Classifying Influential Information to Discover Rule Sets for Project Disputes and Possible Resolutions

ABSTRACT

Public-private partnership (PPP) is a strategy that governments encourage private institutions to financially support public construction projects, by providing proper incentives based on collaboration with private institutions. However, disputes may occur during a contract management. This paper investigates various Public-private partnership (PPP) disputes and their critical influential factors for associating fundamental project information and dispute resolutions. In this study, knowledge is extracted from the association rules so that dispute handling patterns can be identified from historical database. Analytical results show that the rule sets achieve 83.92% confidence level. By applying the results in practice, project managers can determine the likely method for dispute resolutions with known project attributes, dispute items, and the phase in which a dispute occurs. This research demonstrates an effective application and valuable reference for early notice of dispute handling methods in public infrastructure projects.

Keywords: project management; public-private partnership; project dispute; data mining.

1. Introduction

Public-private partnerships are intended to inject private capital and dynamism into public infrastructure projects, thus reducing the financial burden on the government, accelerating construction schedules and improving the quality of public services, thus enhancing the effectiveness of government operations and promoting economic growth. The promotion of private participation in public works, also known as public-private partnerships (PPP) entails a partnership between private enterprises and government agencies, where the government provides appropriate incentives to attract private funding for the construction and operation of public works projects[9,18].

Therefore, the content of investment contracts emphasizes the composition of private investment groups, along with their expertise, financial resources and other factors related to the quality of infrastructure construction and operation. PPP projects allow the government to improve the service efficiency and functionality of public works projects while redirecting funding to other investments. PPP helps reducing capital costs, increasing access to expertise, creating needed facilities, reducing operating costs, and improving service quality, but the motivation for private participation will vary with the type of public works project.

PPP can provide access to needed expertise in areas such as engineering, law, finance, operations management and administration, and allows the lifecycle to be divided into three stages: preparation, construction, and operations. In the preparation stage, the Public Construction Commission (PCC) plays a guiding, supervisory, and inspection role in the construction and operation stages. With the assistance of the PCC, the competent authority will spend the majority of its time discussing feasibility assessments or contractor status. Only when the investment contracts are signed does the partnership between the competent authority and the private institutions begin.

In Taiwan, PPP has been playing a major part in the social and economic development, which creates a positive impact on the expansion of public services and construction. However, the wide range of PPP projects will inevitably give rise to controversy [9,18]. Thus, to improve conflict resolution in such cases, Article 22 of the Promotion of Private Participation in Infrastructure Projects Act (hereinafter the “PPP Act”) of Taiwan states that “investment contracts should specify the timing, manner and operating mechanism of the coordination committee handling contract negotiations and disputes” [2]. Therefore, when the competent authority and private institutions sign investment contracts in accordance with the PPP Act, they must specify the formation of a joint committee to negotiate the handling of disputes over contractual matters [9,21].

To attain effective control of diverse projects, and to design proactive dispute resolution management strategies and knowledge, such as rule sets before disputes occur, it is essential to providing the governmental PPP Taskforce with information about future countermeasures. Additional preparation is generally beneficial since the effort, time, and cost to multiple parties can be reduced during dispute settlement once a dispute occurs.

Although numerous studies[14-16,19,20,30] demonstrated that an efficient, effective, and fair dispute resolution process is essential for PPP project success, this study focuses on identifying potential handling methods by associating project information with dispute resolutions. The proposed association mining technique can provide project stakeholders with the information needed to implement proactive measures during project preparation.

To achieve this objective, this study applies classification techniques to identify critical project attributes and association algorithms to extract rule sets from data. First, this study acquired historical dispute data for PPP projects which store fundamental project information and their corresponding dispute resolutions. Differing from conventional construction project disputes, PPP project disputes may occur during the building phase, as well as the operating, renting, or transfer phases. Thus, association mining approach with only dispute cases was implemented to identify the rule sets of dispute resolutions with known project attributes, dispute items, and the phase in which a dispute occurs.

The rest of this paper is organized as follows. Section 2 comprehensively reviews PPP development trends, promotion experience and challenges in major countries in addition to applications of data mining for dispute prediction, and compile factors which could potentially impact PPP case characteristics and the occurrence of disputes. Section 3 then explains the research methodology, providing a theoretical basis for classification and association models adopted in subsequent investigations. Section 4 presents the project dispute data descriptions. Section 5 describes the modeling process and interprets the analytical results. Conclusions are finally drawn in Section 5, along with recommendations for future research.

2. Literature review

Public works projects provide the infrastructure needed for a country's overall economic development while also raising residents' standards of living. Therefore, expediting such projects is a key national goal. Policy formulation and resource allocation must further consider the use of expertise and resources from the private sector, and many countries are now encouraging private enterprises to participate in public works [9,18,21]. In most of the democratic countries, raising taxes to fund the public infrastructure projects is no easy task. However, with the public's continuous demand on various types of basic infrastructure, this conflict often puts the national governments in financial difficulties which can lead to unsustainable debt levels and financial crises.

To solve this problem, private investment in public works construction is introduced, which is commonly known as PPP. PPP refers to public agencies acting under their respective authority to engage in all processes entailed in a given public investment project, including negotiating and signing contracts, planning private investment in public works, design, construction, operations, and management. This practice is able to bring in business ideas and capital, while significantly reducing the financial burden of the government, increasing the quality of public services, and accelerating the construction process. Thus, the PPP model is common and widely used all over the world [29,42].

According to the Article 8 of the PPP Act, private participation in public infrastructure projects includes government-planned cases and privately-developed cases. In government-planned cases, private investment and participation are solicited for public works after the evaluation by the competent authority. While for privately-developed cases, private operators respond to a request for proposal on the part of the competent authority by submitting plans for the construction or operations of public works, along with financial plans and other relevant documents [1].

