to the vast number of objective and subjective aspects that interfere with the decision-making process. Identifying the factors that most influence the business and the most relevant elements is not a simple task. Therefore, organization and planning are necessary to carry it out satisfactorily[8].

Given this situation, the need to use Multi-Criteria Decision Support (MCDM) methods is visible to support selecting the best alternative according to the established criteria. Many works in the literature have used methods MCDM combined with Artificial Intelligence (AI) technologies toimprove the analysis of alternatives and decision making such as[9-12]. However, there are still manygaps in understanding how intelligent prioritization is applied in asset management, especially physical assets.

In this context, we diagnose state-of-the-art to build aknowledge base on this field of research. Therefore, as a methodological procedure it was used the Systematic Literature Review (SLR) defined by[13-16]. It was possible to identify, evaluate and synthesize the studies, answering research questions about how intelligent prioritization is applied in asset management. This type of procedure has already been used in different studies related to asset management such as intelligent asset management[17].

MATERIALS AND METHODS

This is a SLR whose purpose is to provide more information about intelligent prioritization in asset management. Arigorous search process was adopted to conduct this review because this is a factor that distinguishes an SLR from other types of reviews. The guidelines broadly defined by[13] and its updates[14, 15] and their updates[16] were followed. The process of searching, selecting and analyzing the studies was carried out in five distinct steps:

Step 1: (Preliminary selection): Definition of the main and secondary research questions, choice of research sources, execution of the search string and search in the databases.

Step 2: (First Selection): Reading the titles, keywords and abstracts. Studies that did not fit the context of this SLR were excluded, considering the inclusion and exclusion criteria.

Step 3: (Second Selection): Reading the introduction and conclusion. In this step, studies that did not fit the context of this SLR were also excluded, considering the inclusion and exclusion criteria.

Step 4: (Final Selection): Full reading of potentially relevant studies, considering the quality criteria. Works that did not reach the minimum grade were excluded.

Step 5: (Data Extraction and Discussion of Results): Verification of relevant information from each primary study selected in the previous steps for analysis and discussion of the results obtained. Figure 1 presents all the steps of this systematic review, with a brief description of the activities performed in each one of them, all the digital libraries that were used with the number of studies returned in each library, the number of studies that were included and excluded at each step, as well as the reason for removing the studies at each step.

This SLR seeks to diagnosis how intelligent prioritization happens in asset management. Thus, this SLR intends to build a knowledge base to answer the main research question: How is intelligent prioritization applied in asset management? Based on this central question, ten other secondary research questions were defined with their respective descriptions and motivations.

Research Questions:

- QP1: Which multi-criteria decision support methods are used intelligently in asset management?
- QP2: Which artificial intelligence technologies are used with prioritization in asset management?
- QP3: Which infrastructure categories use asset management with intelligent prioritization?
- QP4: Which asset management technical competency areas use intelligent prioritization?
- QP5: What types of contributions are proposed by the studies to solve asset management problems through intelligent prioritization?
- QP6: What tools are used to support intelligent prioritization in asset management?
- QP7: Which steps of the contributions proposed by the studies are mentioned?
- QP8: What empirical methods are used to analyze the contributions proposed by the studies?
- QP9: Which organizations supported the contributions produced by the studies?
- QP10: How did the organizations support the contributions produced by the studies?

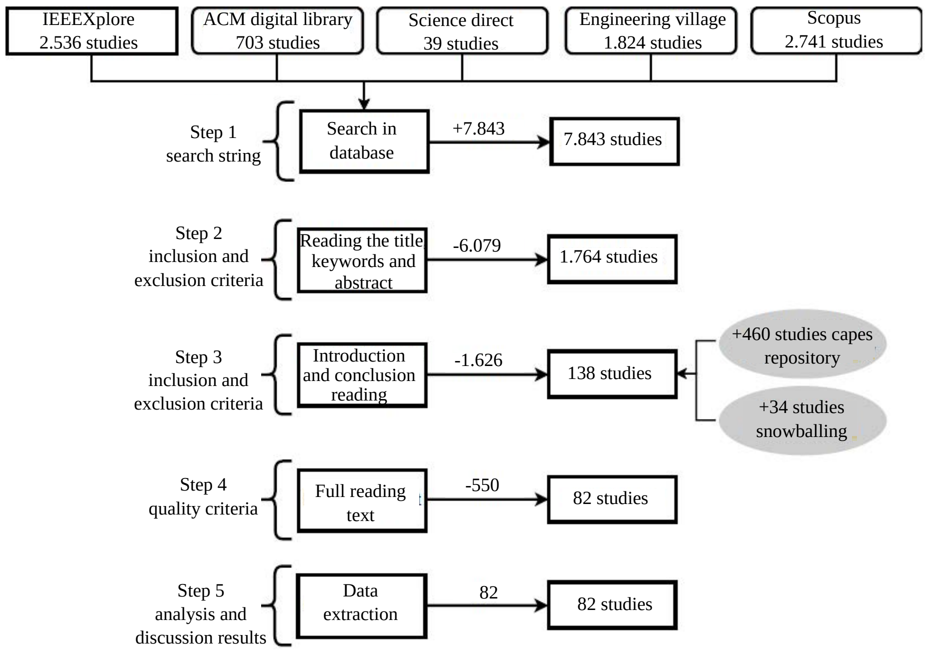

Fig. 1: Overview of systematic literature review research methodology

Digital libraries: The digital libraries used in this SLR were selected because they are highly visible repositories in the academic world with many studies published in journals, conferences, symposium and workshops. Furthermore, they proved to be quite relevant to the research. In all, five search sources were used for this research, IEEEXplore, ACM Digital library, Science Direct, Scopus, Engineering Village. In order to bring greater completeness to the results, we chose to carry out an analysis of the references cited in the studies included so far, that is, snowballing. Since, most studies have been developed in Brazil, we also decided to include another digital library, the Capes dissertation and theses repository. As most studies had Brazil as a place of development, therefore, a strategy to deepen knowledge in this field of research would be to investigate the publication of dissertations and theses from universities in that country.

Search string: The search string was designed to cover as many synonyms and variations as possible for the expressions "artificial intelligence", "prioritization", "asset management" and "approach". We chose to include the first three terms to cover the 3 areas that are being covered in this SLR and the last term was included due to the search for some form of structured procedure for applying intelligent prioritization in asset management. Therefore, a search string was: (intellig* OR algorit* OR smart) AND (priorit* OR "decision making") AND ("asset management" OR "resource management" OR "equipment management" OR "network management") AND (approach OR technique OR method* OR model* OR guide).

In order for this study to be reapplied in the future, some points must be improved and others must be taken in to account to improve the steps of this SLR and refine the results obtained. In order to better organize this the threats to validity were classified into Internal, external, construction and completion as presented by[18-21].

