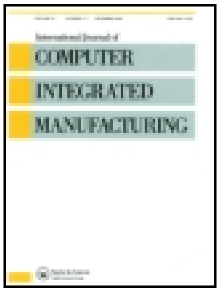

International Journal of Computer Integrated Manufacturing
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tcim20

Mining business knowledge for developing integrated key performance indicators on an optical mould firm

Shu-Hsien Liao [a] & Pei-Yuan Hsiao [b]
[a] Department of Management Sciences, Tamkang University, New Taipei City, Taiwan
[b] Department of Management Sciences, Graduate School of Ph.D. program, Tamkang University, New Taipei City, Taiwan

Version of record first published: 15 Feb 2013.

To cite this article: Shu-Hsien Liao & Pei-Yuan Hsiao (2013): Mining business knowledge for developing integrated key performance indicators on an optical mould firm, International Journal of Computer Integrated Manufacturing, DOI:10.1080/0951192X.2013.766933

To link to this article: http://dx.doi.org/10.1080/0951192X.2013.766933

International Journal of Computer Integrated Manufacturing, 2013
http://dx.doi.org/10.1080/0951192X.2013.766933

Mining business knowledge for developing integrated key performance indicators on an optical mould firm

Shu-Hsien Liao[a]* and Pei-Yuan Hsiao[b]

[a]*Department of Management Sciences, Tamkang University, New Taipei City, Taiwan;* [b]*Department of Management Sciences, Graduate School of Ph.D. program, Tamkang University, New Taipei City, Taiwan*

(*Received 7 February 2012; final version received 14 December 2012*)

The supply chain for Taiwanese optical components accounts for 39.7% of the total supply chain of the optical mould industry. However, some critical elements of the optical mould industry are difficult to predict; these include personnel, mechanical equipment, material, environmental and complex management factors. Therefore, these enterprises need flexibility to fine-tune their organisational structure, so that the main functions of various departments operate with the best processes. Beside case firm database, this study collects subjective data by designing a questionnaire with nominal scale question to investigate employees' potential attitude and behaviour in relation to the case firm's key perfomance indicators (KPIs). A total of 250 questionnaires were sent and 220 questionnaires were returned, including 207 effective questionnaires. All data source are designed on a entity relationships (ER) model and constructed on a relational database. In addition, this study applies a data mining approach using association rules, an Apriori algorithm, and cluster analysis to develop the integrated KPIs for a Taiwanese optical mould company. This study investigates the data mining process and considers how the development of the integrated KPIs for this company might serve as a business intelligence example for other firms and industries.

Keywords: data mining; association rules; cluster analysis; optical mould firm; key performance index (KPI); business intelligence

1. Introduction

Since the 1970s, the high-tech industry has been the main basis for regional economic development in Taiwan, which is an important industrialised country. The industry is not only a source of high-tech development, improving the momentum of regional economic growth, but it also supports a more balanced regional development. The performance of the optical mould industry, in Taiwan, has attracted much attention. As the global economic recovery continues, global mobile phone sales are steadily growing, with the sales of high-end mobile phone cameras and video cameras stimulating demand. The Taiwanese optical components industry has also grown with the expanded economy (Figure 1). It is estimated that the 2010 full-year production value of Taiwan's precision optical components increased to about 34.0 billion, representing a 36% increase from the 2009 figure (Ho 2011).

A key performance indicator (KPI) is a measure of the effectiveness of the most important indexes and an important tool for business management, in general. Thus, it must be an objective measure of performance. Ahmad and Dhafr (2002) believed that a KPI should include safety, environment, flexibility, innovation, performance, quality and reliability. Challis, Samson, and Lawson (2002) separated the manufacturing KPI into two parts: employee performance and manufacturing performance. In addition, Zorzut et al. (2009) proposed a closed-loop control structure utilising production performance indicators as a possible solution to investigate the synthesis of plant-wide control structures on production-management design problems for a polymerisation plant.

KPIs are often used for internal financial, operational, organisational and other performance measurements, both quantitative and qualitative. As an important performance measure to help improve an organisation, a KPI must be consensual. An effective KPI to measure a system should combine individual and organisational goals, so that organisations can detect faults and make rapid and transparent improvements, on an objective and measurable basis, to enable the most effective application of organisational resources. Academic literatures used for this study's definition of KPI are summarised in Table 1. However, a few studies to investigate the KPI on a manufacturing firm with a subjective and objective attributes integrated KPI's consideration.

On the other hand, data mining has been defined as 'the nontrivial extraction of implicit, previously unknown and potentially useful information from data' and as 'the science of extracting useful information from large data sets or databases' (Frawley, Piatetsky-Shapiro, and Matheus 1991). Previous studies have included many data mining models, such as classification, estimation,

*Corresponding author. Email: michael@mail.tku.edu.tw

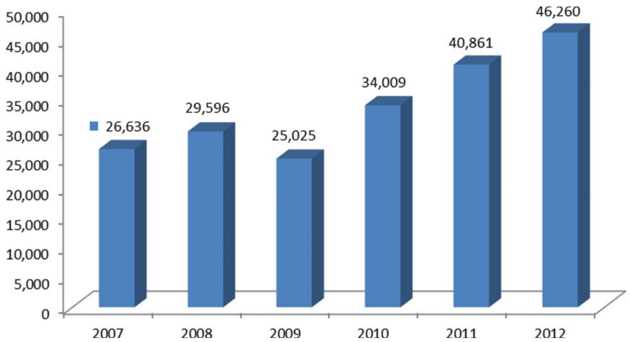

Figure 1. The trend in export values of Taiwanese optical component.

predictive modelling, clustering/segmentation, affinity grouping or association rules, description and visualisation, as well as sequential modelling. Similarly, there are many methods of application, including association rules, sequential patterns, grouping analysis, classification analysis and heuristic probability analysis (Mehta and Bhattacharyya 2004, Musaev 2004; Liao, Chen, and Hsu 2009b; Liao, Chen, and Tseng 2009c). Thus, the knowledge inherent within departments, when it has been extracted through data mining, can be integrated with business intelligence and provided to firms (Chryssolouris et al. 2008; Choudhary, Harding, and Tiwari 2009; Liao et al. 2009a; Efthymiou et al. 2011).

This study developed integrated KPIs using surveys of corporate sector personnel, mechanical equipment, materials, environment and management factors, through data mining, to determine the relationships between them and to find the KPI. A large part of an integrated KPIs derives from analysis of the data, in mining useful information, to provide a basis for decision-making and to act as a tool for performance evaluation (Xu, Wang, and Newman 2011). Accordingly, this study investigated the development of integrated KPIs for a Taiwanese optical mould firm. Two stages of data mining were implemented. The Apriori algorithm is a methodology that consists of the association rules for data mining; this is used to mine business knowledge from different functional departments. Knowledge extracted from data mining is illustrated as knowledge patterns and rules to generate integrated KPIs to propose suggestions and solutions for the example firm, to allow the generation of integrated KPIs. The study is organised as follows. In Section 2, the background of the case firm is presented. Section 3 introduces the proposed data mining system, including the system framework and design of the relational database and physical database. Section 4 describes the data mining process, including the Apriori algorithm, the K-means algorithm and knowledge extraction. Section 5 analyses the results of data mining. Research findings, managerial implications and conclusion are presented in Section 6. Finally, future work is described in Section 7.

2. Case firm: E optical company

2.1. About E optical company

The case firm, E optical company, directs a great deal of manpower in managing its processes and finances, it imports high-precision machines and tools, and it has a program to develop high-tech professional techniques and technology. This is intended for allowing a scale and quality on an international level for trials, production and overall processes. E optical firm was founded in Taipei, Taiwan, in 1979. For the past 30 years, it has developed its strengths on the basis of rapid technological development, all-around product management and continuous quality improvement. Its product quality is ensured by dedicated, high-precision measurement technologies. The company is supported by its five oversea operations, located in China's Weihai, Nanjing and Sanxin and in Malacca, Malaysia. There are more than 30,000 employees serving a global market, with a zero-defect policy for quality management. With an open-minded attitude, reasonable costs and advanced technology, this company provides versatile and customised technical services and products to its customers, continuing from product development through mass production.

Why the case firm needs integrated KPIs? As given in Table 1, different departments/divisions have their own KPI to achieve sub-goals. However, since 2009, the case firm's growth of market share and net profit are declining year by year, not only because of global economic situation, but also because of global competitors, such as Japan and China. To reduce cost and enhance its capability, the case firm considers that integration of all departments/divisions as a complete combat unit is an aggressive business model for gaining competitive advantage on the market. Thus, integrated KPIs could provide the case firm a complete vision for examining how to work together tightly on different sectors by combining different KPIs to see if any progress can be done by finding current and potential problems.

Table 1. Definitions of a key performance indicator.