To expand the scope of private participation in public works, the PPP Act provides 14 incentive items in 20 categories including industrial and commercial facilities for transportation, culture, education, social welfare, and tourism and recreation. These incentives include relaxed land use, financing, and legal restrictions, providing financing concessions, tax breaks and others, and regulates the rights and obligations of the government and private entities, stipulating the authority and supervision of the validation process.

To date, PPP and public work construction is being actively pursued to help push social and economic development in Taiwan, and is providing positive results for public services and infrastructure. However, disputes inevitably arise from restrictions imposed by traditional administrative procedures and modes of operation, along with different levels of knowledge and understanding among participants. PPP systems are novel and complex, and some may be under the impression that such cases are entirely funded by private enterprise with no investment required from the government. At the same time, disputes may arise from early termination or cancellation of a contract, or due to adjustments or revisions to the contract during the compliance process [18,28].

Internationally, many studies have examined different data mining techniques to predict performance disputes and litigation results for general construction work [4-8,10,13,23,32]. PPP covers a wide range of technical expertise, including engineering, law, finance, management, and administration. Compared to general construction projects, PPP cases require long compliance periods entail the considerable risk of conflict in the construction, operation and transfer stages. In such cases, the working relationship between government agencies and private enterprises must be planned and managed from the outset, in which lessons from the past can be applied to work around potential conflicts. Engineering disputes often involve complex interactions. Nevertheless, by applying data mining theory and techniques, one can effectively obtain important information about the hidden relationships between different variables.

Arditi *et al.* surveyed the conventional engineering literature from 1998-2010 to examine applications of artificial intelligence to predict engineering conflicts and litigation results [3-8]. Chen and Hsu (2007) reviewed US court records of disputes arising from engineering changes in an attempt to forecast judgments results [3,5-8,12], and reached a 84.38% classification accuracy using the K-Nearest Neighbor (KNN) method [11,12]. In addition, Chen and Hsu (2007) applied the combined ANN-CBR model in a case-based reasoning approach to explore the circumstances of project conflict, which achieved a model accuracy rate of 84.61% [11,12].

In addition, Chou proposed a data mining method to predict approaches to PPP conflict resolution in 2012, with analysis results showing the combined (QUEST+CHAID+C5.0) model had an optimal accuracy of 84.65% [13]. In 2013, Chou used four machine learning techniques (ANNs, SVMs, DL, and TAN), four classification and regression techniques (CART, Exhaustive CHAID, QUEST, and C5.0), and two multivariate statistical methods (LR, DA) to explore the high accuracy of the classification model to predict domestic PPP conflict scenarios [16].

However, in recent years, conflict prediction research has largely failed to explore the resolution of conflicts generated from general engineering or design changes at various development stages including contract signing, construction, operation, and transfer. Although classification techniques have been applied to build prediction models for different disputes types and resolution methods, machine learning association rules have not yet been applied to analyze PPP case studies. This paper attempts to address this shortcoming by analyzing the results of available information for management decision making. In the next section, the data mining techniques and algorithms used in the present study will be briefly described.

3. Research Methodology

Data mining is a type of data transformation. It collects together disorganized numeric and text data which is then converted into information through statistical methods, and then into knowledge through the application of machine learning. The knowledge will combine with the wisdom of crowds to generate relevant decision support as the outcome [22]. Leading companies including SPSS, NCR, Daimler Chrysler and OHIRA have adapted the Cross-Industry Standard Process for Data Mining (CRISP-DM) as a set of data mining standard operating procedures [27].

CRISP-DM emphasizes that data mining does not simply entail rearranging data or applying statistical models for data analysis. Rather, it is a complete, widely accepted and validated process of understanding needs, searching for solutions, and extracting knowledge. This process is not a progressive implementation of linear steps, but a checklist and review process which can be repeatedly amended at any time [24].

Applying the Knowledge Discovery of Databases (KDD) process to information technology produces acceptable computational efficiency limitations in creating a characteristic data style. The KDD process includes steps for the application of fields of cognition and data cleaning, data integration, data selection, data transformation, data mining, pattern evaluation, and knowledge presentation [25,27].

Among these steps, data mining is mostly used to filter seemingly useless information, creating a complex mapping function through careful analysis, statistical filters and layered filtering. Different data mining methods are used for different types of problems, and using the appropriate tool helps ensure a satisfactory outcome [35]. Given the data characteristics used for this study, data mining functions are applied as follows:

A. Classification

Classification is the most common type of data mining operation, which is defined as ‘the creation of models to predict the class of an unseen instance’ [43], and is a fundamental human behavior involved in the production of knowledge. Under this type of operation, groups are defined and created according to the properties of the subject of analysis, using classical methods including decision trees, memory-based reasoning, and link analysis. Manually classified data are used to build classification models, which are then applied to generate predictions for unsorted or new data [26,27]. Thus, the main purpose of classification is to understand the characteristics of a particular group or a set of groups, and these characteristics will be used as a basis for defining decision-making rules or classification processes.

B. Association

Association rules take the form of “If antecedent, then consequent,” along with a measure of the support and confidence associated with the rule [37]. Association rules search historical data to relationships between events, a process also known as market basket analysis. This function can be used to determine direct and indirect inter-variable correlation, primarily using the Apriori, Partition and DHP algorithms [40]. The advantage of this approach is that it attempts to find multiple rules, each of which can provide corresponding conclusions [26,27]. In addition, association analysis can be roughly divided into two main stages [26,27]:

Stage 1: To find the collections of classifications with high support from the data for the searched group,

Stage 2: Establish association rules for the most commonly occurring collections. The confidence indicates the degree of correlation between events.