Construct validity: There is a possibility that the search string does not have all the necessary terms to return the desired studies. In order to minimize this threat, several variations of the main terms of this SLR were used. For the first concept, prioritization, the root "priori" and the term "decision making" were used to ensure all selected studies were related to decision-making approaches. For the second, intelligent concept, the roots "intellig" and "algorit" along with the term "smart" were used to ensure that as many synonyms were returned. Finally, for the third concept, asset management, the terms "asset management", "resource management" and "equipment management" are used to ensure high coverage of potentially relevant studies. It is also possible that the secondary research questions failed to fully answer the main research question of this SLR (How is intelligent prioritization applied in asset management?). To mitigate this threat, 10 widely varied sub-research questions have been developed covering different aspects of intelligent prioritization in the specific context of asset management.

All 10 research questions have been answered and their results are presented, analyzed and discussed throughout this SLR. Furthermore, to analyze whether the returned studies were answering the research questions elaborated, it was decided to carry out preliminary tests in the databases. Coverage and representativeness of the retrieved studies were tested including automatic and semi-automatic searches in search engines.

Internal validity: Some studies relevant to the theme of this SLR may have been wrongly excluded because the number of returned studies was huge which made the execution of the review steps a time-consuming process. Added to this, the theme of this SLR encompasses three distinct areas (prioritization, AI and asset management) that are not the areas of expertise of any of the participants. To minimize possible errors in selecting studies and data extraction, an effort was needed to understand the intersection between these areas. For this, several pieces of research were carried out through books and scientific articles as well as meetings with experts (mainly in the area of asset management) to develop prior knowledge about the topic addressed in SLR. This entire process took place before starting the review and during its preparation and execution. In addition, the stage of study selection, data extraction and inclusion, exclusion and quality criteria were carefully planned and discussed by the participants of this SLR iteratively and collaboratively, providing several exchanges of ideas so that all conflicts were discussed and resolved, minimizing the risk of excluding relevant studies. In this way, an attempt was made to mitigate the threats arising from the personal bias of each participant. It is also important to mention that the participant responsible for the preparation and execution of this SLR is a graduate student at the doctoral level with previous experience in SLR and the other 2 participants responsible for the analysis and supervision of the stages of the review are professors researchers from federal universities with extensive academic careers, extensive experience in various segments of computer science and areas for purposes, in addition to several publications including mapping and SLR.

External validity: The studies of this SLR include scientific articles, dissertations and theses that use prioritization intelligently, that is, employing some SLR technology to perform the prioritization. Furthermore, studies should only cover intelligent prioritization that is applied explicitly in asset management. All studies that were not at the intersection of the 3 areas (prioritization, AI and asset management) were excludedfrom this SLR, that is, studies that encompassed prioritization in asset management without AI, intelligent prioritization outside of asset management and application of AI in asset management without prioritization.

Conclusion validity: This SLR followed the guidelines broadly defined by[13] and its updates[14, 15] and its updates[16]. The studies' rigorous and systematic search, selection and analysis process were applied, totaling 5 distinct steps that range from selection in search engines to extraction and discussion of the results obtained. Figure 1 illustrates a summary of all the steps of this SLR.

RESULTS AND DISCUSSION

This section presents the consolidated result of the extraction and analysis of data from all studies (scientific articles, dissertations and theses) selected throughout the steps of this SLR and the answer to each of the 10 secondary research questions. The complete list of all selected works with their respective quality scores can be seen in Appendix A. To better recognize the studies of this SLR, it was decided to compose an identifier using a letter followed by a number. The letter 's' was attributed to studies of the scientific article type. For studies of the dissertation type, the letter 'd' was assigned and for theses, the letter 't' was assigned.

RQ1: What multi-criteria decision support methods are used intelligently in asset management? The results of this research question are essential to identify the different MCDM methods used together with some intelligent mechanisms in asset management. To answer it, it was first necessary to identify and analyze the selected studies to recognize if and which of them specified some MCDM method(s).

The results shows a summary of studies that specify the method(s) MCDM used intelligently in asset management. Thus, we verify that most studies do not specify the method(s) MCDM they use (78.05%; 64 studies), leaving a small number of studies that specify (21.95%; 18 studies).

Few studies were identified that specify the MCDM method(s) used intelligently in asset management (only 18 studies). From them, it was possible to identify the name of these MCDM methods and their respective characteristics. It is important to note that in this SLR the categorization of these methods was based on the works of[22, 23, 19, 24].

Therefore, with the results present the MCDM method that stands out the most is the AHP (83.33%;15 studies); TOPSIS (33.33%; 6 studies); PROMETHEE (11.11%; 2 studies) and ELECTRE (5.56%; 1 study).

The results of this research question show that a small number of MCDM methods were identified (only 4) that are used and supported intelligently within the asset management. It is believed that this occurs mainly due to two situations: first because prioritization is often performed in an ad-hoc way, that is, without a well-defined and systematic process, consequently without the use of a specific MCDM method because several researchers in the field of asset management do not know the prioritization area to be able to identify and classify which MCDM method is being used in their study.

Among the identified MCDM methods, AHP is the most frequently addressed by the studies with 83.33%. This result was expected, since, AHP is widely cited, referenced, exemplified and used in MCDA and several other fields of science due to its proven effectiveness in supporting and justifying the chosen alternatives.

TOPSIS also has a representation in the included studies with 33.33%. This result is also interesting, as it shows that most studies used analysis and logical reasoning to select the ideal alternative. It is essential to highlight that, counting only once the common studies, the AHP and TOPSIS methods correspond to more than 88% of all the studies. Wich were included and that specifies the MCDM method(s) indicating an interest in using these methods not only for making choices, selecting alternatives and ordering the execution of tasks in asset management but also for performing analyses, reasoning and planning for future activities.

There is also interest in using the PROMETHEE method in asset management. This result may indicate that the studies aimed to apply a multi-criteria decision support method in which the criterion can be indicated by the decision-maker according to the context or established fixedly by the technique used. It is worth noting that this MCDM method is part of the French school; that is, this type of method does not use the concept of compensatory result which means that a positive result cannot compensate for another negative result.

On the other hand, the use of the ELECTRE method in asset management is not as expressive, around 5%, compared to other methods. This result may indicate that researchers in the asset management area are less concerned with developing research using MCDM methods that are rarely cited in the literature and with few published results compared to other methods already consolidated.

Among the 18 studies included in this SLR and that specify the MCDM methods, none address all four identified methods but some studies addressed two methods such as s52 with AHP and TOPSIS and d22 with AHP and ELECTRE. Another interesting point is that the AHP and TOPSIS methods have five studies in common: t33, s52, s67, s79 and s82.

Given the potential of using MCDM methods in the context of asset management, the results of this research question suggest that the use of prioritization to support asset management is an area that is on the rise but needs to be further investigated. As several MCDM methods well consolidated in the literature were not included in the results such as VIKOR, ANP (Analytic Network Process method) and MAUT (Multi-Attribute Ultility Theory), according to[23, 24].

RQ2: What artificial intelligence technologies are used with prioritization in asset management? This research question aimed to identify which intelligent mechanisms are employed and prioritization in asset management. It is important to note that in this SLR the categorization of AI technologies was based on the works of[25-27].