Simons (2000)	KPI is used to compare quantitative measures of values, to ensure that the target can be specifically implemented.
Tesoro and Tootson (2000)	KPI can explain a set of figures, used to measure a process or outcome, so that the performance within the organisation is determined, relatively easily.
APICS (2001)	KPI is a kind of integration-related nature of the job content or on behalf of a lagging index of business objectives. Lack of an indicator means that companies have no performance measure for the behaviour of management.
Parapob (2009)	KPIs are evaluation and measurement tools and processes, for business performance development and evaluations.

2.2. E optical company's product line and KPIs

E optical company is committed to the design of optical products and optical systems together with their manufacture, processing and R&D. It is engaged in the production of a variety of flat and spherical glasses, aspherical lens die casting, as well as grinding to improve the characterisitics of glass lenses used in cameras and lenses. It is also involved with optical multilayer overlays of plastic lenses and with injection moulding (Figure 2).

Especially, in 2011, the KPIs of the various departments of the company revealed the possibility of conflict. For example, the management and sales department's performance targets for delivery rate may be limited by the quality assurance department's need to achieve good quality control. Similarly, the purchasing department concentrates on the supplier's price and the reduction of purchasing costs, while customer service and customer complaints are dedicated to customer satisfaction. There is a need for a balance between quality, price, delivery and service to find the best balance between the various departments within the enterprise. This requires the establishment of common priority factors for a KPI (Table 2). For example, there are 11 departments on the case firm. Because of their different natures and functionalities, the case firm sets up various KPI objectives in different cycles. All these KPIs are designed and modified by referencing portocols from the optical mould industry and according to its business and operational objectives. In the case of optical department, its KPI is 'rate of design progress achieved' in a quarterly basis. In 2011, this indicator was achieved by 100%.

If financial ratios are maintained, a firm's profitability, solvency, capacity, developing power and cash flow can support the firm's personnel and mechanical equipment, material, environment and management. Then the critical success factors of these elements may influence each other more significantly. Thus, this study investigates the relationship between these elements. In the macro strategy, a performance evaluation system is used to evaluate the performance of every department and employee and to predict the future trends in market development. It is also used to assist the company in developing an organisational strategy, guided by business intelligence (BI) and the analysis of past data. This study uses a data mining approach, applied to the E optical company, to explore the integrated KPIs that affect moulds, in a specific period of time. Using BI and the data mining tool of SPSS Clementine, analysis of KPIs can allow the management to achieve better leverage in controlling the critical to success factors that affect optical mould industry.

Figure 2. Product category of case firm.

3. Data mining system

3.1. Research framework

The questionnaire design divides the KPIs into the factors of personnel, mechanical equipment, materials, environment and management, since these have an important influence on the integrated KPIs. Following Fayyad, Haussler, and Stolorz (1996), the proposed data mining steps first established a database, to allow the user system for each employee within the company, for the processing of survey data and the integration of information to be compiled into a database of KPIs. Therefore, an analyser can understand the interaction of the information, by analysing the KPIs, obtained by mining the important factors that aid senior management's decision-making processes.

3.2. System framework and physical database

This study constructed a database, with every employee in the system as a user. During the survey process and data integration, the KPI database was used to understand how these data affected each other and to analyse these relationships (Figure 3).

In this study, the conceptual design of the database must be more abstract because it is used to analyse the information structure and to determine the user needs. Chen's (1976) entity relationships (ER) model, which cites the relationship between methodology and individuals, is the conceptual design shown in Figure 4. Totally, there are 30 entities and 85 attributes on the ER model for developing the entire database design.

3.3. Questionnaire design and data collection

Beside case firm's database, this study collects subjective data by designing a questionnaire with nominal scale questions to investigate employees' potential attitude and behaviour in relation to KPIs. More specific content is illustrated in Figure 4. The study was conducted from 1 July 2009 to 30 July 2009. A total of 250 questionnaires

Table 2. Case firm's key performance indicators.

KPI			2011			
Departments	Key performance indicators objectives	Cycle	Q1 (%)	Q2 (%)	Q3 (%)	Q4 (%)
Quality Assurance Department	Failure cost reduction	Monthly	10	10	10	10
	Rate of customer complaints	Monthly	10	10	10	10
	Reached a rate of customer complaints	Monthly	95	95	95	95
	CAR failure control	Monthly	2	2	2	2
	Failure rate of incoming supplier	Monthly	10	10	10	10
	Pass rate shipments	Monthly	95	95	95	95
Mold Department	Part test pass rate	Monthly	90	90	90	90
	Outsourcing pass rate	Monthly	95	98	95	95
	Equipment utilisation rate	Monthly	95	95	90	90
	Engineering inspection yield	Monthly	95	95	95	95
	Pass rate shipments	Monthly	95	95	95	95
Nano Department	Inspection pass rate	Monthly	95	95	95	95
	Equipment utilisation rate	Monthly	90	90	90	90
	Delivery rate	Monthly	90	90	90	90
Mould Glass Department	Pass rate shipments	Quarterly	85	90	90	90
	Delivery rate – production plans	Monthly	85	85	85	85
Marketing Management Department	Delivery rate – mass production	Monthly	98	98	98	98
	Delivery rate – samples	Monthly	90	90	90	90
	Customer grievance	Monthly	5	5	5	5
	Customer satisfaction	Annually	80	80	80	80
Management Division	Monthly turnover	Monthly	5	5	5	5
Optical Department	Rate of design progress achieved	Quarterly	100	100	100	100
Laser Development	Reached a rate of progress on product		95	95	95	95
Lens Development	development		95	95	95	95
Sensor Division			95	95	95	95
Project Management	The average success rate of project	Quarterly	60	75	85	90

were sent and 220 questionnaires were returned, including 207 effective questionnaires. The response rate for effective questionnaire was 82.83%. Statistics on the content are shown in Table 3.

Of the respondents, 72.46% were male and 27.54% were female. Most respondents were between 26 with 40 years old, with those from 31 to 35 years old accounting for 42.03%, followed by those from 26 to 30 years old, who accounted for 23.6%. Respondents with between 4 and 6 years of service in this company accounted for 52.66%, followed by those with 1 to 3 years, who accounted for 22.22%. The largest portion had graduated from university, accounting for 39.13%, followed by those with master degree, who accounted for 32.37%. In terms of manufacturing centres, the majority were working in the distribution department, accounting for 57.49%, followed by R&D centres, which accounted for 13.04%. The manufacturing centre in the mould sector accounts for the largest portion (45.38%), followed by the moulding sector, which accounts for 21.01%. R&D centres using laser machines accounted for 25.93%.

The business marketing centre and the sales management department comprised the majority of employees, with 40% each, followed by the purchasing department, accounting for 20%. The administrative management department accounted for the largest position, with 43.75%, followed by the finance department, accounting for 31.25%. The independent logistics centre for each department formed a 64% majority, followed by forward-looking technology, representing 16%.

4. Data mining process

4.1. *Association rules*

Discovering association rules is an important data mining problem (Agrawal, Imilienski, and Swami 1993), and there has been considerable research on using association rules for data mining problems. The association rules algorithm is used mainly to determine the relationships between items or features that occur synchronously in databases. For instance, during a trip to the shopping centre, if people shopping at a store buy item X and also buy item Y, there exists a relationship between item X and item Y. Such information is useful for decision-makers. Therefore, the main purpose of implementing the association rules algorithm is to find the synchronous relationships by analysing random data and to use these relationships as a reference for decision-making. The association rules are defined as follows (Wang et al. 2004):

Make $I = \{i_1, i_2, ..., i_m\}$ the item set, in which each item represents a specific literal. D stands for a set of transactions in a database, in which each transaction T represents an item set such that $T \subseteq I$. That is, each item set T is a non-empty sub-item set of I. The *association*