The above descriptions show that data mining starts with data observation, and then applies information technology to extract interesting patterns and models [33]. This study uses the IBM SPSS data mining software Clementine 12.0 which presents an interface combining a variety of analytical techniques and provides a user-friendly visual programming environment. Through modeling nodes, it can provide data import, data processing, data visualization, machine learning and prediction, and classification and association modeling.

Data mining results depend on the characteristics of the original data, the analysis requirements, algorithm performance, data field types and other factors. Using different analytical models and technologies, the results can primarily be categorized as statistical or artificial intelligence:

A. Artificial Neural Networks

Artificial Neural Networks (ANNs) refers to a biological system that can perform pattern detections and predictions [31]. ANNs apply structures similar to synaptic connections to carry out mathematical modeling of information processing. This approach is also referred to as “neural networks” [17,26]. Neural networks are composed of many artificial neurons linked to form a complex network, and can learn to adapt to stimuli from the external environment. The network is commonly modeled on algorithms found in nature or a functional approximation, and may be a reflection of a logical strategy. Neural networks feature high-speed computing, memory, learning, noise filtering and fault-tolerance, allowing them to solve many types of complex problems such as classification or prediction [19,36].

B. Support Vector Machine

Support Vector Machines (SVMs) are a type of monitoring system learning method [17,26] which are widely used in statistical classification and regression analysis. SVM is a generalized linear classifier which simultaneously minimizes experiential errors and maximizes the geometric marginal zone. SVM primarily handles data classification problems by using the separating hyperplane to separate data to two or more different classes. However, not all data can be used to find the linear separating hyperplane. If nonlinear problems are encountered, the linear separating hyperplane cannot be found in the original data space, and a nonlinear mapping function must be applied to convert the raw data into a high-resolution feature space in which linear classification is performed to provide greater accuracy.

C. Bayesian Network

Bayesian networks (also referred to as belief networks or directed acyclic graphical models) are a kind of probability pattern model that can process incomplete or noisy data sets to resolve data inconsistencies even with interdependency issues. When making inferences with a Bayesian network, a multi-connection graph can become a single-connection graph for handling, and allow for bottom-up or top-down deductions [39]. The graph nodes of directed acyclic graphical models of Bayesian networks represent random variables, which may also be observable variables, potential variables or unknown parameters. Through learning, Bayesian networks describe system behavior as the transformation of a joint probability distribution to the product of a set of conditional probabilities, with the integration of incremental learning features of *a priori* knowledge [19,26].

D. Classification And Regression Tree

Classification and Regression Trees (CARTs) is a binary tree algorithm which can partition data and generate accurate subgroup. CART is a tree structure with two outgoing edges for every internal node [38], and that the non-leaf nodes represent the testing conditions, while the branches represent the testing results, and the leaf nodes represent the classification tag obtained, which is the classification result. If the analysis target variable is a categorical variable, it is represented as the classification tree. If the target variable is a continuous variable, it is called a regression tree. A regression tree is suggested as one of the important characteristics in CART, where the leaves can predict real number instead of a class [38]. CART can also generate an estimation model with flexible data formats and scale measurement methods without extensive training, in which the predicted field includes numeric data or classification data. CART iterations do not require advance discrete steps, but repeatedly builds a binary branching from the roots until the homogeneity of the leaf nodes reaches a set standard or triggers the iteration termination condition [19,26].

E. Chi-squared Automated Interaction Detection

Chi-squared Automated Interaction Detection (CHAID) can quickly and effectively explore data using tree algorithms to perform statistical tests, and is able to build sections and basic data related to the desired result. In the process of building the decision tree, it primarily uses the chi-square test to find the optimal branch. The analysis method uses Bonferroni's adjusted chi-square as the basis for the sample population, thus sample homogeneity is attributed to a single group, and successive searches are completed in the division process. CHAID prevents excessive data samples from terminating the division of the decision tree and generates a ρ-value for the category from the calculation node, and the size of this ρ-value determines whether the decision tree will continue to grow [26,27].

The Exhaustive CHAID algorithm, on the other hand, is a modified form of CHAID which checks all possible branch splits. In the branching process, if no further need for merging is found, CHAID will stop, but Exhaustive CHAID will continue to merge the attribute variables, eventually forming two combinations. With the ability to conduct branch variable selection, Exhaustive CHAID is considered as a more thorough technique than CHAID.

F. Quick Unbiased Efficient Statistical Tree

Quick Unbiased Efficient Statistical Tree (QUEST) mainly selects unbiased variables to quickly and efficiently establish an accurate binary tree. For the classification of each node, a statistical test (F or chi-square) is conducted to find the best predictor variables. Discriminant analysis is then used to find the optimal split nodes [19]. Similar with CHAID, QUEST is also applied to prevent the over-application of data causing the tree to terminate segmentation, in which the size of the ρ-value of the category from the calculation node is a determinant factor [19,36].

G. C5.0

C5.0 is a type of supervised learning, which is also known as the rule-based reasoning model. It can analyze continuous variables and categorical variables, and generate a decision tree or rule sets according to the user's specifications [19]. C5.0 not only performs binary segmentation but can produce multi-branches at each node, making it different from other decision tree classification methods. Segmentation decisions are based on information gain, followed by decision tree pruning based on the predicted error rate for each internal node, and selecting the property of the greatest increment as the node segmentation property [19,36].