According to the results found the AI technology that stands out the most is the Genetic Algorithm (37.80%; 31 studies). Subsequently, Fuzzy System (30.49%; 25 studies). Later, Evolutionary Algorithm and Artificial Neural Network (14.63%; 12 studies). Next, Swarm Intelligence and Expert System (8.54%; 7 studies). In sequence, Unsupervised Machine Learning (3.66%; 3 studies). Soon after, Distributed Artificial Intelligence (2.44%; 2 studies). Finally, Bayesian Network (1.22%; 1 study). This research question shows that a fair amount of AI technology has been identified, nine technologies used by the MCDM methods within the asset management area.

Genetic algorithm is the most frequent type of AI technology addressed by the studies, with approximately 38%. In a way, this result was already expected because the Genetic algorithm is widely used for search and optimization to find the optimal solution or as close as possible to the ideal, so that, this technology can be applied to different contexts different problems in addition to being used mainly in the domain of AI problems involving planning and communication.

Fuzzy system is also an AI technology that significantly represents the included studies, around 30%. This result is also interesting, as it shows that most studies used logical reasoning with a certain degree of certainty to select the best alternative.

It is essential to highlight that, counting only once the common studies, together with these technologies, Genetic algorithms and fuzzy systems, correspond to just over 68% of all included studies indicating a commitment of researchers to use AI technologies. Thus, it is possible to enhance the search for the alternative that best suits the context of the problem and provide the development of reasoning based on uncertain data to infer new information.

The AI technologies, evolutionary algorithm and artificial neural network also significantly represent the included studies with just under 15% each. It is worth mentioning that evolutionary algorithm encompasses studies that use different implementations to support intelligent prioritization such as improving the strength pare to evolutionary algorithm (t29, t30) and non-dominated sorting Genetic algorithm II (t11, s74). Similarly with artificial neural network with back-propagation artificial neural network (s66), for example.

Swarm intelligence also has a representation in the included studies with 8.54%. Interestingly, researchers seek to analyze the organization and behavior of swarms or colonies of social living organisms to prioritize asset management. It is also worth considering that, like evolutionary algorithm and artificial neural network, swarm intelligence also includes studies with different implementations such as ant colony algorithm (s62, s63 and s64) and expert system (s50, s54 and s72).

There is also interest in using AI, expert system technology to support intelligent prioritization in the context of asset management. The use of an expert system was already expected because the main characteristic of this AI technology is to determine rules for specific domains, apply and execute them through the use of logic that helps in solving problems and inference of possible solutions.

The Swarm intelligence and expert system technologies account for approximately 14% of all studies included in this SLR. This result may indicate that the studies aimed to apply multi-objective AI technologies to solve selection/ordering problems and infer possible solutions facilitating decision-making.

On the other hand, the use of AI unsupervised machine learning, distributed artificial intelligence and Bayesian network technologies is not so expressive to perform prioritization in asset management, considering that joining all 3 technologies, the result obtained was about 7.32% of the total included studies, removing the shared ones. This result points to a lack in the development of research that uses a greater variety of AI technologies to perform the prioritization intelligently, especially concerning pattern recognition, grouping or deep learning technologies such as k-Means and k-Nearest neighbors algorithm, among others.

Among the studies that were included, some showed 2 or more AI technologies in common such as t11 and s74 with Genetic algorithm, fuzzy system and evolutionary algorithm, t5, s60 and s65 with fuzzy system and artificial neural network, t29, t30, s50 with Genetic algorithm and evolutionary algorithm, s44, s45, s56 with Genetic algorithm and fuzzy system e, d34 with Genetic algorithm and artificial neural network.

Considering all the ability to use AI technologies to perform prioritization in the context of asset management, the results obtained indicate that more investment and dedication is needed in this area. Many studies have focused on some technologies with similar characteristics about the paradigm and problem domain[27], failing to cover some relevant AI technologies or even covering little such as for example, deep learning, natural language processing, unsupervised machine learning and support vector machine.

RQ3: Which infrastructure categories use intelligent prioritization asset management? This research question intended to identify which are the infrastructure sectors of a country where asset management with intelligent prioritization is applied. It is worth noting that the classification of these categories was based on the works of[28, 29].

According to the results found the infrastructure category that stands out the most is energy (69.51%; 57 studies). Subsequently, communication (15.85%; 13 studies). In sequence, transport (13.41%; 11 studies). Finally, industry (2.44%; 2 studies).

Although, the variety of infrastructure categories specified in the studies was small (only 4 categories), based on them, it was possible to identify in the included studies which sub-categories use asset management with intelligent prioritization. It is important to note that in this SLR the classification of these subcategories was also based on the works of[28, 29].

The results found expose the electric energy network subcategory of the energy category is the one that stands out the most (70.18%; 40 studies). Subsequently, the Pipeline network subcategory of the energy category (29.82%; 17 studies). Next, the IT Infrastructure network subcategory of the communication category (76.92%; 10 studies). In sequence, the road transport subcategory of the transport category (45.45%; 5 studies). Soon after, the rail transport subcategory of the transport category (36.36%; 4 studies) and the telecommunications network subcategory of the communication category (23.08%; 3 studies). Finally, the maritime and air transport subcategories both from the transport category (9.09%; 1 study) and (9.09%; 1 study), respectively.

This research question shows that a minimal diversity (only 4) of infrastructure categories that use asset management with intelligent prioritization was identified. We believed that this is because many specialists who work in the economic sectors of society do not yet know the benefits that prioritization provides, mainly when it is associated with some AI technology. Although few categories were identified, it was also possible to recognize subcategories in the included studies that brought relevant information to this SLR. All these results are discussed after.

The energy category is most frequently addressed by studies with almost 70%. This result was already expected as this category is directly linked to the generation, transmission and distribution of various types of energy that supply a region or country[29]. In addition, the subcategories identified in the studies included are electric power network and pipeline network, that is, two types of networks essential for conducting modern life[30]. Due to this, several pieces of research are developed to mitigate the gaps in this infrastructure category increasingly.

Furthermore, hydroelectric power plants are one of the primary sources of electricity-generating energy in the world, corresponding to approximately 20%[31]. In Brazil, a country where many studies of this SLR were developed, the scenario is quite similar. In this country, the electricity generated by hydroelectric plants represents around 70%[31]. It is important to note that there is a strong tendency in severalcountries to explore other renewable energy sources to generate electricity such as wind, solar, geothermal, among others[32].

Similarly, the pipeline network also plays an important role in contemporary society by driving several different types of commodities, often flammable and dangerous[32]. By analyzing the type of product that the pipeline networks displace, it was found that water is the one that stands out themost (72.22%; 13 studies). Subsequently, sewage (11.11%; 2 studies) and oil and its derivatives (11.11%; 2 studies). Finally, natural gas (5.56%; 1 study). It is worth mentioning that, although, pipeline networks have much lower failure rates when compared to transport such as road or rail, unfortunately, failures still occur and sometimes the consequences are dire[33, 34]. It is believed that this is one of the factors driving research to prioritise risks and maintenance sites in this infrastructure category, according to[35-37].