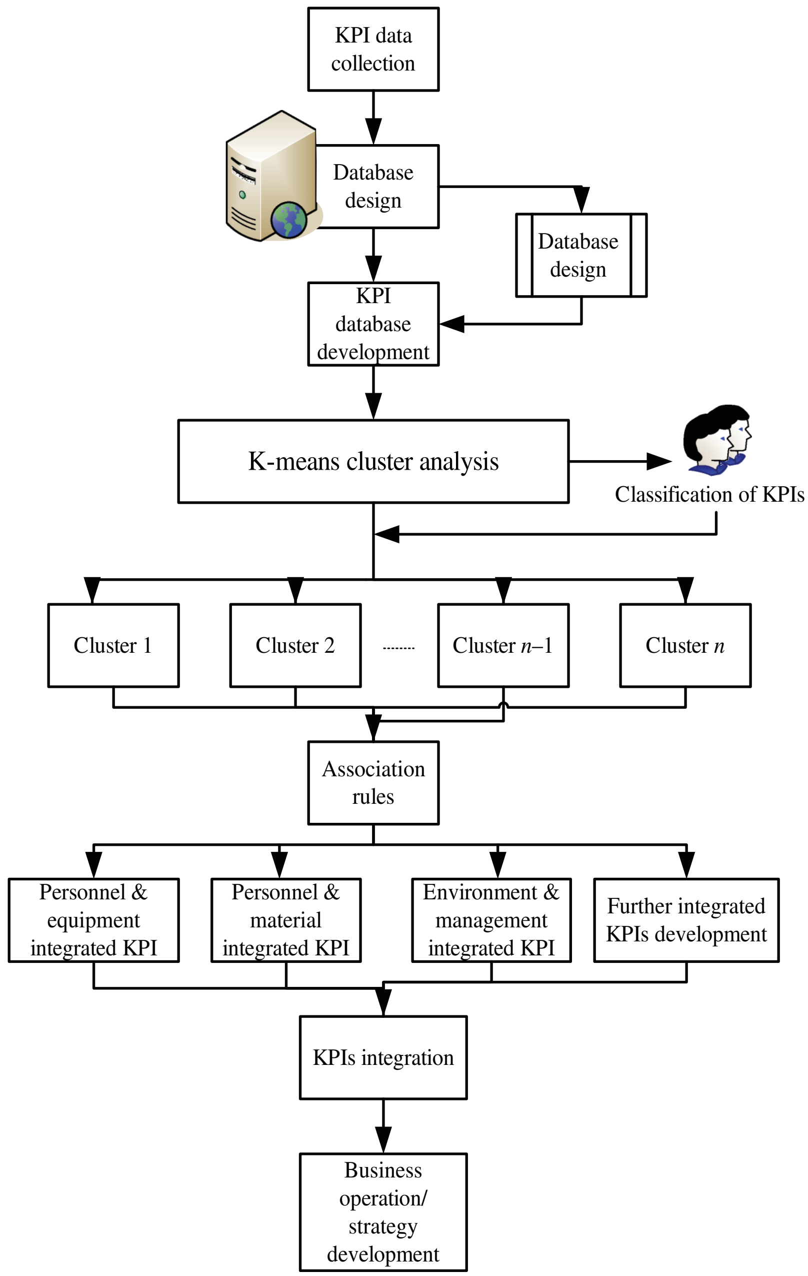

Figure 3. Research design.

rules are an implication of the form $X \rightarrow Y$, where $X \subset I$, $Y \subset I$ and $X \cap Y = \Phi$. The rule $X \rightarrow Y$ holds in the transaction set D according to two measurement standards – *support* and *confidence*. Support (denoted as_$Sup(X, D)$) represents the rate of transactions in D containing the item set X. *Support* is used to evaluate the statistical importance of D, and the higher its value, the more important the transaction set D is. Therefore, the rule $X \rightarrow Y$ which has *support* $Sup(X \cup Y, D)$ represents the rate of transactions in D containing $X \cup Y$. Each rule $X \rightarrow Y$ also has another measuring standard called confidence (denoted as $Conf(X \rightarrow Y)$), representing the rate of transactions in D that contain both X and Y. That is, $Conf(X \rightarrow Y) = Sup(X \cap Y)/Sup(X, D)$.

In this case, $Conf(X \rightarrow Y)$ denotes that if a transaction includes X, the chance that this transaction also contains Y is relatively high. The measure of confidence is then used to evaluate the level of confidence about the association rules $X \rightarrow Y$. Given a set of transactions D, the problem of mining association rules is used to generate all transaction rules that have certain levels of user-specified minimum support (called *Min* sup) and confidence (called *Minconf*) (Kouris, Makris, and Tsakalidis 2005). According to Agrawal and Shafer (1996), the problem of

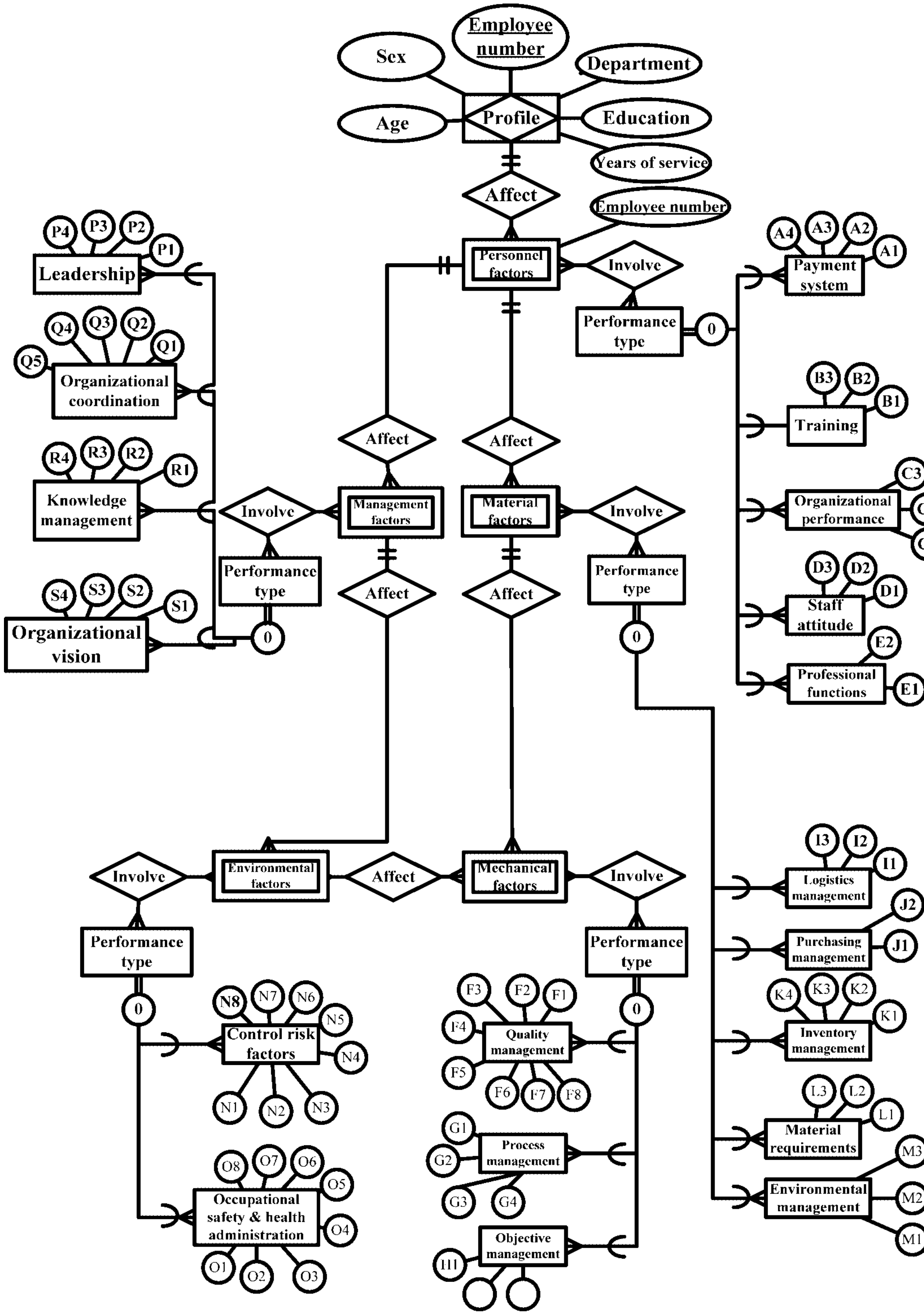

Figure 4. Conceptual database design ER diagram.

mining association rules can be broken down into two steps. The first step is to detect a large item set whose support is greater than *Min* sup, and the second step is to generate association rules using the large item set. Such rules must satisfy the following two conditions:

(1) $Sup(X \cup Y, D) \geq Min\,\mathrm{sup}$
(2) $Conf(X \rightarrow Y) \geq Minconf$

To explore association rules, many researchers use the Apriori algorithm (Agrawal, Imilienski, and Swami

Table 3. Questionnaire responses – statistical data.

	Variable	Sample	Percentage	Total
Sex	Male	150	72.46	207
	Female	57	27.54	
Age	Under 20 years	0	0	207
	21–25 years	3	1.45	
	26–30 years	53	23.6	
	31–35 years	87	42.03	
	36–40 years	39	18.84	
	41–45 years	16	7.73	
	46–50 years	7	3.38	
	Above 51 years	2	0.97	
Service years	Under 1 years	12	5.80	207
	1–3 years	4	22.22	
	4–6 years	109	52.66	
	7–9 years	28	13.53	
	More than 10 years	12	5.80	
Education	Under junior	1	0.48	207
	Senior	21	10.14	
	College	67	32.37	
	University	81	39.13	
	Above institute	37	17.87	
Department	Manuf. centre	119	57.49	207

1993). To reduce the possible biases incurred when using these measurement standards, the simplest way to judge the standard is to use the *lift* judgment. *Lift* is defined as $Lift = Confidence(X \rightarrow Y)/Sup(Y)$ (Wang et al. 2004).