H. Generalized Rule Induction

The Generalized Rule Induction (GRI) uses the relevance of data attributes to identify available rule sets. Algorithms can conduct assessments based on support or confidence. Support represents the likelihood of an event occurring, and is defined as the proportion of support for decision variables appearing in the database [15] where a higher proportion denotes a higher degree of support, while confidence is the degree of credibility obtained using this association rule. Both formulae are expressed as follows:

$$Confidence(A \rightarrow B) = P(B|A) = \frac{P(A \cap B)}{P(A)}$$

$$Support(A \rightarrow B) = P(A \cup B)$$

where A and B are disjoint item sets.

4. Project Information

This section explains the pre-processing of the questionnaire data, including building the database fields, checking data field values for abnormalities, and data type conversion to facilitate subsequent survey implications for decision-making information. Descriptive statistics for the database fields are then used to conduct cross-comparison analysis for a preliminary inquiry into factors impacting the occurrence of disputes in PPP cases and their various types.

4.1.Statistical data description

This study surveyed a total of 584 contracted PPP cases from 2002 to 2010. Cases which entailed multiple disputes were split into multiple samples, giving a total of 645 samples overall, with a total of 152 disputes. The data is grouped into 13 categories, which is generalized and induced according to previous literature.

First, the data is categorized according to the sponsoring agency, and displayed the following rate of dispute occurrence: the center (26.6%), directly under (31.1%), and local government (14.4%). The projects sponsored by the municipal governments showed the highest dispute rate, which might due to the lower number of projects that are sponsored by the municipal government, leading to a relatively high rate of dispute occurrence.

The data are then differentiated by the type of infrastructure project, and rated according to dispute occurrence: transport (13.7%), Common Utility Culvert (0%), environmental pollution control facilities (26.7%), sewage (57.1%), water utility facilities (100%), water conservancy facilities (93.8%), health care facilities (19.4%), social welfare facilities (28%), labor welfare facilities (50%), cultural and educational facilities (12.3%), major tourism and leisure facilities (32.4%), electrical power facilities (0%), gas utility facilities (0%), sports facilities (33.3%), parks (6.3%), major industrial facilities (33.3%), major commercial facilities (41.7%), major scientific facilities (0%), new town development (0%), agricultural facilities (47.2%), and other (0%).

It's worth noting that water utility facilities, water conservancy facilities, and sewage facilities all had higher rates of disputes, and the preliminary inference should be the high degree of technical difficulty of public infrastructure projects, which may make the PPP compliance process seems highly cumbersome, thus resulting in a higher rate of disputes.

Next, reference data is used to classify the public infrastructure by location and to screen for disputes. Projects were distributed through Taiwan's five main regions as follows: North (21.4%), Central (10.2%), South (39.9%), East (23.5%) and Offshore Islands (0%). Statistics show that the rate of disputes was higher in the South region than in the North. Data from the case review found that cases in the South region were relatively larger and more complex, which probably made the plans for projects in this region more prone to disputes.

The data is classified by execution organizations, and showed the following dispute occurrence rate: the center (29.7%), directly under (17.2%), and local government (23.9%). Projects that are executed by the central government displayed the highest rate of dispute.

The reference data can be classified by the industrial background of the private institutions involved as follows: Primary industries (0%) are those that extract raw materials including mining, agriculture, fisheries, *etc*.; secondary industries (22.5%) process raw materials, which include manufacturing, construction, etc.; tertiary industries (19.6%) refers to the service industries such as the legal, medical and retail industries; and quaternary industries (47.1%) are industries that pursue scientific or technological research. Based on these classifications, quaternary industries are the most active sector, and also have a high rate of disputes.

The cases can also be categorized by the types of the project plan. The data show that government plan on government land has the highest rate of disputes of 23.9%, followed by the private plan on government land (23.7%). Private plan on private land has the lowest dispute rate of 15%, which may be due to the high financial pressure to speed up and control the development process.

Classifying the reference data by private participation mode shows the disputes rates as follows: Build-Operate-Transfer (BOT) (49%), Operate-Transfer (OT) (14.4%) and Rehabilitate-Transfer-Operate (RTO) (18.4%). According to the Article 8 of the PPP Act, BOT refers to cases that once the operation period has expired, the facilities are transferred to the government. In OT cases, the facilities are built using government funds but are operated by the private organization, which then transferred back to the government at the end of the operating period. In ROT cases, either the government contracts the private institution or private institutions rent existing facilities to expand and operate the facilities until the end of the contract period, at which point the facilities are returned to the government [1]. Under this classification, the reference data shows that BOT mode creates the largest rate of disputes among the others, while OT has the lowest.

Moreover, the reference data indicate that the rate of disputes is related to the project scale, with major projects (defined under the PPP Act) having a disputed rate of 18% as compared to 45.7% for non-major projects. The reason for a lower rate of disputes for major projects is that they are eligible for significant incentives including the expropriation of private land, relaxed credit, five-year income tax exemptions, lower income tax rates, investment credits, and tariff exemptions for imported equipment and components [16]. Also, major public works projects are large engineering projects that would be in consultation with the Ministries of the Interior and Finance, along with competent authorities in the central government, which could reduce the rate of disputes occurrence

On the other hand, the data can also be classified according to the project value. For projects over NT$50m, there is a 45.7% chance of having disputes. If the projects are between NT$5m-50m, the rate of disputes is lower (13.5%), followed by projects less than NT$5m (9.6%). For projects that are funded by the government, the figures are as follows: Projects less than NT$5m (20.6%), NT$5m-50m (31.6%), over NT$50m (65.8%). It's worth noting that the rate of disputes increases with the amount of government investment. Similarly, dispute rates for projects financed by private capital also demonstrated the same pattern: Projects less than NT$5m (9.6%), NT$5m-50m (14.0%), over NT$50m (46.4%).