The communication infrastructure category also has expression in the included studies with approximately 16%. This result is also interesting, as it shows that researchers are concerned about using prioritization intelligently in categories that provide services to the population of information transmission and data exchange. In addition, the subcategories identified in the included studies are IT infrastructure network and telecommunications network, that is, networks that have constantly evolving content and that need much research such as network selection wireless[38-40].

Right after the communication category is transport, with just over 13%. This result did not coincide with our expectations and was very negative, as this category of infrastructure is extremely important for the transport and movement of goods and people from one place to another, making the world economy busy[41]. The information generated by these results points to a great lack in the development of research in this category of infrastructure. Unfortunately, the representativeness of the industry category is not significant in the identified studies with approximately 2.4%. As in the transport category, the result in the industry category did not correspond to our expectations. This result shows that many professionals and researchers in this category of infrastructure are unaware of the advantages that are linked to intelligent prioritization in asset management. Some of these advantages can be conferred through the works of[42-45].

RQ4: Which asset management technical competency areas use intelligent prioritization? The purpose of this research question was to identify the areas of technical competence that asset management encompasses and that employ intelligent prioritization. The classification of these areas identified in the studies was defined according to[2, 46] and its updates[47].

According to the works mentioned before, asset management involves several different segments. For this reason, ISO 55 000 emphasizes that the areas of competence that make up asset management are not limited to those listed in its annex A.[46] and its updates[47] complements by citing some examples of the technical competence areas covered by asset management. Some of these areas were identified in the included studies and are discussed after.

According to the results found the area of technical competence that stands out the most is maintenance management (73.17%; 60 studies), dependability management (41.46%; 34 studies), quality management (21.95%; 18 studies), risk management (8.54%; 7 studies).

This research question shows that intelligent prioritization is used by a minimal number (only 4) of technical competence areas of asset management. Assume that this happens because many professionals in industry and academia have the stigma that prioritization is an exclusively manual, expensive and time-consuming procedure. This fact causes a great scarcity of studies in this area[48]. Despite this, there is a growing interest in evolving this area as will be analyzed and discussed after. Among the few areas of technical competence in asset management identified, maintenance management is the area with the highest frequency according to the studies included with just over 73%. This result was already expected, since, this area of competence causes a significant impact on organizations, primarily when it is performed without quality as this often causes delays in the schedule, production losses, user complaints, among others[49, 50]. It is not uncommon for organizations to be negatively affected with financial losses and indirect costs, when they need to carryout maintenance operations on their physical assets such as installation or replacement, especially when these assets need to be temporarily shut down or deactivated. It is essential to highlight that, even with the growing advancement in this field of research, it is believed that there are still several gaps in the literature that intelligent prioritization in asset management could help to mitigate[51].

Dependability management is the second most portrayed area of technical competence in asset management in the studies with approximately 41.5%. This result was also expected because, like maintenance management, this area of competence is also very critical as it directly affects the production and financial operations of[52] companies. If the service or product offered by the organization is not available or unreliable, for example, the consumer will be unable to use it, generating several harmful consequences for the business and for the company's visibility[52].

The area of technical competence quality management presents unexpected representation with almost 22% of the studies. This result did not match expectations. However, it was very positive and promising because it shows that researchers are seeking initiatives to incorporate measures that help analyze alternatives, criteria and decision-makingto raise the standard of processes, services and products offered.

Unlike the previous areas of competence, the results of risk management pointed to a low representation in the included studies with approximately 8.5%. We did not expect this result because this area of competence is an essential component of the entire asset management process. After all, in addition to complying with current legislation, it isessential to optimize and prioritize rational actions basedon various criteria such as costs, risks and time spent on maintenance[53]. Because of these factors, it is believedto be very important to develop intelligent prioritization approaches to assist in analyzing decisions that involve riskin the asset management area.

RQ5: What types of contributions are proposed by the studies to solve asset management problems through intelligent prioritization? The purpose of this research question was to identify the types of contributions produced by the studies that help solve asset management problems through intelligent prioritization. It is worth noting that the classification of contributions was based on the works of[54, 20, 55].

According to the results found the most special type of contribution is the method/methodology (47.56%; 39 studies). Subsequently, model (43.90%; 36 studies). In sequence, tool (24.39%; 20 studies). Finally, process (7.32%; 6 studies).

The results indicate that the contributions (method/methodology and model) proposed by studies to solve asset management problems through intelligent prioritization correspond to >90% of the identified studies. This result was very positive because many studies that perform intelligent prioritization establish some procedures for the construction and application of their respective proposals in asset management.

Unfortunately, when analyzing these procedures, we found that the studies describe them very superficially, without details and do not specify the planning and execution stepsof the developed intelligent prioritization process. Unfortunately, we already expected this result, especially concerning the type of contribution model, as many technologies of AI are based on mathematical models and studies that produce this type of contribution rarely make available a detailed description about her.

Furthermore, around 24% of the included studies decided to automate their contributions (method/methodology, model and process) through some tool. We considered this information to be very positive evidence as it demonstrates the researcher's concern with automating their contributions and encouraging their practical use. It is essential to highlight that only 4 studies (d2, d10, s55 and s69) used or exclusively developed a tool as a contribution.

Six studies (s52, s54, s57, s64, s65 and s67) presented the process as a type of contribution. However, only onestudy (s67) presents a structured, well-defined and systematic process. Thus, given the results obtained, it is undeniable that this information complements and corroborates the fact that there is a significant gap in the related literature in the development of approaches that specify, in detail, the stepsof intelligent prioritization in asset management.

RQ6: What tools are used to support intelligent prioritization in asset management? This research question identify which tools, academic and commercial, are used to assist with intelligent prioritization in asset management. It was possible to identify the different tools that are used from the studies that have the tool contribution type, according to the results presented of the previous research question. It is worth noting that the answer to this question was obtained gradually during data extraction.

According to the results found, most studies (50%; 10 studies) only mention that a tool was used but did not provide details about it such as the name of the tool if it is web or desktop if it is free or commercial if it was developed by the authors or was purchased. On the other hand, studies that specified the tools used were analyzed more carefully to extract information. Thus, the results also show that the SADTRAFOS, EPANET and APRIORI (10%; 2 studies) tools have the exact representation. Similarly, it happens with the SINAP, EXPERT, EDSP and UbiPaPaGo (5%; 1 study) tools.

After verifying the results obtained, we chose to analyze the relationship between the MCDM methods and the developed tools. It is essential to highlight that most studies that used tools did not specify any MCDM method.

According to the results found the tools that are not specified by the studies use the MCDM AHP and PROMETHEE methods, corresponding to a minimal amount of the included studies (75%; 3 studies). Finally, the UbiPaPaGo tool uses the MCDM AHP and TOPSIS methods and is approached by a unique representation in the included studies (25%; 1 study).