In the optical moulding industry, various departmentsare responsible for different functions. In this study, personnel, mechanical equipment, materials, environment and management factors (such as the KPI of the database) are classified using cluster analysis to identify different cluster groups. SPSS Clementine provides a different classification of clustering in the modelling node, then the data analysis process and the main set of nodes are linked together to complete the analysis of the data stream processing. Therefore, this study implements ODBC bridge, into Clementine data, to establish the analysis process, as shown in Figure 5.

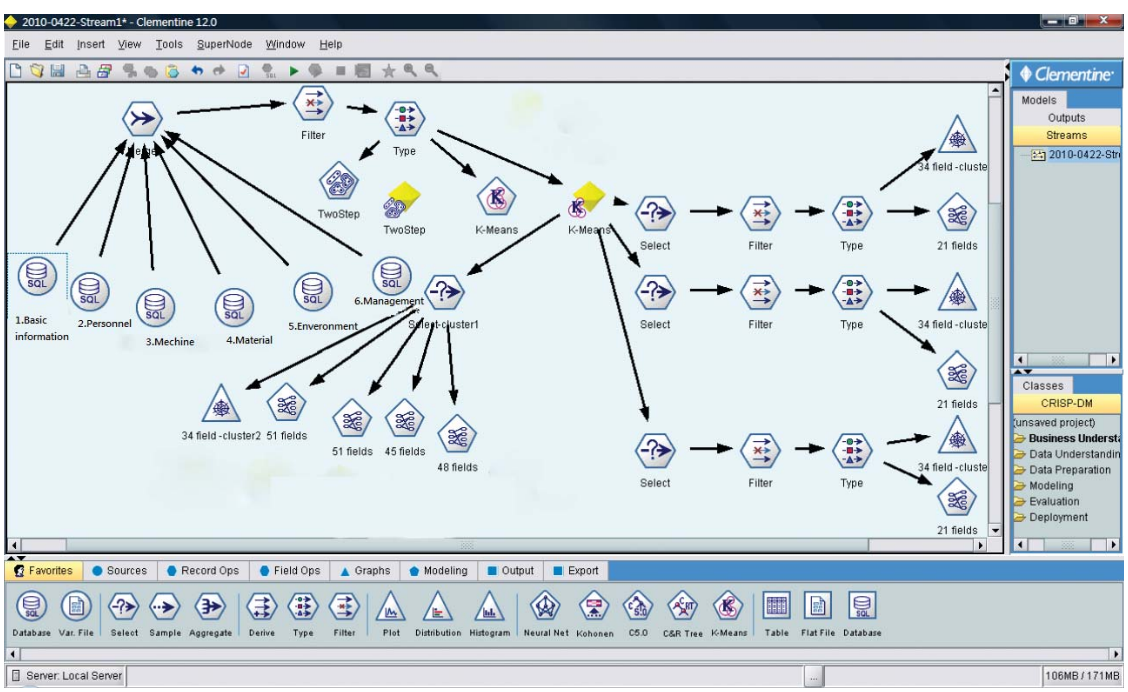

Figure 5. Stream map data nodes.

The purpose of this classification is to establish a model containing good information, which can be classified, analysed and retrieved from the decision tree using the rules. Each decision point in the internal nodes and external nodes uses If–Then logical rules to describe the data classification. The system's main advantage is that it is very fast, and in this study, it was soon learned that C & R Tree classification and regression trees could be used to classify the data from the departments as classification points, through a single input variable function. Separate data on each node is used to construct a dichotomous decision tree. The results of the classification are shown in Figure 6.

Figure 6 shows that in node 1, the C & R Tree classification and the regression tree hindered the control of risk factors as a classification principle, and the risk factors for chemical operations and exposure to noise in the manufacturing centres accounted for 89.34%.

4.2. Cluster analysis and K-means

The process of partitioning a large set of patterns into disjoint and homogeneous clusters is fundamental in knowledge acquisition. It is called *Clustering* in most studies, and it has been applied in various fields, including data mining, statistical data analysis, compression and vector quantisation. The *k-means* algorithm is very popular since it is one of the best for implementing the clustering process. *K*-means clustering proceeds in the following order. First, K numbers of observations are randomly selected from the total N number of observations according to the number of clusters, and these become centres of the initial clusters. Second, for each of the remaining $N-K$ observations, the nearest cluster is found in terms of the Euclidean distance with respect to $xi = (xi1, xi2, \ldots, xip, \ldots, xiP)$. After each observation is assigned to the nearest cluster, the centre of the cluster is re-computed. Finally, after the allocation of all observations, the Euclidean distance

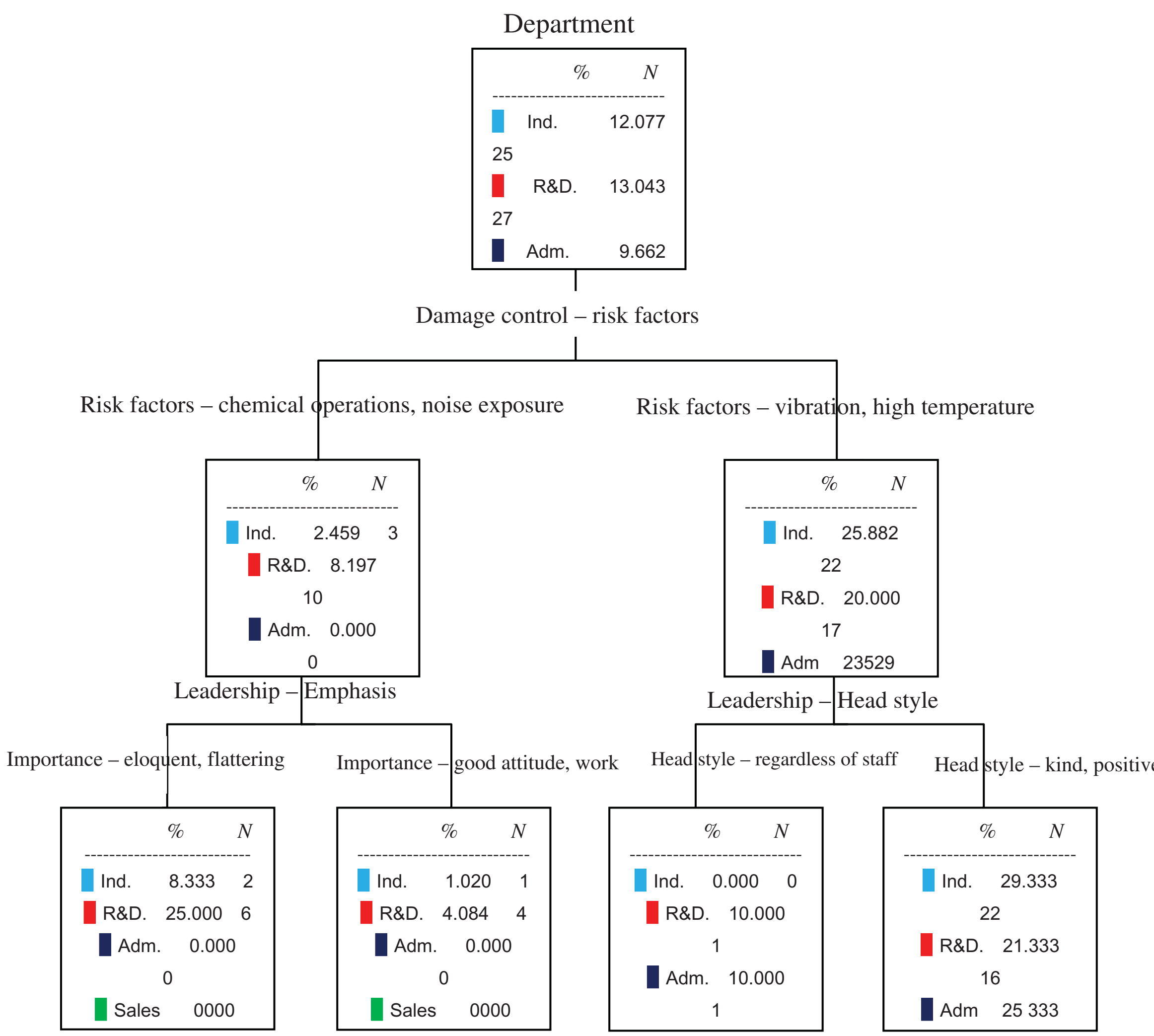

Figure 6. Departmental C & R tree classification and regression tree.

between each observation and the cluster's centre point is calculated to confirm whether they have been allocated to the nearest cluster. In addition, several studies have discussed implementation of the *k*-means algorithm for cluster analysis as a data mining approach (Ture et al. 2005).

