Data Mining of Project Management Data: An Analysis of Applied Research Studies

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ABSTRACT

Data collected and generated through and posterior to projects, such as data residing in project management software and post-project review documents, can be a major source of actionable insights and competitive advantage. This paper presents a rigorous methodological analysis of the applied research published in academic literature, on the application of data mining (DM) for project management (PM). The objective of the paper is to provide a comprehensive analysis and discussion of where and how data mining is applied for project management data and to provide practical insights for future research in the field.

CCS Concepts

• Data mining • Association rules • Enterprise information systems • Enterprise resource planning • Enterprise information systems • Industry and manufacturing.

Keywords

Data Mining; Project Management; Business Analytics; Industrial Applications.

1. INTRODUCTION

A project is a “temporary endeavor (with a definite beginning and definite end), with the characteristics of progressive elaboration (developing in steps, continuing in increments), undertaken to create a unique product, service, or result”. Project management (PM) involves the “application of knowledge, skills, tools, and techniques to project activities to meet project requirements” [1]. Project management is very important, because projects are undertaken at all levels of the organization, in almost any industry, and can have long-term effects.

There exists a vast literature on project management, even specialized academic journals, as well as professional institutions, such as Project Management Institute (PMI), dedicated to project management field. However, real world projects usually fall behind the performance goals or fail frequently. For example, a study conducted by McKinsey & Company [2] investigated more than 5,400 large scale information technology (IT) projects and revealed that on average large IT projects run 45% over budget and 7% over time, while delivering 56% less value than predicted. Even more critically, 17% of large IT projects fail in such a big scale that they threaten the existence of the company.

As science and technology advance, real world projects are becoming increasingly complex, and are involving larger amount of data. Huge strategic projects, such as the production of a satellite, already generate amounts of data that can be classified as big data. Project managers and planners make use of data, while new data is generated as a project progresses.

Data collected in electronic databases, as well as other types of information generated, such as post-project reviews, can be a major source of actionable insights and competitive advantage for companies [3][4]. To this end, a multitude of studies have been carried out by researchers to use data mining techniques for analyzing data coming from projects. Data mining is the growing field of computer science focusing on the discovery of actionable insights from –typically large and complex- data [5]. Through data mining, businesses and governments can tap into the information hidden in databases and unstructured documents, and use it for advantage [6][7][8].

Data mining has also been extensively used in manufacturing, as surveyed in [9]. However, despite the importance of project management, and the growing application of data mining in industry and specifically in project management, to the best of our knowledge, the research literature does not contain an analysis of data mining applications for project management. To this end, we have conducted a thorough investigation of the literature on this topic, and present the results and analysis in this paper. We provide detailed discussion of the analyses and results, as well as gaps in the current literature and opportunities for future research. Overall, our paper is aimed at providing an understanding of data mining, an important and underlying field for big data analytics, for project management researchers and project managers, as the world is moving towards the new age of big data [10].

The remainder of the paper is organized as follows: Section 2 provides a brief review of the data analysis methodologies used in the paper, as the background. Section 3 discusses how the data was collected and developed. Section 4 is devoted to the results and analysis of the collected and developed data, where new insights are obtained. Finally, Section 5 presents some conclusive remarks.

2. METHODS

In this section, we review the methods used for the analysis. Our review of the used methods begins with an overall discussion of data mining, and continues with the introduction of association mining, which is used to analyze the database that lists the characteristics of the projects and data mining methods in the selected papers.

2.1 Data Mining

Data mining is the growing field of computer science and informatics that deals with discovering new and useful information and knowledge from data [5]. Data mining can be thought as a toolbox, containing a collection of various methods and algorithms, where each method or algorithm, or each combination of them is appropriate or most suitable depending on the characteristics of data.