The results of this research question show that a reasonable number of studies included in this SLR (20 studies) have developed or used some tool to help with intelligent prioritization in asset management. This result was very positive because it shows the researcher's concern to disseminate, make flexible and facilitate the contributions proposed by the studies to solve asset management problems through intelligent prioritization. The results showed that in studies that had the type contribution tool, the area of competence that stood out the most was maintenance management, being referenced by almost all studies (18 studies). Only 2 studies (t24, s67) did not apply intelligent prioritization in the maintenance management technical competency area and they used intelligent prioritization in the dependability management and quality management competency areas. It is assumed that this fact has occurred due to the need for maintenance management to adopt tools that support the manager or decision-maker in certain actions such as checking which maintenance tasks must be performed first which criteria must be used to select the physical assets for maintenance, what are the costs associated with the shut down of physical assets that are in maintenance, among others.

As well as the maintenance management competence area, the energy infrastructure category was also the one that stood out the most in studies that had a tool type contribution being referenced by the vast majority of studies (17 studies). Only 3 studies (t5, s38, s67) did not employ intelligent prioritization in the energy infrastructure category and they used intelligent prioritization in the communication and transport categories. It is interesting to mention that the studies that addressed the energy category included the pipeline network subcategory only in 4 studies (d10, t16,s37, s55). The electric power network subcategory was included in all other 13 studies.

We were already expecting this result, as it is believed that energy is one of the important infrastructure sectors for a country's economy. Without electric power network, possibly, modern society would have many difficulties to progress with its[31] activities. This subcategory supplies several cities around the world through an entire complex grid that works together to generate, transmit and distribute electricity[56]. The Pipeline Network also supplies several cities by transporting products, often flammable and dangerous, along several kilometers of[57, 58]. Failures in any of these networks can represent significant production, financial and perhaps even human losses. It is assumed that, for these reasons, these sectors are constantly evolving and many researchers are working to improve intelligent prioritization in asset management in these categories and subcategories.

It is revealing to observe the interest of researchers (even if small) in developing studies in the communication and transport infrastructure categories. This result exceeded expectations positively as it shows that in the infrastructure network of TI, telecommunications and rail transport subcategories, there is also a desire to understand and apply intelligent prioritization in asset management.

A negative result is that only 4 AI technologies (Genetic algorithm, fuzzy, evolutionary algorithm and expert system) of the 9 identified in this review are applied in studies with a tool-type contribution. It is supposed that these 4 technologies are most frequently used in the tools due to their great popularity in the academic and professional environment, the abundance of research materials in the literature and several available algorithms implementations of these technologies in different programming languages.

It is essential to point out that none of the studies that had tool-type contributions referenced the MCDM TOPSIS and ELECTRE methods. This same absence occurred with the risk management technical competence area, the industry infrastructure category and the road, air and maritime transport subcategories. Similarly, happened with AI artificial neural network, Swarm intelligence, unsupervised machine learning, distributed artificial Intelligence and Bayesian network. This event shows a severe shortage of tools that support intelligent prioritization in various asset management segments. This is an excellent opportunity for the development of research and tools in these fields.

Unfortunately, 50% of the tool-type contribution studies (10 studies) do not specify its details (not even the name), making it very difficult to identify. On the other hand, an analysis was made of the studies that specified their tools in more detail and it was found that none of them were included in the list of software with MCDM made available by the International Society on MCDM. This list is maintained by an international organization dedicated to research in the area of MCDA. It lists various software used in the MCDA process and classifies them into three categories: free, semi-commercial and commercial. In addition, the list made available by the international society on MCDM can be accessed through the websitehttps://www.mcdmsociety.org/content/software-related-mcdm-0. Although, a large gap is identified in the literature on tools that support intelligent prioritization in asset management, it is necessary to transform this scenario.

RQ7: What steps of the contributions proposed by the studies are mentioned? The objective of this research question was to identify the different steps that constitute the contributions proposed by the studies for intelligent prioritization in asset management. To answer it, it was first necessary to analyze and identify the studies included to recognize if and which of them specified the steps of their respective contributions.

We also considered it necessary to classify the studies based on the analysis of the degree of detail of the steps described in each study, so, it was decided to establish the following categories: no, partially and yes. Thus, some studies were classified as no because they only mentioned the steps they performed in intelligent prioritization in the context of asset management. On the other hand, the studies that were classified as sim describe the steps in detail. Finally, some studies were classified as partially because they only superficially mention their steps.

The results shows of studies that specify the stepsof the contributions produced. It is observed that most studies do not specify the steps (53.66%; 44 studies) and a significant number of studies specify only partially (35.37%; 29 studies) with a few studies specifying in more detail (10.98%; 9 studies).

This research question shows that a small number of studies were identified that specify the steps of the contributions produced, <10. This is because often, the studies do not describe or describe very superficially the procedure that was adopted to obtain a particular result.

It is essential to point out that some of the studies that specify the steps of their contributions (10.98%; 9 studies) also specify one or more MCDM methods. Thus, with thisset of studies identified, a brief description of the steps ofthe contributions produced by each one of them will be presented, together with the method(s) MCDM if he specifies.

Studies d1 and s68 propose, firstly, to verify, from analysis methods which were the evidenced defects, to later analyzethe equipment. From this, the identification of alternatives and their associations with the analysis methods is carriedout; only then are the criteria that will be used determined. The goal is to employ a fuzzy inference system to calculate the severity of each detected failure mode and finally, apply the MCDM PROMETHEE method.

Studies d19 and s75, on the other hand, propose to identify low-voltage networks with an operational problem or whose customers have made complaints, to later carefully analyze the improvements according to planning, criteria, investment, voltage levels, losses, reliability and customer complaint. Based on this information, an improvement database is created with all the necessary improvements to the electrical distribution system. Subsequently, investments are prioritized, considering legal requirements, fines for non-compliance, cost of losses and availability of resources. Finally, a list ofall improvements is made. The MCDM method applied is not specified.

S56 first proposes defining the desired objective, e.g., repair a physical asset or relocating a physical asset. Then, we are guided to apply all constraints and optimizations. Next, the assets with the most significant risk are verified. After that, prioritization occurs and finally, a solution is recommended. The MCDM method used is AHP.

Like study s46, study s59 also presents a more detailed process with very distinct and evident steps. First, the objectives to be achieved are defined, then each alternative related to the proposed objectives is identified. Then the criteria for each alternative are determined. From there, a hierarchical tree is structured for each alternative. Afterward, all data and alternatives for each objective are analyzed in pairs. Finally, the best alternative for each objective is selected. As with studies s52 and s56, the MCDM method used is also AHP.

As with studies s46 and s59, in s67, it also exhibits a more meticulous process compared to the studies described before: A hierarchical tree with the alternatives is structured. Each alternative's weight is calculated. After that, the weights are integrated to build and normalize a context matrix. From there, the attribute weights are configured and the solutions are determined as positive or negative. Prioritization is carried out and results are achieved. As with the s52 studies, the MCDM methods used are AHP and TOPSIS.