In this study, for 'staff basic information', the KPI is defined by a group of variables. Cluster analysis is performed through the use of the Apriori algorithm, with association rules. The *K*-means clustering results are shown in Figure 7. The *K*-means cluster analysis creates the following three groups:

(1) Manufacturing group (Cluster-1): This group is mostly male, with ages ranging from 31 to 40 years and a level of education to 'skill worker' and are mostly engaged in manufacturing work.
(2) Research and development group (Cluster-2): This group is mostly male, with ages ranging from 26 to 35 years and a level of education to 'university', are mostly engaged in R&D.
(3) Strategy layout group (Cluster-3): This group is mostly female, with ages ranging from 26 to 40 years and a level of education 'Institute' and are mostly engaged in administrative and financial tasks.

5. Data mining results: integrated KPIs development

There are several association rules generated by using Minsup (Sup(%)), Minconf (Con(%)) and Lift value (Lift). For example, the results in Table 4 show that if the 'Management by objectives – Technology Assessment – generally low' (Lift value = 1.13) affects the (Imply) 'Quality Management – resonance –generally high', the association is strong and 'Quality Management – Precision Instruments – Generally high' (Lift value = 1.04) and 'Quality Management – the machine precision – generally low' (Lift value = 1.04) also have a positive correlation. Then 'quality management – Resonance – Generally high' is improved by ' Management by objectives – Technology Assessment – generally low' and 'Quality Management – instrument accuracy – generally high'. In addition, 'Process management – accurate reporting to – a very small error' (Lift value = 0.91) cannot be affected by the key factors, although the association diagram in Figure 8 shows that, under analysis, it has a strong relationship with 'Quality management – Resonance – generally high' in the machinery factor's KPI.

The 'Research and development group' (Cluster 2) in the 'Hazard Control – Organic – A generally high' project will 'Endanger control – Organic – A generally high' under the conditions of the preceding paragraph. The environmental factor's KPI is assigned to the latter through analysis of the results of association rules, as shown in Table 5. The results showed that 'Harm control – Organic – A generally high' is more highly correlated to 'harm control – essential oils – generally high' (Lift value = 1.42) than 'Crimes against control – Air smell – malodorous uncomfortable' (Lift value = 1.31) and

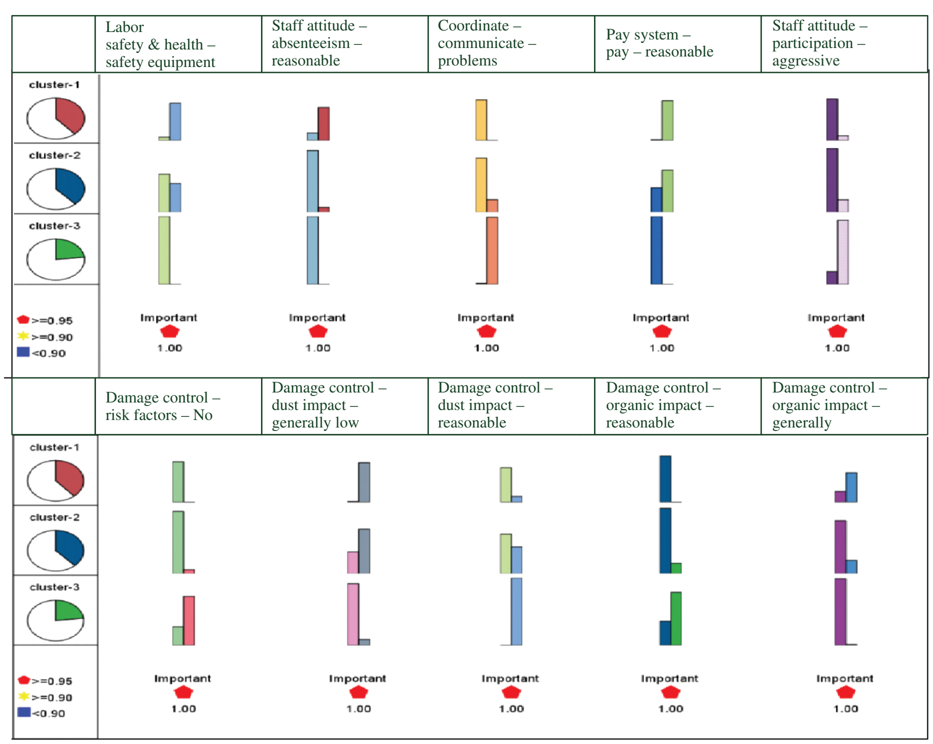

Figure 7. Results of *K*-means clustering.

Table 4. Association rule analysis of cluster 1.

Rule	Sup (%)	Con (%)	Lift	Consequent	Antecedent
R1	62.68	80.95	1.13	Quality management – equipment resonance – generally high	Target management – Technology Assessment – generally low
R2	76.11	76.47	1.04	Quality management – equipment resonance – generally high	Quality management – instrument accuracy – generally high
R3	68.65	76.08	1.04	Quality management – equipment resonance – generally high	Quality management – the machine precision – generally low
R4	61.19	75.60	1.03	Quality management – equipment resonance – generally high	Quality management – process capability – reasonable
R5	77.61	75.01	1.02	Quality management – equipment resonance – generally high	Process management – working hours errors – generally low

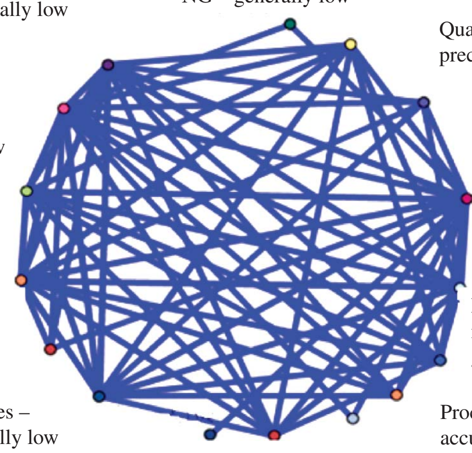

Figure 8. Mechanical factors association diagram.

Table 5. Association rule analysis of cluster 2.

Rule	Sup (%)	Con (%)	Lift	Consequent	Antecedent
R1	98.51	85.73	1.42	Damage control – essential oils – generally high	Damage control – organic – a generally high
R2	97.43	84.85	1.31	Damage control – air odor – malodorous	Damage control – organic – a generally high
R3	97.41	80.30	1.22	Damage control – risk factors – chemical operations	Damage control – organic – a generally high
R4	98.51	78.79	1.13	Employee health and safety-workplace safety – emergency	Damage control – organic – a generally high
R5	97.21	77.27	1.12	Damage control – noise situation – loud noisy	Damage control – organic – a generally high

'Hazard Control – risk factors – chemical operations' (Lift value = 1.22), which also have a positive correlation with the 'Hazard control – oil Volatile – generally high'. The 'Endangering control – air smell – malodorous uncomfortable' situation can be improved by 'Harmful Control – Organic – A generally high'. As with the 'Labor Safety and Health – illumination – Brightness moderate' (Lift value = 0.991), the correlation is weak, so they do not affect the process as key factors.

Analysis can identify the various groups – personnel, equipment, materials, environment and management factors – and the KPIs of individual factors, which can improve many of the KPIs associated with the optical mould industry and create niches. The KPIs of various departments often cause conflicts; for example, the purchasing department must ensure that the cost of the tooling department's EC243 Mold is less than the purchase amount of 5% of market conditions, but the production management department wants to shorten the delivery time to 3 days. However, the quality control department cannot meet its goal if the mould is of unacceptable quality.

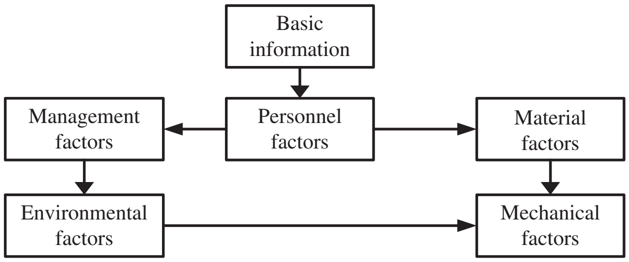

Figure 9. Schematic diagram of key performance indicators.

Figure 9 shows that for the key factors of performance indicators to analyse each other's association rules, as in the example company's 'research and development group,' ratio of about 43% of the whole company, so in order to 'research and development group'. For example, a group of factors require association rules analysis to understand whether there is a correlation with sex. These include personnel factors and material factors, material factors and machinery factors, environmental factors and mechanical equipment factors, human factors and management factors and management factors and environmental factors. Correlations between the KPIs provide valuable information for decision-making.