In this study, we applied a particular selection of data mining techniques for our analysis, that we found most appropriate to the analysis of the data that we developed. This data is a database that contains the project characteristics and data mining characteristics reported in the collected papers, as illustrated in Tables 1 and 2, respectively. This data is in a structured tabular format. For this data, exploratory analysis, summary tables, and association mining were found appropriate and applied. Among machine learning methods, the unsupervised learning method of association mining has been selected as a method for the analysis, because the developed data consists mainly of categorial attributes.

2.2 Association Mining

Association mining is a highly popular and useful data mining technique that is used in both academia and industry for both production and service systems [6][11][12]. Association mining is the technique of identifying associations between elements (items) of a set (set of items), based on how these elements appear in multiple subsets (transactions) of the set. The input to association mining is a transaction data, where each transaction contains a subset of items coming from a given set. The typical output of association mining, also referred to as association mining results, is the list of item sets that appear together frequently in transactions, and the rules that describe how these associations affect each other [5]. The first output is referred to as frequent itemset, and the second output is referred to as association rules. Frequent itemset is a set, whereas association rule is a rule in the form "IF [Antecedent A] THEN [Consequent B]", or simply written as "A⇒B". The frequent itemsets and the association rules can be extremely numerous, and hence it is typical to specify a threshold support value while computing these results.

Support of an itemset (e.g.: {A,B}) or a rule (e.g. A⇒B) is the percentage of transactions that the items in the itemset or the rule appear in. Support is also the primary metric related with an itemset or rule that signifies importance. Another common metric in association mining is confidence, and is defined only for association rules (when only the above two outputs are generated). Confidence of a rule A⇒B is the conditional probability of item B appearing in a transaction, given that item A readily appears in that transaction. A mathematical description of the mentioned concepts can be found in [12].

The standard algorithm for association mining is the Apriori algorithm, which was first introduced by [13] and has gained increased popularity ever since. Association mining is a standard module in almost every data mining platform (SAS, RapidMiner, WEKA) while it can also be conducted through specialized software [14][15].

3. DATA

The applied research papers to be analyzed were collected and through searching through Google Scholar as a meta-search engine, and searching through all papers of all journals in the Google Scholar database for the application of data mining to project management data. In total, more than 3000 papers were searched, more than 1500 were downloaded and skimmed, and 250 were read in detail. Eventually, 116 papers, most of which coming from 32 journals, were found to be related to the theme of "data mining for project management", and included in the analysis. Many papers were excluded from detailed analysis, due to not conforming to the literature selection criteria discussed next. The literature survey includes only research until end of 2013. The full dataset can be accessed online [16].

4. ANALYSIS AND RESULTS

In this section, we present the analysis and results of Tables 1 and 2, which have been constructed based on the project and data mining characteristics of the most relevant 116 papers. The analysis has been conducted in using cross-tabulation analysis and association mining. The analysis framework is shown in Figure 1, and consists of Data Collection, Data Preparation, and Data Analysis stages.

Table 1. Project characteristics

PaperID	Year	Citation	IsMultiProject	NoOfProjects	RelationshipBetweenProjects
1	2009	Abdelsalam and Gad (2009)	Multiple	11	SharingResource
2	2011	Abdul-Rahman et al. (2011)	Multiple	NotAvailable	Independent
…	…	…	…	…	…

ProjectsNature	ProjectGoal	ScopeOfProjects	Industry (ISICCodes)	ProjectDescription	CountryOfApplication
ServingCommonGoal	MultiProjectManagement	Tactical	Construction	Residential construction	Dubai
Independent	SingleProjectManagement	Tactical	Construction	Construction	Malaysia
…	…	…	…	…	…

Table 2. Data mining characteristics

PaperID	DataType	DimensionsConsidered	ProjectObjective	PresentsNewMethods	DataCleaningTechniques
1	MultiProjectData	Cost	NotApplicable	ExistingMethods	NotAvailable
2	SingleProjectData	OrganizationalLearning	NotApplicable	ExistingMethods	NotAvailable
…	…	…	…	…	…