Among the nine studies that specify their steps, only study s52 does not determine the prioritization criteria. Despite this, the studies that specify their steps do not clearly indicate the criteria they use in their process; only study s56 establishes that the prioritization criteria are the highest risk assets.

Therefore, it is understood that the criteria are determined at the time of prioritization according to the specific need of asset management and can also be strongly influenced by the selected MCDM method.

The role of the decision-maker is explicitly mentioned only in study s46, that is, a study of nine that specify the steps of the contributions produced. A similar fact also occurred with criteria and attribution of weights to possible solutions and decision-makers, mentioned directly only in studies s46, s52 and s67. It is assumed that this lack of detail in the prioritization process occurs because researchers and industry professionals often carry it out in an ad-hoc way, without a well-defined and systematic process.

Thus, as shown in the previous paragraphs, the scarcity of methods, methodologies, models, processes, guidelines and structured, systematic procedures and with defined steps for intelligent prioritization in asset management is remarkable. The results suggest that this branch of research needs to be further developed because a significant amount of all studies included in this review (about 53%) do not specify the steps of their contributions or partially specify very superficially (approximately 35%), leaving only a few studies (almost 11%) that describe in a clear and detailed way the steps that are used by their contributions to apply intelligent prioritization in the context of asset management.

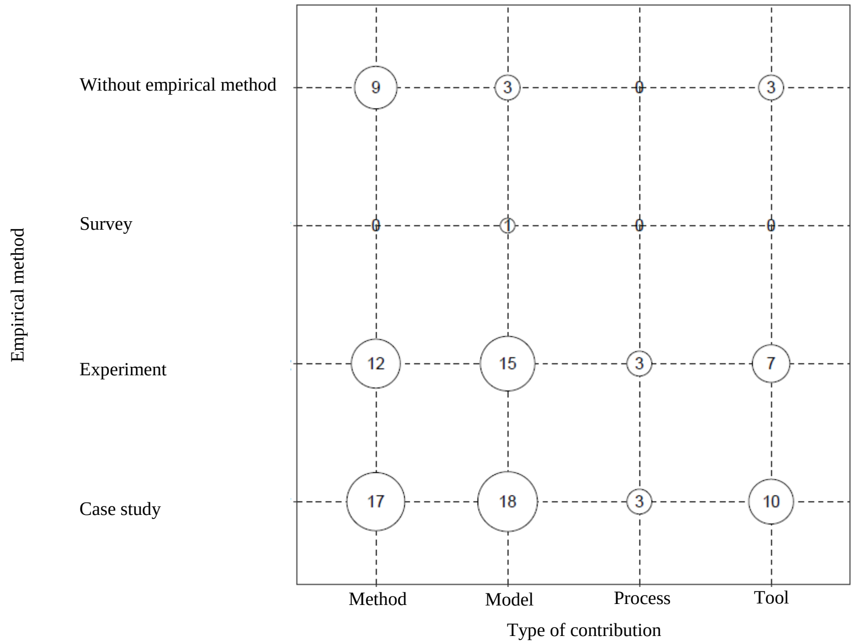

Fig. 2: Bubble chart of the contribution type and empirical method

RQ8: What empirical methods are used to analyze the contributions proposed by the studies? This research question aimed to identify the different types of empirical methods used to examine the contributions proposed by the studies. Importantly, the classification of these methods was based on the works of[59, 16] and their updates[17].

According to the results found the empirical methods that stand out the most are case study (46.34%; 38 studies) and experiment (39.02%; 32 studies), both with the result positive. Later, some studies also showed a positive result but they did not specify the empirical method used (14.63%; 12 studies). Finally, a study was identified that used the empirical method survey and obtained a negative result (1.22%; 1 study).

In order to better analyze the results, it was decided to present in Fig. 2 a bubble chart distributed in two dimensions, namely: an empirical method used (Y-axis) and type of contribution produced by the studies (X-axis). This graph denotes the relationship between the two dimensions. The size and number within a bubble represent the number of studies that use a specific empirical method with a specific type of contribution.

The case study is the most systematic empirical method addressed by the studies identified in this review (38 studies). This type of method is represented in all types of contributions including, a significant part of the studies focus on the development of method/methodology and model with the second having a slightly lower value than the first. It is believed that this is due to the growing search of researchers to examine their contributions with real industry scenarios.

Similarly to the case study, the experimental empirical method is also present in a significant amount of studies (32 studies) and is also used in all types of contributions produced by the studies, being the most prominent in method/methodology and model with the second having a slightly lower value than the first. As in the case study, this event is supposed to happen because researchers are looking to use data from real industry projects to assess their contributions.

The results without an empirical method are covered by a reasonable number of studies (12 studies), emphasizing the method/methodology contribution type. The tool and model contributions are used in the same proportion and on the other hand, no study was identified that produced the contribution type process without an empirical method. We did not expect to have studies included that would not specify the empirical method used. This fact makes extracting information more difficult. It is believed to be important that studies are as detailed as possible to be more easily understandable and reproducible.

The survey had the worst performance because, exclusively, the study s59 applied this empirical method and obtained a negative result. Furthermore, this same study presented the model contribution type. It is worth mentioning that the author of this study emphasizes that it was necessary to finish the analysis of the results before all the answers were returned to him for time. Possibly this fact influenced the negative result obtained by the author.

Therefore, it is possible to observe the notorious absence of approaches that support the planning and implementation of intelligent prioritization in asset management. We believed it to be of fundamental importance to the development of a detailed and systematic approach for supports intelligent prioritization in the context of asset management. This approach would guide the application of MCDM methods and AI technologies to analyze and verify the best results according to asset management. At the time this SLR was written, no approach with the characteristics described earlier has been identified.

Given the analysis of the results obtained in this research question, it is possible to observe a missing observation of methods/methodologies, frameworks, lessons learned, models, processes, guidelines, guides and procedures that support the planning and execution of intelligent prioritization in asset management. Including the tool and process contribution types and the empirical method survey are very little explored in the studies included in this review.

It is believed that the development of a detailed and systematic approach is of fundamental importance to assist with intelligent prioritization in asset management, as such an approach would guide the application of prioritization in the context of asset management, supported by methods MCDM and AI technologies. So far, no approach with the specific characteristics described earlier has been identified in the literature.

RQ9: Which organizations supported the contributions produced by the studies? The purpose of this research question was to list all organizations that directly or indirectly helped to develop, apply or evaluate the contributions produced by the studies. It is important to note that, like some of the previous research questions, the answer to this question was also obtained gradually during data extraction.

To answer this research question, it was first necessary to analyze and identify the selected studies to recognize if and which ones had support from some organization. With the results found it is possible to verify that most studies do not specify whether they received support, directly or indirectly, in the development, application, or evaluation of their contributions (76.83%; 63 studies), leaving a quantity reduced number of studies specifying that they received support from some organization (23.17%; 19 studies).