The data can also be grouped by the percentage of private investment contribution. The dispute incidence rate are as follows: less than 25% (11.4%), 25～50% (0%), 50～75% (37.5%), over 75% (24.2%). For projects that involve 50% to 75% of private investment, the dispute rate is the highest, which might due to the lower number of cases that fall into this category, thus showing a relatively higher rate of dispute.

Finally, classifying the reference data in terms of concession period shows the following dispute rates: Less than 5 years (7.3%), 5-10 years (15.9%), 10-15 years (31.9%), 15-20 years (50%) and over 20 years (50.8%). This indicates that the rate of disputes tends to rise with the duration of the concession period.

4.2. Dispute content and resolution methods

The validation procedures stipulated in the PPP Act are a part of public law, and investment contracts signed between private institutions and the competent authority are constituted as civil contracts. Article 47 of the PPP Act provides procedures for objections and appeals, and permits the government to use the Government Procurement Act to handle tenders, audits or disputes. Disputes usually arise from the application or audit processes of PPP cases; however once the investment contracts have been signed between the private institutions and the competent authority, both sides establish a civil contractual relationship [16].

Therefore, when a dispute arises in a PPP case, it does not fall under the Government Procurement Act in principle, and thus engineering committee's mediation mechanism will not intervene, and the parties must revisit the investment contract agreement. Typically, procedures for handling disputes in PPP cases are similar to those for handling disputes in government procurement cases, with the first negotiation, followed by mediation, then arbitration or litigation, with different dispute resolution mechanisms established by the coordination committee [16].

This study collected records for 584 PPP cases from 2002 to 2010. If each instance of the dispute is treated as a unique case, then the total sample size is 645 cases, including 152 disputes. These cases were further classified according to their nature of dispute, which generated the following results: contract and legal disputes (17.8%); design, construction and commissioning (17.8%); execution or maintenance (18.4%), investment and taxes (23.7%); market and income (3.3%); government commitments (14.5%); and asset ownership and transfer (4.6%).

Contract and legal disputes refer to insurance and performance guarantees, vendor qualification (including subcontractors), contract rescission and termination, and non-financial contract rescission and termination. Design, construction, and commissioning disputes include investment scale and construction scope, extensions to work period, and inspections.

Disputes related to implementation and maintenance includes investment regulatory authority (including quality), operation duration, operation stages and other issues. While for investment and tax disputes, which accounted for the highest dispute rate, comprise of financing, other financial issues (including health insurance settlements), reduced or delayed royalty income, and reduced land lease fees.

Market and revenue disputes have the lowest share, which includes income adjustments, excess profits, and paid items. Government commitment disputes refer to government obligations and the acquisition of relevant development permits. Last but not least, asset ownership and transfer disputes comprise of the rights of local residents, property determination, and real estate tax or land value tax.

The rate of dispute occurrence is also found to be distinct during different stages. Our analysis found that 55.9% of dispute happened in the operation stage, while 40.8% and 3.3% in the construction and transfer stage respectively. In the PPP construction stage, the primary work flow is as follows: Contract signing → land grant → planning and design → start work → construction → review → testing, commissioning and operational simulation → completion → other. During operation stage, which incurs the highest rate of dispute, the primary work flow is as follows: Pre-operational preparation → commence operations → operational period → pre-expiry operations. While, for the transfer stage, the main work flow is as follows: Asset audit → asset transfer inventory → transfer → cross check → transfer complete → case closed.

The reference data were then classified according to the conflict resolution method, which shows the following results: Mediation (59.2%), arbitration (8.6%), litigation (7.9%), consultation (15.8%) and other (8.6%). Mediation relies on the resorting to an impartial third party, such as an arbitrator or court, to reconcile the two disputing parties. It is noted that mediation is different from negotiation, which does not involve a third party.

Dispute arbitration means that both parties have consented to submit the dispute to arbitration, with each side selecting an arbiter to jointly form an arbitration tribunal to reach a verdict through certain procedures.

Litigation means that the dispute will be referred to the courts, with each side advocating for its legal rights in proceedings governed by national judicial procedures to obtain a binding judgment to resolve the dispute.

Dispute consultation refers to the attempt of both parties to negotiate in good faith in seeking consensus and reconciliation on an appropriate and mutually-agreeable compromise to end or prevent disputes.

5. Analytical Results

The artificial intelligence data mining software SPSS Clementine 12.0 is used in this study. Based on the data characteristics and requirements, and according to the aforementioned parameters, we applied machine learning, and classification and regression techniques to build models, and to cross-validate the accuracy of each one. Sensitivity analysis is also conducted to rank factors by their impact on the dispute incidence. The classification model results could serve as a reference for a future prediction on potentially useful dispute resolution methods base on the dispute types.

To conduct the analysis, the data preprocessing stage must first transform the raw data into machine-readable formats through data grouping, new variable creation, data format conversion, and inspecting missing, blank and extreme values etc. Table 1 shows the properties and content of the data processing classification fields, while Table 2 presents descriptive statistics of the Numeric type.

<<Table 1>>

<<Table 2>>

5.1. Modeling

During modeling, the model is subjected to testing and validation. This study used k-fold cross validation because the small size of the data set made the division of direct data collection inappropriate, and when comparing the accuracy of predictions obtained using two or more methods, k-fold cross validation can ensure that the samples are independently modeled and tested, thus reducing errors from random sampling. In cross-validation, a set of samples were first randomly divided into a k-sub sample group from which a rotating k-1 sub-sample group is used as the training sample, while the remaining samples are used for testing. This action is repeated k times to build the model [41]. Kohavi (1995) further pointed out that 10-level cross-validation provides the most reliable accuracy [34].