5.1. Integrated KPIs for personnel factors and material factors

In the optical mould industry, the mould operators' working attitude and mastery of technology determines the quality and quantity of the product yield. The stability of the source material is the responsibility of product quality assurance, which is highly dependent on the personnel and material factors of each mining association. Table 6 shows the following results: the minimum support Sup = 70% and the minimum reliability Conf = 70%. The best association rules are found in 5 (Rule), such as 'professional functions – design cycle – generally is shorter' (1 week or less) (red colour line). 'Inventory management – material costs – generally high' (Lift value = 1.21) has a strong correlation (blue colour line). The search for lower costs can be expected to extend the design cycle and reduce the generation of unnecessary factors.

The association between the personnel factor and the material factor is shown in Figure 10, where each line shows the strength of any correlation between the two levels of decision variables. Solid lines denote a strong correlation, while dashed lines denote a weak correlation. Before the adjustment, the associated number is complex, but it is difficult to find significant associations since too much information causes biased decision-making.

5.2. Integrated KPIs for personnel factors and management factors

The personnel department is responsible for the company's assets, and management of this system has a great relationship. Table 7 (Sup = 70%, Conf = 70% of the cases) presents the five best association rules, such as 'Education Training – technical license – no' is strongly correlated with 'Knowledge Management – Strategies for – discrepancies expected' (Lift value = 1.15) and 'Knowledge Management – Knowledge promotion – discrepancies expected' (Lift value = 1.13).

The promotion of knowledge management may require employees to receive training and certification exams in preparation techniques, which contribute to the professional growth of the staff and promote the accumulation of intellectual capital. In the association diagram for personnel and management factors shown in Figure 11, it can be seen from the status of modified plans for the 'research and development group' that the distribution of resources in the sector is relatively average and that 'education and training budget – generally high' and 'Equivalent feedback – exceeded expectations' and the relevance of strong experience in this population often leads to covert resistance, in 'lack competent' situations.

5.3. Integrated KPIs for management factors and mechanical equipment factors

Table 8 shows the correlation between mechanical equipment and management factors. The results (Sup = 70%,

Table 6. Association rules for personnel factors and material factors.

Rule	Sup (%)	Conf (%)	Lift	Consequent	Antecedent
R1	70	77.14	1.21	Professional functions – design cycle – generally is shorter	Inventory management – material costs – generally high
R2	70	82.86	1.15	Education and training – training budget – modest reasonable	Inventory management – to wait days – reasonable moderate
R3	74	72.97	1.14	Professional functions – design cycle – generally is shorter	Purchasing management – purchasing failure – moderate
R4	70	71.43	1.12	Staff attitude – contribute to proposal – positive understanding	Inventory management – material costs – generally high
R5	70	71.43	1.12	Professional functions – design cycle – generally is shorter	Logistics management – return costs – reasonable moderate

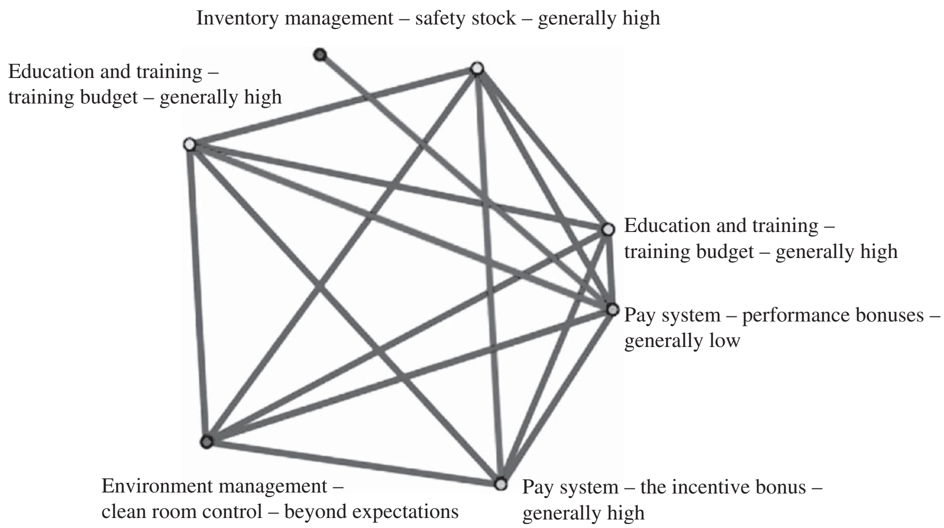

Figure 10. Analysis of the association between personnel and material factors.

Table 7. Association rules for the personnel factors and material factors.

Rule	Sup (%)	Conf (%)	Lift	Consequent	Antecedent
R1	71.11	70.31	1.15	Education and training – technology license – no	Knowledge management – strategy – discrepancies expected
R2	71.11	70.31	1.13	Professional functions – design changes – generally high	Organisational vision – equal feedback – discrepancies expected
R3	79.10	83.02	1.05	Education and training – training frequency – occasional	Knowledge management – knowledge promotion – discrepancies expected
R4	80.60	77.78	1.04	Pay system – performance bonuses – generally low	Leadership – importance – strong ability to work
R5	91.04	81.97	1.04	Education and training – training frequency – occasional	Knowledge management – management system – responsibility centre

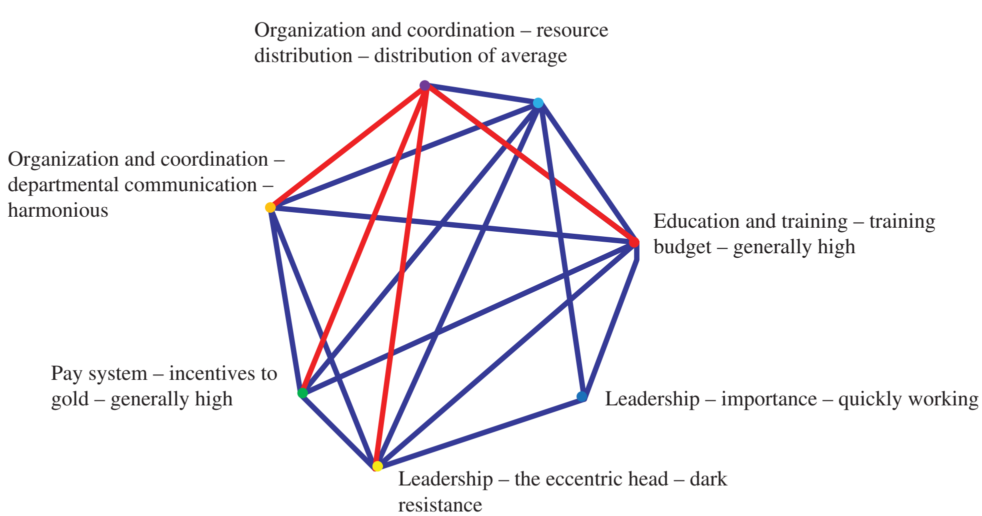

Figure 11. Analysis of the association between personnel and management factors.

Table 8. Association rules for management factors and mechanical equipment factors.

Rule	Sup (%)	Conf (%)	Lift	Consequent	Antecedent
R1	56.57	56.21	1.05	Process management – accurately reporting – minimum error	Organisational vision – equal feedback – discrepancies expected
R2	51.04	55.25	1.04	Process management – accurately reporting – minimum error	Knowledge management – management system – responsibility centre
R3	59.10	59.25	1.04	Quality management – instrument accuracy – generally high	Knowledge management – knowledge promotion – discrepancies expected
R4	57.61	58.85	1.03	Process management – working hours errors – generally low	Knowledge management – strategies for – discrepancies expected
R5	56.57	52.76	1.03	Process management – accurately reporting – minimum error	Knowledge management – knowledge promotion – discrepancies expected

Conf = 70% cases) show that when conditions are adjusted to reflect Sup = 50%, Conf = 50%, associations cannot be found for the 6 cases. Associaton rules can be found, but the Lift value is too low and the minimum support and minimum reliability is no higher than 50%. This result suggests that management factors are weakly correlated with mechanical equipment factors. The only correlation exists between 'Organizational Vision – equivalent feedback – discrepancies expected' and 'process management – accurate reporting to – minimum error' (Lift value = 1.05).

6. Conclusions and suggestions

6.1. Conclusions

The case company's three main groups – 'production group', 'research and development group' and 'strategic layout group' – generate the basic information for employees, personnel, equipment, materials, environmental and management factors, as well as other KPIs. Association rules identify the most profitable relationships between factors and map the KPIs to aid decision-making. The following conclusions can be drawn:

(1) 'Production group' integrated KPI association maps: For the 'production group' presented in Table 9, the material and environmental factors associated with the analysis, Sup = 75%, Conf = 75% of the cases, 'Hazard Control – volatile oil – generally high' influence 'Environmental management – mould flow analysis – does not match expected' (Lift value = 1.17) very strongly. Top executives can identify the hazard of oil products close to the wire EDM Cutting machine. The exhaust flow analysis mode can be used to move the machine away from volatile oil and gas production equipment to avoid the problem.