From the recognition of studies that had the help of some organizations, it was possible to identify which organizations supported the contributions produced by the studies. According to the results shown, 17 organizations contributed to support the studies included in this SLR. Interestingly, the organizations are from very diversified segments such as electricity, education and information technology companies.

The results shown indicate that almost 53%of the organizations identified are from the electricity sector and of these, 44% are publicly traded corporations. This result was already expected because the electric power network infrastructure subcategory represents almost 50% of the studies identified in this SLR.

It is also relevant to mention that 41% of all organizations are international. This fact is positive evidence, as it indicates that researchers are seeking national and international support to improve their studies. These international organizations are headquartered in Switzerland, the United States, Canada, China and Hungary.

In addition, the results also show that within organizations operating in the electricity sector, the area that stands out the most is electricity distribution. Despite this, the generation and transmission areas lag with a slight difference.

The results shows that, in Brazil, the organizations that most supported the contributions produced by the studies are geographically located in the Midwest, Southeast and Northeast regions, in the states of Minas Gerais, Sao Paulo, Mato Grosso from the South, Bahia, Ceara and Pernambuco. Minas Gerais has the most significant prominence among the states mentioned because it concentrates the most significant number of organizations. This information corroborates the general analysis of the data carried out concerning the place of development of the studies and the distribution of studies by publication source.

Therefore, the results obtained through this research question are auspicious as they indicate that there is a growing interest in researchers in seeking to evaluate their studies outside the national context and the academic environment, providing new perspectives. On the other hand, there is also a positive receptivity on organizations to help researchers who are analyzing this specific area in more detail.

We believe that the results obtained through this research question are auspicious, as they indicate a growing concern on the part of researchers to seek organizations that support the contributions produced by their studies outside the national context and from the academic world, providing new perspectives. On the other hand, there is also positive reciprocity in helping investigators analyze and apply intelligent prioritization in asset management.

RQ10: How have organizations supported the contributions produced by the studies? This research question aimed to present how organizations helped develop, apply or evaluate the contributions produced by the studies. It is essential to mention that, like the previous research questions, the answer was also obtained gradually during data extraction.

The results shows how organizations supported the contributions produced by the studies. According to the results shown the type of support that stands out the most is provision of a database with technical information (73.65%; 14 studies). Subsequently, equipment concession (26.32%; 5 studies). Finally, permission to deploy the developed module and integrate with existing systems (5.26%; 1 study).

The results shown indicate that how organizations supported the contributions produced by the studies was identified in all the studies included in this SLR.

Importantly, in more than 76% of all organizations, the type of support that stood out the most was the provision of a database with technical information. This result was already expected because it is the type of contribution with the lowest cost and impact for companies, often requiring a confidentiality agreement.

Furthermore, >17% of all organizations identified in this SLR perform the equipment concession type of support. This fact is positive evidence, as it indicates that researchers seek to evaluate their studies in a practical way directly on the equipment and also, organizations are helping researchers to make the equipment available.

On the other hand, the type of contribution allowed to implement the developed module and integrate with existing systems corresponds to just over 5% of all studies identified in this SLR. This negative result was already expected, since, it is the type of contribution with the institution’s most significant risk and consequence.

On the other hand, the type of support permission to implement the developed module and integrate with existing systems corresponds to just over 5% of all studies identified in this review. This result was also expected because it is the modality of contribution with the most significant risk and consequence for organizations.

Therefore, the results obtained through this research question are pretty promising, as they show a relationship of collaboration and partnership between academic researchers and business organizations.

CONCLUSION

This article presented an SLR on 3 very different areas: prioritization, AI and asset management. The intersection between these areas is the focus of this SLR because we sought to investigate how intelligent prioritization is applied in asset management. Therefore, from research in 5 digital libraries, an initial set of 7.843 studies was obtained. After applying the inclusion and exclusion criteria in the title, keywords and abstract, a total of 1.764 studies were selected for a later stage. Then the inclusion and exclusion criteria were applied in the introduction and conclusion, resulting in138 studies selected for the next step.

In addition, we chose to carry out an analysis of the references cited in the studies selected so far, that is, to perform snowballing. We also decided to include another digital library, the capes repository, as most studies had Brazil as a place of development. Therefore, a strategy to deepen knowledge in this field of research would be to investigate the publication of dissertations and theses from universities in that country. As a result, 494 studies were included. Finally, a complete reading of the studies was performed and the quality criteria were applied, resulting in the selection of 82 studies.

Thus, 82 studies encompassing scientific articles, dissertations and theses were analyzed, resulting in the characterization of the research topic. These studies made it possible to answer the main research question and all 10 secondary research questions. Thus, this SLR contributed by showing: General results about the years of publication, the context of the application, place of development and types and sources of publication by studies; 4 MCDM methods from different schools and categories are applied in this field of research; 9 very different AI technologies are employed to implement the prioritization intelligently in the asset management; 4 infrastructure categories and 8 subcategories use intelligent prioritization in asset management; 4 asset management technical competency area apply this research field; 4 types of contributions have been proposed to solve asset management problems through intelligent prioritization; 8 tools are used to support this field of research. The steps used by the contributions produced by the studies; 3 different empirical methods are used to analyze the contributions proposed by the studies; 17 organizations that supported the contributions proposed by the studies; 3 types of support the organizations that supported the contributions proposed by the studies.

Much was discovered with this SLR because there are already several studies in this field of research and this one is very relevant and promising. Despite this, many gaps are still open and should be addressed to improve how intelligent prioritization is applied in asset management. Some questions that exemplify these gaps and that can be developed in future research are:

- How to plan intelligent prioritization in asset management?

- What are the preparatory activities for intelligent prioritization in asset management?
- How to define the stakeholders and the criteria for intelligent prioritization in asset management?
- How to implement intelligent prioritization in asset management?
- What are the necessary steps for intelligent prioritization in asset management?
- How to evaluate the results obtained by intelligent prioritization in asset management?
- What metrics should be used to assess the results obtained by intelligent prioritization in asset management?
- How a tool would be like to automate the implementation of intelligent prioritization in asset management?

Therefore, we believed that developing an approach to support this research field is crucial. This approach would guide the planning and implementation of intelligent prioritization in asset management through MCDM methods and AI technologies. Besides analyzing and verify the best results according to the criteria established by the stakeholders.

Unfortunately, until the moment of conclusion this SLR, we did not identify in the literature any approach with the characteristics described earlier. We were also not identified no a tool to help in automation this approach. Thus, we intend to develop an approach to fill some of the gaps that still are open regarding how intelligent prioritization is applied in asset management.

We aim to improve this field of research by the creation of an approach for support the planning and implementation of intelligent prioritization in asset management and likewise a tool to automate this approach.

Author contributions: Cinthya and Fernanda conceived the study design; Cinthya collected data; Cinthya, Fernanda and Silvio analyzed data; all the authors wrote the manuscript and approved the final version.