The binary classifier in SPSS Clementine software is adopted to process the original survey data from 584 PPP cases, of which 91 cases involved one or more disputes. The target variable Y1 is set, and decision variables are set as X1-X13 to construct the predictive models using machine learning, classification and regression algorithms. There are a total of 10 binary classification methods provided by Clementine. The methods with the highest accuracy are chosen, which are Artificial Neural Networks (ANNs), Support Vector Machines (SVM), Bayesian Networks (Bayes Net), Classification and Regression Trees (C&RT), Chi-squared Automated Interaction Detection (CHAID), Quick Unbiased Efficient Statistical Tree (QUEST) and classification trees (C5.0).

5.2. Performance disputes and association mode

Validation and testing of the models is an important step in performing data mining. To minimize inaccuracy, cross-validation is carried out in this study. Table 3 summarizes the average rate of model cross-validation using the above-mentioned methods. The table shows a 83.92%, 83.70%, and 83.42% accuracy of the incidence of disputes (Y1) in PPP cases for C5.0, ANN, and QUEST respectively. The best prediction results were produced using C5.0, and decision sensitivity analysis results show that the incidence of disputes in PPP cases is impacted by several key factors such as the length of the compliance period (X13), project value (X9), public works location (X3), the project scale (X8) and project type (X2).

Using the Generalized Rule Induction (GRI) mode, the association model showed the highest accuracy of 80.47%. Given the support level of 20% and a confidence level of 50%, the associated decision rules are as follows:

1. For a project located in the South region, with a budget exceeding NT$50m, the support and confidence levels for a PPP conflict are 42% and 50%, respectively.
2. For a large-scale public works project located in the South region, the support and confidence levels for a PPP conflict are 26% and 54%, respectively.
3. For a large-scale public works project located in the South region with a budget exceeding NT$50m, the support and confidence levels for a PPP conflict are 22% and 65%, respectively.

<<Table 3>>

5.3. Relevance of PPP conflict type

To perform another round of testing, the decision variables remain the same as X1-X13, while the target variable is changed to Y2 – the conflict type for data cross-validation, training, and testing, with the resulting average accuracy for each model shown in Table 4.

Table 4 shows that the classification tree C5.0 provides the best predictions, and according to the sensitivity analysis, the effect of the decision variables on conflict type ranked as follows: X9 Project Scale (NT$1,000), X13 Licensing Compliance Period (years), X2 Public Construction, X3 Project Location and X11 Private Investment (NT$1000). Applying the GRI model to reference data for 152 PPP cases featuring disputes obtains an association model accuracy rate of 76.59%. The support level and confidence level of the retrieved association mode are 5% and over 50%, respectively, which are associated with the following decision rules:

1. For a public water facility located in the South region and with a concession period of less than 21.335 years, the support and confidence levels for a design, construction or commissioning dispute are 8% and 50%, respectively, and are associated with 12 of the 152 PPP dispute cases.
2. For a major tourism and recreation facility with a budget greater than NT$2,434,876,000, the support and confidence levels for a government obligation dispute are 7% and 50%, respectively, and are associated with 10 of the 152 PPP dispute cases.
3. For the construction of a public sports facility with a budget greater than NT$57,150,000, the support and confidence levels for a government obligation dispute are 5% and 50%, respectively, and are associated with 8 of the 152 PPP dispute cases.

<<Table 4>>

5.4. Associated model for PPP dispute resolutions

Table 5 shows the results of target variable being changed to dispute handling method (Y3), which reveals the cross-validated prediction accuracy for mediation, arbitration, litigation, consultation and other methods.

<<Table 5>>

In Table 5, the best prediction results are provided by SVM, and key factors impacting the dispute handling method for PPP cases in rank order include project type (X2), private investment amount (X11), length of concession period (X13), project value (X8) and project scale (X8). Constructing the association model gives an accuracy of 71.01%. Given a support level of 50% and a confidence level greater than 50% for the GRI association model, the associated decision rules are as follows:

1. For a major infrastructure project with a private investment of over NT$50m and a concession period of 20 years, the support and confidence levels for mediation are 54% and 50%, respectively.
2. For a water infrastructure project, the support and confidence levels of a dispute in the construction stage are 11% and 81%, respectively.

5.5 Associated model for the stage of PPP dispute occurrence predictions

Another round of testing is performed by changing the target variable to Y4 – the cross-validated accuracy for the stage at which a dispute occurs. As presented in Table 6, ANN was found to produce optimal prediction accuracy for dispute stage, and according to the decision variable sensitivity analysis, the key impact factors for dispute stage are ranked in the following order: type of project (X2), project location (X3), sponsoring agency (X1), industrial background of private institution (X5) and concession period length (X13). shows that The GRI model is applied using X2, X3, X1, X5 and X13 as input field values, and using the Y4 variable as the output field value to explore a collection of high-frequency items, and the model returns an accuracy rate of 80.31%. Given the support and confidence levels of 10% and over 70%, respectively, the associated decision rules are as follows:

1. For a project under the direct authority of the relevant agency, with a concession period of more than 20 years, the support and confidence levels for a dispute occurring in the construction stage are 13% and 74%, respectively, and disputes are found to occur in 19 of the 152 samples.

2. For a waterworks facility, the support and confidence levels for a dispute occurring in the construction stage are 11% and 81%, respectively, with disputes occurring in 16 of the 152 samples.
3. For a project under the direct authority of the relevant agency, executed by private institutions belonging to the secondary industrial sector, and a concession period of more than 20 years, the support and confidence levels for a dispute occurring in the construction stage are 11% and 75%, respectively, with disputes occurring in 16 of the 152 samples.