In Figure 12, it can be seen that a reduction in 'Quality Management – Equipment resonance – generally high' is impacted by 'Hazards control – Risk factors – vibration

Table 9. Production group key performance indicators.

Association rules	Rule	Sup (%)	Conf (%)	Lift	Consequent	Antecedent
Material factors and environmental factors	R1	82.09	80.00	1.17	Environmental management – mould flow analysis – does not match the expected	Damage control – essential oils – generally high
Basic data and personnel factors	R2	79.10	77.36	1.15	Education and training – technical license – 1 license	Male 4–6 years manufacturing centre
Environmental factors and mechanical factors	R3	76.12	80.39	1.10	Quality management – equipment resonance – generally high	Damage control – noise situation – loud noisy damage control – risk factors – vibration operation
Personnel factors and Management factors	R4	79.10	83.02	1.05	Education and training – training frequency – occasional	Knowledge management – knowledge promotion – does not match the expectations
Personnel factors and material factors	R5	79.10	84.91	1.02	Environmental management – mould flow analysis – does not match the expected	Education and training – training frequency – occasional

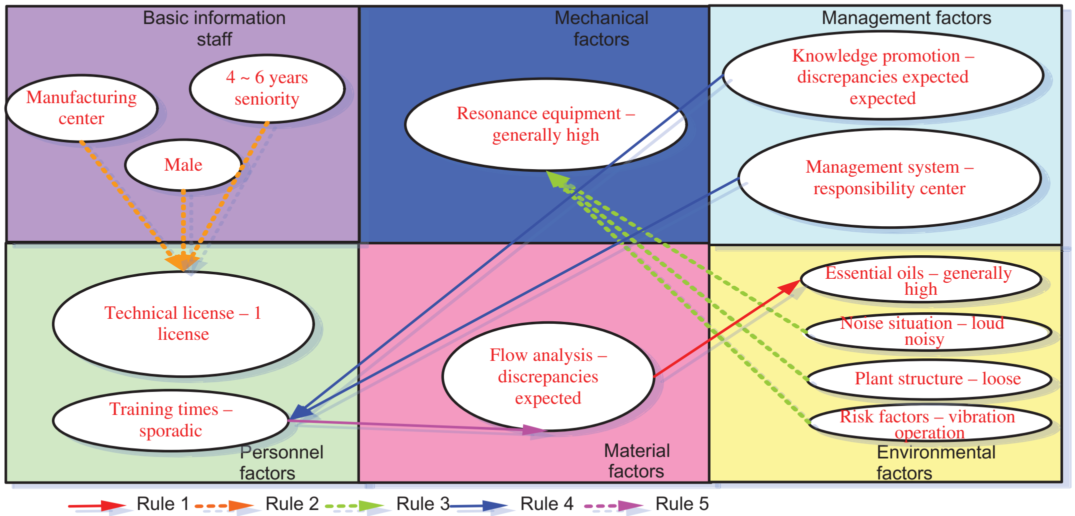

Figure 12. Production group map of integrated key performance indicators.

operation', 'Hazard Control – Noise situation – noisy' and reinforcing 'Labor safety and health – Plant Structure – loosely'.

(2) 'R&D group' integrated KPI association maps: the 'Research and development group' mainly works on optical lens design. Rule 2 is generated by the Sup = 70%, Conf = 70% of the cases. The association is strong, and the operators must wear clean clothing in the clean room and use a clean room particle counter to sample dust levels on a regular basis for health and safety reason. This can ensure that the damage level is less than 1000 μm/cubic feet, which will increase product yields. Rule 3 shows that 'Electronic business – does not match expected' is subject to 'Training budget – generally low effect'. To improve the electronic side of the business, it is recommended that the staff undergo in-house or external training in the near future (Figure 13).

(3) Strategy group integrated KPI association maps: the 'Strategies layout group' has the greatest effect on optical products from the point of view of business marketing strategy and operation of logistical support. Table 8 shows that the strategies layout group using Rule 3 Sup = 70%, Conf = 70% for the situation of the 'education and training – training budget – a reasonable

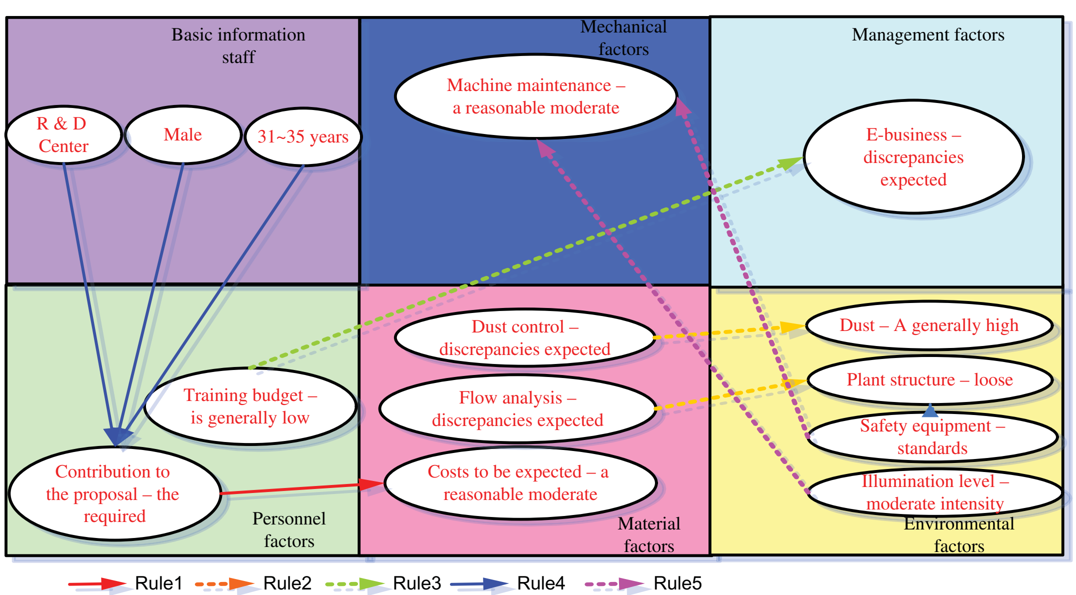

Figure 13. R&D group map of integrated key performance indicators.

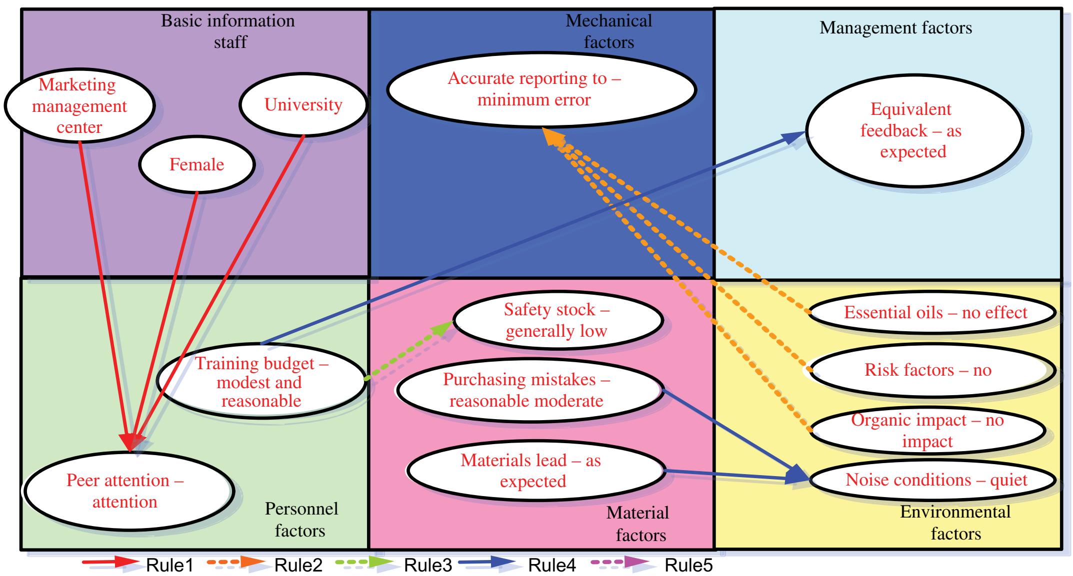

Figure 14. Strategy group integrated key performance indicators maps.

moderate' affecting 'inventory management – safety stock – generally low' (Lift value = 1.1) has a strong association (Figure 14).