APPENDIX

Appendix 1: List of all selected works with their respective quality scores

ID	Ref.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Sum	%
d1	[60]	1	1	1	1	1	1	0.5	1	1	0.5	9.0	90
d2	[61]	1	0.5	1	1	1	0	1	1	1	0.5	8.0	80
d3	[62]	1	1	1	1	1	0	1	1	1	0.5	8.5	85
d4	[63]	1	1	1	1	1	0	1	1	1	0.5	8.5	85
t5	[64]	1	1	1	1	1	0	1	1	1	0.5	8.5	85
d6	[65]	1	0.5	1	1	1	0.5	1	1	1	0	8.0	80
d7	[66]	1	1	1	1	1	0.5	0.5	1	1	0.5	8.5	85
t8	[67]	1	0.5	1	1	1	0	1	1	1	1	8.5	85
t9	[68]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
d10	[69]	1	0.5	1	1	1	0	1	1	1	1	8.5	85
t11	[70]	1	1	1	1	1	0.5	0.5	1	1	0	8.0	80
t12	[71]	1	0.5	1	1	1	0.5	1	1	1	0	8.0	80
d13	[72]	1	0.5	1	1	1	0	0.5	1	1	1	8.0	80
d14	[73]	1	1	1	1	1	0.5	0.5	1	1	0	8.0	80
d15	[74]	1	0.5	1	1	1	0.5	1	1	1	0	8.0	80
t16	[75]	1	1	1	1	1	0.5	1	1	1	0.5	9.0	90
d17	[76]	1	1	1	1	0.5	0	0.5	1	1	0.5	7.5	75
d18	[77]	1	1	1	1	1	0.5	0.5	1	1	0	8.0	80
d19	[78]	1	0.5	1	1	1	1	1	1	1	0	8.5	85
d20	[79]	1	1	1	1	1	0.5	0	0.5	1	0.5	7.0	70
d21	[80]	1	1	1	1	1	0.5	1	1	1	0.5	9.0	90
d22	[81]	1	0.5	1	1	1	0	1	1	1	0	7.5	75
d23	[82]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
t24	[83]	1	1	1	1	1	0	1	1	1	0.5	8.5	85
d25	[84]	1	1	1	1	0.5	0	1	1	1	0.5	8.0	80
t26	[85]	1	0.5	1	1	1	0.5	1	1	1	0	8.0	80
d27	[86]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
d28	[87]	1	0.5	1	1	1	0	1	1	1	1	8.5	85
t29	[88]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
t30	[89]	1	0.5	1	1	1	0.5	1	1	1	0	8.0	80
t31	[90]	1	0.5	1	1	1	0.5	1	1	1	0	8.0	80
t32	[91]	1	1	1	1	0.5	0	0.5	1	1	0.5	7.5	75
t33	[92]	1	1	1	1	1	0.5	1	1	1	0.5	9.0	90
d34	[93]	1	1	1	1	0.5	0.5	0.5	1	1	1	8.5	85
s35	[94]	1	1	1	1	0.5	0	1	1	1	0.5	8.0	80
s36	[95]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70

Appendix 1: Continue

ID	Ref.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Sum	%
s37	[96]	1	1	1	1	1	0.5	1	1	1	0.5	9.0	90
s38	[97]	1	1	1	1	0.5	0.5	0.5	1	1	1	8.5	85
s39	[98]	1	1	1	1	0.5	0.5	0.5	1	1	1	8.5	85
s40	[99]	1	1	1	1	1	0.5	1	1	1	0.5	9.0	90
s41	[100]	1	1	1	1	0.5	0	0.5	1	1	0.5	7.5	75
s42	[101]	1	1	1	1	0.5	0	1	1	1	0.5	8.0	80
s43	[102]	1	1	1	1	0.5	0	1	1	1	0.5	8.0	80
s44	[103]	1	1	1	1	0.5	0.5	0.5	0.5	1	0.5	7.0	70
s45	[104]	1	1	1	1	0.5	0	0.5	1	1	0.5	7.5	75
s46	[105]	1	1	1	1	0.5	1	0.5	1	1	1	9.0	90
s47	[106]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
s48	[107]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
s49	[108]	1	1	1	1	0.5	0.5	0.5	1	1	0.5	8.0	80
s50	[109]	1	1	1	1	0.5	0.5	0.5	1	1	1	8.5	85
s51	[110]	1	1	1	1	0.5	0	0.5	1	1	0.5	7.5	75
s52	[111]	1	1	1	1	0.5	1	0.5	1	1	0.5	8.5	85
s53	[112]	1	1	1	1	0.5	0	1	1	1	0.5	8.0	80
s54	[113]	1	1	1	1	0.5	0.5	0.5	1	1	1	8.5	85
s55	[114]	1	1	1	1	0.5	0	0.5	1	1	0.5	7.5	75
s56	[115]	1	1	1	1	0.5	1	1	1	1	0.5	9.0	90
s57	[116]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
s58	[117]	1	1	1	1	0.5	0	0.5	1	1	0.5	7.5	75
s59	[118]	1	1	1	1	1	1	1	1	1	0.5	9.5	95
s60	[119]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
s61	[120]	1	1	1	1	1	0.5	1	1	1	0.5	9.0	90
s62	[121]	1	1	1	1	1	0.5	1	1	1	0.5	9.0	90
s63	[122]	1	1	1	1	1	0.5	1	1	1	0.5	9.0	90
s64	[123]	1	1	1	1	0.5	0.5	0.5	1	1	1	8.5	85
s65	[124]	1	1	1	1	0.5	0	1	1	1	0.5	8.0	80
s66	[125]	1	1	1	1	0.5	0.5	0.5	1	1	1	8.5	85
s67	[126]	1	0.5	1	1	1	1	0.5	1	1	0.5	8.5	85
s68	[127]	1	1	1	1	1	1	0.5	1	1	0.5	9.0	90
s69	[128]	1	0.5	1	1	1	0	1	1	1	0.5	8.0	80
s70	[129]	1	1	1	1	1	0	1	1	1	0.5	8.5	85
s71	[130]	1	0.5	1	1	1	0.5	1	1	1	0	8.0	80
s72	[131]	1	0.5	1	1	1	0	1	1	1	1	8.5	85
s73	[132]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
s74	[133]	1	1	1	1	1	0.5	0.5	1	1	0	8.0	80
s75	[134]	1	0.5	1	1	1	1	1	1	1	0	8.5	85
s76	[135]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
s77	[136]	1	1	1	1	0.5	0	0.5	0.5	1	1	7.0	70
s78	[137]	1	1	1	1	0.5	0	0.5	0.5	1	1	7.0	70
s79	[138]	1	1	1	1	1	0.5	1	1	1	0.5	9.0	90
s80	[139]	1	0.5	1	1	1	0	1	1	1	1	8.5	85
s81	[140]	1	1	1	1	0.5	0	0.5	0.5	1	0.5	7.0	70
s82	[141]	1	1	1	1	1	0.5	0.5	1	1	0	8.0	80

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