<<Table 6>>

6. Conclusion and Recommendation

It is without a doubt that policies to promote private participation in public infrastructure projects have effectively contributed to the social and economic development of Taiwan, and have had a positive impact on the quality of public services and construction while increasing the availability of engineering, legal, financial, management and administrative expertise. However, disputes in the PPP process are difficult to avoid. To provide an initial understanding of the factors contributing to the occurrence of such disputes along with effective dispute resolution methods, this study surveyed past PPP cases, using data mining techniques to predict dispute types, resolution methods, the stage at which disputes occur, and to investigate the relevance of key contributing factors.

This study conducted cross-validation analysis of various variables in association with the rate of dispute occurrences in PPP cases from 2002 to 2010. The findings indicated that large-scale infrastructure projects located in Southern Taiwan region had a disputed rate of 71.1%, while projects with a total budget exceeding NT$50m and a concession period exceeding 15 years had a disputed rate greater than 50%. Using the Y1 model and cross-validation, we found that the decision tree C5.0 model had the highest accuracy of 83.92%.

In addition, accuracy levels of 77% and above were achieved for data training and testing using machine learning and classification and regression algorithms, such as ANN, SVM, Bayes Net, C&RT, CHAID, QUEST and C5.0 for target variables including dispute type (Y2), dispute resolution method (Y3), and dispute stage (Y4). Sensitivity analysis was conducted and the factors are ranked in the order of importance: Project type (X2), project location (X3), concession period (X13), sponsoring agency (X1), the industrial background of a private institution (X5) planning mode (X6) and the private capital ratio (X12).

It's worth noting that when the output fields are PPP disputes (Y1), GRI modeling achieved an accuracy of 80.47%, with an association count of 28. Of these, the primary association showed that, for projects located in the Southern region, and with budgets exceeding NT$50m, the support and confidence levels for dispute occurrence was 42% and 50%, respectively.

In addition, GRI modeling of dispute type (Y2) had an accuracy of 76.59%, with an association count of 75. The primary association showed that, for waterworks facilities projects in the Southern region with a concession period less than 21.335 years, the support and confidence levels for a dispute in the construction and commissioning stages was 8% and 50%, respectively. GRI modeling for dispute resolution method (Y3) had an accuracy level of 71.01%, with an association count of 73. The association rules showed that for a major construction project with private investment exceeding NT$50m and a concession period exceeding 20 years, the support and confidence levels of conflict mediation was 54%

and 50%, respectively. For dispute stage (Y4), GRI modeling generated an accuracy level of 80.31%, with an association count of 64. For projects directly under the authority of the sponsoring agency and a concession period exceeding 20 years, the support and confidence levels for disputes arising in the construction stage was 13% and 74%, respectively.

To conclude, the results of this study can provide PPP management agencies with supporting references for initial planning and decision-making, and can also be applied to develop precautionary measures during the contract negotiation stage in reducing the likelihood of disputes and conflicts occurrence during the performance period.

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Table 1

The properties and content of the data processing classification fields

Attribute	Description
X1- sponsoring agency	1- The center（59.5%）2- directly under（11.5%）3- Local Government（29%）
X2- project type	1- transport（18.1%）2- Common Utility Culvert（0%）3- environmental pollution control facilities（2.3%）4- sewage（1.1%）5- water utility facilities（0.5%）6- water conservancy facilities（2.5%）7- health care facilities（20.8%）8- social welfare facilities（3.9%）9- labor welfare facilities（1.2%）10- cultural and educational facilities（25.3%）11- major tourism and leisure facilities（10.5%）12- electrical power facilities（0%）13- gas utility facilities（0%）14- sports facilities（3.3%）15- parks（2.5%）16- major industrial facilities（0.5%）17- major commercial facilities（1.9%）18- major scientific facilities（0.2%）19-new town development（0%）20- agricultural facilities（5.6%）
X3- public works location	1- North（48.5%）2- Central（21.2%）3- South（24.5%）4- East（5.3%）5- Offshore Islands（0.5%）
X4- execution organ	1- The center（36.0%）2- directly under（36.1%）3- Local Government（27.9%）
X5- industrial background of private institution	1- Primary industries（0.2%）2- secondary industries（38.6%）3- tertiary industries（50.7%）4- quaternary industries（10.5%）
X6- planning mode	0- Government plan, government land（91.0%）1- Private plan, government land（5.9%）2 Private plan, private land（3.1%）
X7- private participation mode	0-BOT（23.7%）1-OT（52.7%）2-ROT（23.6%）
X8- the project scale	0-No（19.9%）1-Yes（80.1%)）
X9- major infrastructure project	1- Projects less than NT$5m（35.7%） 2-NT$5m-50m（28.7%）3- over NT$50m（35.7%）
X10- Government Investment	1- Projects less than NT$5m（35.7%） 2- NT$5m-50m（28.7%） 3- over NT$50m（35.7%）

X11- Private Investment	1- Projects less than NT$5m（35.7%） 2- NT$5m-50m（29.9%） 3- over NT$50m（34.4%）
X12- private capital ratio	1- less than 25%（6.8%） 2-25～50%（0.5%） 3-50～75%（2.5%）4- over 75%（90.2%）
X13- concession period	1- Less than 5 years（29.6%）2-5-10 years（35.2%）3-10-15 years（10.7%）4-15-20 years（5.0%）5- over 20 years（19.5%）
Y1- PPP disputes	0-No（76.4%）1-Yes（23.6%）
Y2-dispute type	0- no dispute（76.4%）1- contract and legal disputes（4.2%）2- design, construction and commissioning（4.2%）3- execution or maintenance（4.3%）4- investment and taxes（5.6%）5- market and income（0.8%）6- government commitments（3.4%）7- asset ownership and transfer（1.1%）
Y3-dispute resolution method	0- no dispute（76.4%）1- Mediation（14.0%）2- arbitration（2.0%）3- litigation（1.9%）4- consultation（3.7%）5- other（2.0%）
Y4- dispute stage	0- no dispute（76.4%）1- construction（9.6%）2- operations（13.2%）3- transfer（0.8%）