6.2. *Suggestions*

This study identifies integrated KPIs for the case company's problems and then looks for interactions that are associated with the KPIs. The KPI for industrial research typically uses the balanced scorecard approach to identify performance categories and rarely uses data mining for appraisal of performance (Kaplan and Norton 2000). The huge amount of data gathered from the case company may contain unknown and useful information, so data mining methods use association rules to determine relevance and its capability of extracting useful knowledge (Chryssolouris and Wright 1986; Zhang, Cheng, and Chu 2010). The following suggestions are based on the results of this study:

(1) For the 'production group', the discharge processing technology for all parts of the final phase of the mould process depends on the key factors for mould quality, so that the defects are reduced. The technical ability and attention requirements to do so are particularly strict. Only technical personnel with more than 3 years of experience have the technical ability and professional expertise to have a comprehensive understanding of the moulding process. Considering product–service relationship and performance, production map, R&D map and strategy map might provide a better planning and evaluation mechanism for manufacture firms (Sun et al. 2012).
(2) The generally low-performance bonus: More regular recognition of outstanding workers can improve staff morale. Thus, business process interoperability and collaborative performance measurement might be possible solutions to evaluate departmental and workers' performance (Alfaro et al. 2009).
(3) Reinforcing the building structure and enhanced shock machines: The manufacturing centre is located in the parking lot at the top of the building, resulting in heavy cutting machine vibration, which interferes with the processing of 0.006 MM, seriously affecting the precision mould processing. The workshop could be moved to resolve this problem, and this would influence many other operations. Thus, it is suggested that the building structure be reinforced and that the machines be mounted on vibration absorbers.
(4) The training budget is generally low: mould centre employees have experienced job rotation for many years, resulting in staff stagnation and a lack of self-confidence. The proposed solutions of this study could be in-house training, peer exchange or supporting personal growth through group learning. The company could benefit from any of these strategies.

7. Future works

This study agrees with the contention that a KPI does not only represent effectiveness, but standard works on performance management clearly states both effectiveness and efficiency (Neely 1999). However, integrated KPIs might be a solution to see some critical/success factors in a whole picture. In this regard, business intelligence is an alternative way to analyse KPIs with an integration consideration. In addition, different data mining approaches should be used to implement KPIs with the service sector as well as on manufacturing industries. Thus, we suggest that the development of other integrated KPIs for different industries and business models should be a critical research issue in the future.

Acknowledgement

This research was funded by the National Science Council, Taiwan, Republic of China, under contract No. NSC 100-2410-H-032-018–MY3.

References

Agrawal, R., T. Imilienski, and A. Swami. 1993. "Mining Association Rules between Sets of Items in Large Databases." Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data, Washington, DC, May 26–28, 207–216.

Agrawal, R., and J. Shafer. 1996. "Parallel Mining of Association Rules." *IEEE Transactions on Knowledge and Data Engineering* 8 (6): 962–969.

Ahmad, M. M., and N. Dhafr. 2002. "Establishing and Improving Manufacturing Performance Measures." *Robotics and Computer Integrated Manufacturing* 15 (3): 145–156.

Alfaro, J. J., R. Rodriguez-Rodriguez, M. J. Verdecho, and A. Ortiz. 2009. "Business Process Interoperability and Collaborative Performance Measurement." *International Journal of Computer Integrated Manufacturing* 22 (9): 877–889.

APICS 2001. *Master Planning of Resources Session 8*, Version 2.0, Dec.

Challis, D., D. Samson, and B. Lawson. 2002. "Integrated Manufacturing, Employee and Business Performance: Australian and New Zealand Evidence." *International Journal of Production Research* 23 (3): 213–230.

Chen, P. P. S. 1976. "The Entity – Relationship Model Toward a Unified View of Data, *ACM Trans*." *On Database Systems* 13 (1): 23–54.

Choudhary, A. K., J. A. Harding, and M. K. Tiwari 2009. "Data Mining in Manufacturing: A Review Based on the Kind of Knowledge." *Journal of Intelligent Manufacturing* 20 (5): 501–521.

Chryssolouris, G., D. Mourtzis, N. Papakostas, Z. Papachatzakis, and S. Xeromeritis. 2008. "Knowledge Management in Selected Manufacturing Case Studies." In *Methods and Tools for Effective Knowledge Life-Cycle-Management, Part 3*, edited by A. Bernard and S. Tichkiewitch, 521–532. Berlin: Springer.

Chryssolouris, G., and K. Wright. 1986. "Knowledge-Based Systems in Manufacturing." *CIRP Annals* 35 (2): 437–440.

Drucker, P. F. 2002. *Management: Tasks, Responsibilities, Practices*. New York: HarperBusiness.

Efthymiou, K., K. Alexopoulos, P. Sipsas, D. Mourtzis, and G. Chryssolouris. 2011. "Knowledge Management Framework Supporting Manufacturing System Design. (DET 2011)." ISBN 978-960-88104-2-6, 7th International Conference on Digital Enterprise Technology, Athens, Greece, September 28–30, 577–585.

Fayyad, U., D. Haussler, and P. Stolorz. 1996. "Mining Scientific Data." *Communications of the ACM* 39 (11): 51–57.

Frawley, W. J., G. Piatetsky-Shapiro, and C. J. Matheus. 1991. "Knowledge Discovery Databases: An Overview." In *Knowledge Discovery in Databases*, edited by G. Piatetsky-Shapiro and W. J. Frawley, 1–27. Cambridge, MA: AAAI/MIT.

Ho, M. Y. 2011. *Global Optical Mold Market and Taiwan Optical Mold Industry Development*. Taipei: Optical Mold Association Press.

Kaplan, R. S., and D. P. Norton. 2000. *The Strategy-Focused Organization: How Balanced Scorecard Companies Thrive in the New Business Environment*. Boston, MA: Harvard Business School Press.

Kouris, I. N., C. H. Makris, and A. K. Tsakalidis. 2005. "Using Information Retrieval Techniques for Supporting Data Mining." *Data & Knowledge Engineering* 52 (3): 353–383.

Liao, S. H., C. M. Chen, C. L. Chieh, and S. C. Hsiao. 2009a. "Mining Information Users' Knowledge for One-to-One Marketing on Information Appliance." *Expert Systems with Applications* 36 (3): 4967–4979.

Liao, S. H., J. L. Chen, and T. Y. Hsu. 2009b. "Ontology-Based Data Mining Approach Implemented for Sport Marketing." *Expert Systems with Applications* 36 (8): 11045–11056.

Liao, S. H., Y. N. Chen, and Y. Y. Tseng. 2009c. "Mining Demand Chain Knowledge of Life Insurance Market for New Product Development." *Expert Systems with Applications* 36 (2): 9422–9437.

Mehta, K., and S. Bhattacharyya. 2004. "Adequacy of Training Data for Evolutionary Mining of Trading Rules." *Decision Support Systems* 37: 461–474.

Musaev, A. A. 2004. "Analytic Information Technologies in Oil Refinery." *Expert Systems with Applications* 26: 81–85.

Neely, A. 1999. "The Performance Measurement Revolution: Why Now and What Next?" *International Journal of Operations & Production Management* 19 (2): 205–228.

Parapob, S. 2009. *The Survey of Thailand's Military Logistics Key Performance Index*. San Fransico, CA: WCECS.

Simons, R. 2000. *Performance Measurement and Control Systems for Implementing Strategy: Text & Cases*. Upper Saddle River, NJ: Prentice Hall.

Sun, H., Z. Wang, T. Zhang, Z. Chang, R. Mo, and Y. Liu. 2012. "Evaluation Method of Product–Service Performance." *International Journal of Computer Integrated Manufacturing* 25 (2): 150–157.

Tesoro, F., and J. Tootson. 2000. *Implementing Global Performance Measurement System: A Cookbook Approach*. San Francisco, CA: Jossey-Bass.

Ture, M., I. Kurt, K. A. Turhan, and K. Ozdamar. 2005. "Comparing Classification Techniques for Predicting Essential Hypertension." *Expert Systems with Applications* 16 (4): 379–384.

Wang, Y. F., Y. L. Chuang, M. H. Hsu, and H. C. Keh. 2004. "A Personalized Recommender System for the Cosmetic Business." *Expert Systems with Applications* 26 (1): 42–56.

Xu, X., L. Wang, and S. T. Newman. 2011. "Computer-Aided Process Planning – A Critical Review of Recent Developments and Future Trends." *International Journal of Computer Integrated Manufacturing* 24 (1): 150–157.

Zhang, Z., H. Cheng, and X. Chu. 2010. "Aided Analysis for Quality Function Deployment with an Apriori-Based Data Mining Approach." *International Journal of Computer Integrated Manufacturing* 23 (7): 673–686.

Zorzut, S., V. Jovan, D. Gradišar, and G. Mušič. 2009. "Closed-Loop Control of a Polymerisation Plant Using Production Performance Indicators (PIs)." *International Journal of Computer Integrated Manufacturing* 22 (12): 673–686.