DimensionalityReduction	TypesOfDataMining	MethodsUsed	SoftwareUsed	HasDevelopedDSS	MethodsDeveloped
NotAvailable	Descriptive	Visualization	NotAvailable	No	None
NotAvailable	Descriptive	Clustering, Principal Component Analysis (PCA)	NotAvailable	No	None
…	…	…	…	…	…

IsDataFromRealWorld	NoOfTasks	NoOfResources	NoOfRows	NoOfColumns	RowRepresents
Yes	NotAvailable	NotAvailable	13	11	Variables (Types of Costs)
Yes	NotAvailable	NotAvailable	23	125	Project Managers
…	…	…	…	…	…

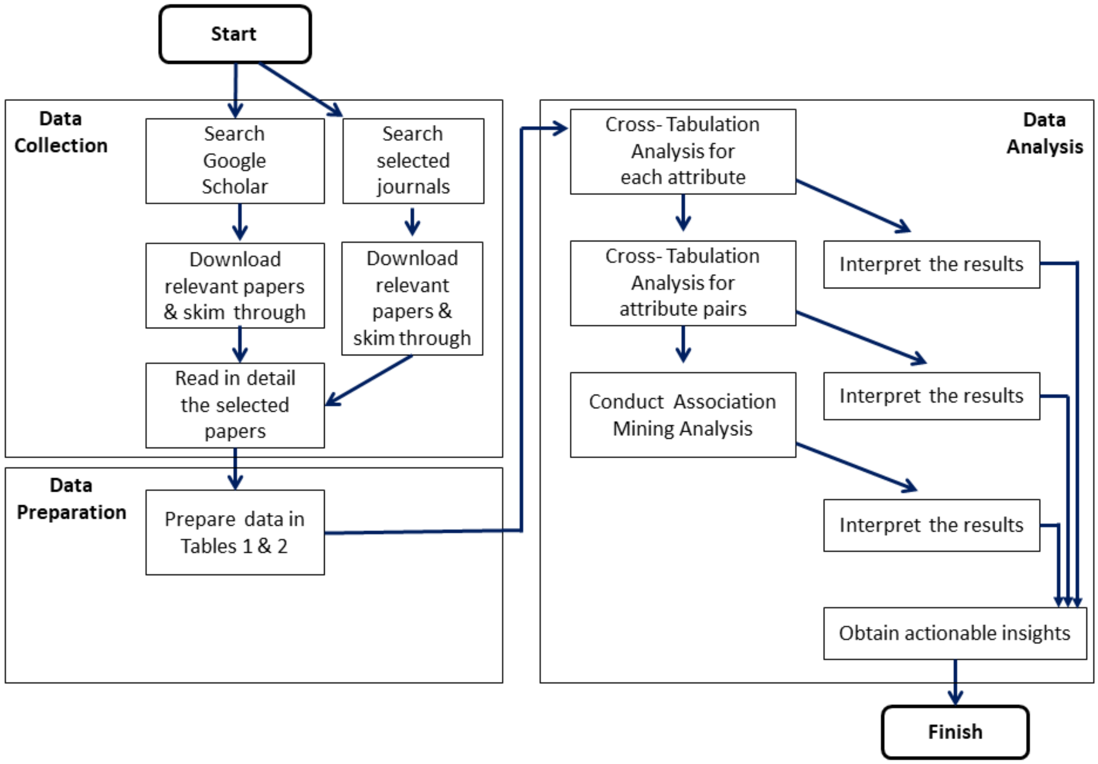

Figure 1. The data analysis framework.

Table 3. Breakdown of number of papers with respect to industry (ISIC codes)

Industry (ISICCodes)	**Number of Papers**
Construction	41
Information and Communication	28
Manufacturing	10
Public administration and defense; compulsory social security	8
Professional, scientific and technical activities	4
Financial and insurance activities	2
Human health and social work activities	2
Electricity, gas, steam and air conditioning supply	1
Cross-industry	10

Table 4. Breakdown of number of papers with respect to methods used and industry.