Table 2

Descriptive statistics of the Numeric type

Attribute	Average	Standard deviation	Maximum	Minimum
X9- major infrastructure project(NT$1000)	841,457	3,520,615	60,000,000	0
X10- Government Investment(NT$1000)	63,648	511,375	9,600,000	0
X11- Private Investment (NT$1000)	777,809	3,324,332	60,000,000	0
X12- private capital ratio （%）	91	25	100	0
X13- Licensing Compliance Period (years)	12	13	60	0

Table 3

The accuracy of the different predictive models for the incidence of disputes (Y1) in PPP cases

	ANN	SVM	Bayes	CART	CHAID	QUEST	C5.0
fold 1	80.00	71.67	80.00	75.00	76.67	80.00	80.00
fold 2	78.33	68.33	78.33	70.00	78.33	75.00	78.33
fold 3	78.33	76.67	80.00	75.00	83.33	80.00	80.00
fold 4	81.67	80.00	66.67	75.00	81.67	81.67	81.67
fold 5	83.33	80.00	85.00	73.33	85.00	83.33	85.00
fold 6	91.67	86.67	81.67	85.00	88.33	88.33	88.33
fold 7	80.00	83.33	80.00	76.67	80.00	80.00	80.00
fold 8	83.33	76.67	83.33	83.33	83.33	83.33	83.33
fold 9	91.67	80.00	91.67	81.67	88.33	91.67	91.67
fold 10	88.64	84.09	90.91	84.09	86.36	90.91	90.91
Average	83.70	78.74	81.76	77.91	83.14	83.42	83.92
Standard deviation	5.17	5.62	7.02	5.19	4.01	5.35	4.86
Ranking	2	6	5	7	4	3	1

Table 4

The classification tree C5.0 provides the best predictions, and sensitivity analysis of the decision variables

	ANN	SVM	Bayes	CART	CHAID	QUEST	C5.0
fold 1	73.85	66.15	64.62	73.85	75.38	73.85	73.85
fold 2	76.92	75.38	72.31	72.31	76.92	70.77	76.92
fold 3	76.92	78.46	73.85	75.38	75.38	75.38	80.00
fold 4	69.23	70.77	66.15	69.23	69.23	69.23	72.31
fold 5	72.31	72.31	73.85	72.31	72.31	73.85	73.85
fold 6	75.38	73.85	76.92	72.31	72.31	70.77	72.31
fold 7	84.62	86.15	76.92	81.54	83.08	83.08	84.62
fold 8	73.85	75.38	72.31	76.92	76.92	76.92	76.92
fold 9	73.85	76.92	76.92	72.31	73.85	73.85	69.23
fold 10	86.67	80.00	81.67	81.67	88.33	90.00	90.00
Average	76.36	75.54	73.55	74.78	76.37	75.77	77.00
Standard deviation	5.4	5.45	5.14	4.14	5.59	6.34	6.33
Ranking	3	5	7	6	2	4	1

Table 5

The best prediction results are provided by SVM, and key factors impacting the dispute handling method for PPP

	ANN	**SVM**	**Bayes**	**CART**	**CHAID**	**QUEST**	**C5.0**
fold 1	73.85	73.85	80.00	81.45	76.92	75.38	78.46
fold 2	83.08	80.00	73.85	83.08	78.46	75.38	83.08
fold 3	76.92	83.08	81.54	81.54	80.00	76.92	80.00
fold 4	70.77	72.31	69.23	69.23	72.31	70.77	72.31
fold 5	81.54	80.00	78.46	72.31	76.92	73.85	72.31
fold 6	76.92	80.00	81.54	76.92	75.38	70.77	76.92
fold 7	89.23	86.15	76.92	83.08	81.54	84.62	86.15
fold 8	80.00	84.62	76.92	81.54	83.08	76.92	83.08
fold 9	83.08	86.15	87.69	78.46	80.00	75.38	83.08
fold 10	88.33	85.00	86.67	90.00	93.33	86.67	86.67
Average	80.37	81.12	79.28	79.76	79.79	76.67	80.21
Standard deviation	5.93	4.9	5.56	5.89	5.69	5.23	5.17
Ranking	3	1	7	5	4	6	2

Table 6

The target variable changed to Y4 – the cross validated accuracy for stage at which a dispute occurs

	ANN	SVM	Bayes	CART	CHAID	QUEST	C5.0
fold 1	76.92	69.23	70.77	78.46	76.92	75.38	76.92
fold 2	78.46	73.85	70.77	80.00	76.92	76.92	78.46
fold 3	76.92	78.46	81.54	78.46	78.46	78.46	76.92
fold 4	76.92	73.85	70.77	73.85	72.31	70.77	75.38
fold 5	76.92	84.62	83.08	75.38	73.85	75.38	73.85
fold 6	80.00	73.85	69.23	80.00	75.38	73.85	78.46
fold 7	84.62	81.54	76.92	83.08	84.62	84.62	83.08
fold 8	81.54	80.00	76.92	81.54	81.54	81.54	83.08
fold 9	75.38	81.54	81.54	73.85	78.46	80.00	80.00
fold 10	90.00	83.33	88.33	90.00	88.33	88.33	88.33
Average	79.77	78.03	76.99	79.46	78.68	78.53	79.45
Standard deviation	4.53	5.06	6.53	4.84	4.92	5.26	4.32
Ranking	1	6	7	2	4	5	3