MethodsUsed	**Construction**	**Information and Communication**	**Manufacturing**	**Cross-industry**	**Other**	**Not Available**
Association rule mining	2	2	0	1	1	1
Classification	8	5	1	0	3	3
Clustering	3	6	2	1	1	0
Decision tree	3	5	1	0	1	2
Regression	4	9	3	1	1	0
Statistical analysis	7	4	4	4	6	1
Visualization	15	8	5	0	6	3
Text mining	2	2	0	0	1	0

4.1 Cross-tabulation Analysis

Table 3 provides the summaries for the attribute Industry, which is the industry in which the project is conducted based on the ISIC codes of United Nations [17], and displays the papers related with each industry. Table 3 shows that 41 of the 116 papers analyzed are from the construction industry. This shows the importance of the construction industry from not only a project management perspective, but also from data mining and information technology (IT) perspectives. The other frequently encountered industries in the papers are information and communication, as well as manufacturing.

The next analysis was for the attribute CountryOfApplication (country in which the project(s) was/were conducted, which is not necessarily the affiliation of the author), and shows the number of papers with respect to countries. It is found out that papers using data from the United States (19 papers) are most frequent, followed by those that use data from Taiwan (14 papers) and China (5 papers). 7 papers report analysis of projects across multiple countries.

Table 5. Frequent patterns in the research studies

	Support
IsDataFromRealWorld=Yes	88.8
PresentsNewMethods=ExistingMethods	85.3
HasDevelopedDSS=No	82.8
IsMultiProject=Single	78.4
RelationshipBetweenProjects=Independent	75.0
ScopeOfProjects=Tactical	74.1
DataType=SingleProjectData	65.5
TypesOfDataMining=Predictive	37.9
Industry=Construction	35.3
TypesOfDataMining=Descriptive	31.0
TypesOfDataMining=Exploratory	31.0
Industry=InformationCommunication	24.1

IsMultiProject=Multiple	21.6
DataType=PostProjectReviews	17.2
HasDevelopedDSS=Yes	17.2
PresentsNewMethods=NewMethods	12.9

Table 6. Frequent patterns in the research studies

AtrributeName	**AttributeValue (Support)**
IsMultiProject	Single (78%), Multiple (22%)
RelationshipBetween Projects	Independent (75%), SingleProject (13%), SharingResources (%9), NotAvailable (3%)
ScopeOfProjects	Tactical (74%), Operational (9%), Strategic (9%), NotAvailable (8%)
Industry	Construction (35%), InformationCommunication (24%), Manufacturing (9%), Cross-industry (9%), NotAvailable (8%), PublicDefense (7%), ProfessionalScientificTechnical (3%), HumanHealth (2%), FinancialInsurance (2%), ElectricityGas (1%)
DataType	SingleProjectData (66%), PostProjectReviews (17%), MultiProjectData (9%), ProjectSchedule (4%), ChangeOrders (3%), Accidents (1%)
PresentsNewMethods	ExistingMethods (85%), NewMethods (13%), NotAvailable (2%)
TypesOfDataMining	Predictive (38%), Descriptive (31%), Exploratory (31%)
HasDevelopedDSS	No (83%), Yes (%17)
IsDataFromRealWorld	Yes (89%), No (6%), NotAvailable (4%), Both (1%)

The next analysis was for the attribute ProjectObjective, listing the number of papers that have each objective. A paper may be counted for more than one value of this attribute, since there may be more than one objective in a study. The most frequent objectives are cost minimization (12 papers) and estimation (8 papers), followed by makespan and time minimization (7 papers each). These are followed by papers on performance and effort estimation and minimization of effort (6 papers each).

The next analysis (Table 4) involved the attributes MethodsUsed and Industry simultaneously, analyzing the number of papers for the cross tabulation of these attributes. Table 4 suggests that visualization dominates all other data mining methods with respect to popularity, followed by statistical analysis. The applications of association rule mining and text mining seem least popular, illustrating the opportunity to conduct research that uses these methods and/or develop new algorithms within these methods, especially for analyzing data from manufacturing projects (e.g.: shipbuilding).

The next analysis was for the software tools used for mining of project management data in the selected research papers. The most popular software tool is the SPSS statistics/data mining software (SPSS) (9 papers), followed by MATLAB (MATLAB) (7 papers) and WEKA (WEKA) (7 papers). Software developed in-house has been used in 4 papers. The software used include not only data analysis and data mining software, but also project management software, showing that the analysis features within project management software are also used in applied academic research on the topic.

4.2 Association Mining Analysis

The next analysis of the developed tabular data (illustrated in Tables 1 and 2) is through association mining. Tables 5, 6, and 7 present the results of association mining analysis conducted using the AssocMiner Software [15].

Attributes entering the association mining analysis are IsMultiProject, RelationshipBetweenProjects, ScopeOfProjects, Industry, DataType, PresentsNewMethods, TypesOfDataMining, HasDevelopedDSS, IsDataFromRealWorld.

Table 5 presents the frequent patterns encountered in the surveyed papers. The support values denote the percentage of papers where the characteristic pattern was observed. Only the patterns with support value ≥ 10% are shown in Table 5. It is apparent that an overwhelming percentage (88.8%) of the papers used data from the real world, which is very favorable. However, 85.3% of the papers used only existing methods, rather than developing new data mining methods for the project management domain, or being applied in the project management domain. This shows an important opportunity for future research. Similarly, 82.9% of the papers did not present the development of a DSS, which points to another important opportunity in future research. The next row shows that 78.4% of the papers considered single project data, showing the opportunity to conduct research on multi-project management. The remaining rows enhance the findings from the first four rows, as well as giving further insights, such as the fact that predictive data mining is the most popular (in 37.9% of the papers), and construction is the most popular application domain.

Table 6 shows the breakdown of values for each of the attributes. The numbers are rounded to the nearest integer. From the first line, it is seen once more that the data type in the papers was mainly (78%) single project data, suggesting that more research might be carried out on multiple-project data. Second line shows that research on multi-project data where projects share resources is very scarce (9%), suggesting that research on multi-project data can especially focus on the case where resources are shared. Next line suggests that more research can be done for operational- and strategic-level projects. The line regarding Industry suggests that there is opportunity to do more research that involves manufacturing, as well as public projects, defense projects, scientific projects, and projects in health, insurance, and energy industries.

Table 7 displays association rules (with Confidence ≥ 20%) discovered regarding the development of DSS. The rules are sorted with respect to decreasing values of confidence (last column). The antecedent is "HasDevelopedDSS=Yes" and the support value is 17.2% in each of these rules, whereas the consequent and hence the confidence is different. The first three rules confirm our earlier findings for the papers where a DSS has been developed. The confidence values for the latter two rules are also consistent with the results in Table 6. However, the sixth rule (shown in italic) provides us with an insight: The rule suggests that development of new methods takes place 55.0% of the time when a DSS is developed. Table 6 had shown that only 13% of all papers developed new methods. Therefore, the development of new methods is much more (approximately four times) common when a DSS is developed. Therefore, the rule tells that the papers where DSS were developed are four times more likely to also contain the development of a new method. One further insight from this rule is that the literature set the standard of developing a new method when a DSS is developed, and vice versa. So any research where DSS or a new method is developed is more likely to contain (and expected to contain by the reviewers of the paper) the other.

5. CONCLUSIONS AND FUTURE WORK

This paper presented a detailed analysis and discussion of the literature on the mining of project management data. Several insights regarding the literature have been provided, as well as opportunities for future research. Some of the insights and future research possibilities are as follows:

1. 41 of the 116 reviewed papers are coming from the construction industry, showing the significance of the construction industry from not only a project management perspective, but also from data mining and information technology (IT) perspectives.
2. Other frequently encountered industries in the papers are information and communication, as well as manufacturing.
3. Papers using data from the United States (19 papers) are most frequent, followed by those that use data from Taiwan (14 papers) and China (5 papers).
4. Most frequent objectives are cost minimization and estimation, followed by makespan and time minimization.
5. Visualization is more popular than all other data mining methods, and is followed by statistical analysis. The application of association rule mining and text mining seems least popular, illustrating the opportunity to conduct research that uses these methods and/or develops new algorithms within these methods, especially for manufacturing.
6. The most popular software tool is the SPSS statistics/data mining software (SPSS), followed by MATLAB (MATLAB) and WEKA (WEKA).
7. An overwhelming percentage (88.8%) of the papers used data from the real world, which is very favorable.

8. 85.3% of the papers used only existing methods, rather than developing new data mining methods for the project management domain, or being applied in the project management domain. This shows an important opportunity for future research for developing new data mining methods for the project management domain.
9. 82.9% of the papers did not present the development of a DSS, which suggests that future research can be enhanced through the development of DSS.
10. 78.4% of the papers looked into single project data, showing a gap, as well as opportunity to conduct research on multi-project management.
11. The data type in the papers was mainly (78%) single project data, suggesting that more research might be carried out on multiple-project data.
12. Research on multi-project data where projects share resources is very scarce (9%), suggesting that research on multi-project data can especially focus on the case where resources are shared.
13. More research can be done for operational- and strategic-level projects, due to the gap regarding projects at these levels.
14. There is opportunity to do more research that involves manufacturing, as well as public projects, defense projects, scientific projects, and projects in health, insurance, and energy industries.
15. Papers where DSS were developed are four times more likely to also contain the development of a new method. So any research where DSS or a new method is developed is more likely to contain (and expected to contain by the reviewers) the other.

Insights numbered 5 & 8-14 highlight key research issues for future work. With regards to methodological focus, there is great opportunity for future research for developing new data mining methods for the project management domain. One specific avenue is research that uses association rule mining and text mining and/or develops new algorithms within these methods, especially for manufacturing. With regards to the application focus, research on multi-project management and using multi-project data, especially focusing on shared resources, is a primary avenue. Furthermore, future research can be enhanced through the development of DSS, and can focus on the operational- and strategic-level projects. Finally, key research issues can focus on the domains of manufacturing, as well as public projects, defense projects, scientific projects, and projects in health, insurance, and energy industries.

While a multitude of studies exist where data mining is applied for project management, there are also a multitude of gaps in the literature, calling for new research in this domain. Research in data mining is ever increasing, in the presence of big data and the challenges brought with it [10]. Some of this big data is being and will be generated in project management, enhancing the already rich data collected by many organizations. Therefore, we expect that the literature on the application of data mining techniques for project management will grow even faster in the coming up years and decades.

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Table 7. Frequent patterns in the research studies

IF [HasDevelopedDSS=Yes] **THEN [Conseq]**		
Conseq	**Support**	**Confidence**
IsDataFromRealWorld=Yes	17.2	80.0
IsMultiProject=Single	17.2	75.0
DataType=SingleProjectData	17.2	70.0
ScopeOfProjects=Tactical	17.2	65.0
RelationshipBetweenProjects=Independent	17.2	60.0
PresentsNewMethods=NewMethods	*17.2*	*55.0*
TypesOfDataMining=Exploratory	17.2	50.0
PresentsNewMethods=ExistingMethods	17.2	35.0
TypesOfDataMining=Predictive	17.2	30.0
Industry=Construction	17.2	30.0
Industry=InformationCommunication	17.2	25.0
IsMultiProject=Multiple	17.2	25.0
TypesOfDataMining=Descriptive	17.2	20.0
RelationshipBetweenProjects=SingleProject	17.2	20.0

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