Cluster-based performance measurement system for emerging technology-based ventures

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Abstract: Performance assessment of technology-based ventures requires consideration of the nature of their businesses and the dynamics of their emerging industries. Science and technology parks need to recognize the best performers as role models, and to identify company strengths and weaknesses, so as to enable effective resource allocation into the emerging ones for a better chance of success. A comprehensive assessment model embedded with relevant performance indicators would enable an effective evaluation of technology-based ventures. This paper explores the development of a cluster-based and quantitative measurement system for science and technology parks to evaluate the performance of technology-based ventures. The proposed method incorporates Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and weight allocation. It ranks the technology-based ventures in different technological clusters, based on a range of indicators pertinent to productivity, Research and Development (R&D) effort, R&D personnel percentage, time to market and financial performance. This method has been implemented through a trial study conducted within the Hong Kong Science and Technology Parks Corporation. The results indicate that R&D spending has a strong impact on a company's performance ranking, but the R&D personnel percentage has a weak correlation with such a ranking. This study suggests that the performance of technology-based ventures should be measured with respect to their R&D investments and their pertinent efforts to commercialize products as evidenced by incremental sales over their course of development and growth.

Keywords:
Technology clusters, Performance measurement system, R&D, Resource allocation, Technology-based ventures

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1 Introduction

While a region with well-developed high-tech industries would induce a positive impact on its economic competitiveness, their effective development and growth continues to be a challenge in an emerging economy. As advocated in prior studies, a high-tech industry could integrate well with the academic, innovative and technological development level, as well as the living standard or environment of a region (Akpore, 1999; Monday & Esoswo, 2008; Sun, 2011). In particular, the performance of an emerging technology cluster should be assessed and monitored so that resources can be allocated effectively to foster its development. A prosperous industry would in turn have a stronger influence over the scientific development of traditional industries (Bielawska, 2010). Assessing the performance of high-tech companies is considered critical as this could ultimately affect the economy of a country (Monck & Peters, 2009). Assessing the performance of high-tech companies is important as it ultimately represents the performance of a science and technology park, and this determines whether the resources provided are used effectively. The best performing companies within the assessing samples can be used as role models for industrial benchmarking by other firms.

However, traditional performance measurements are mainly concerned with cost elements or fixed assets (Ahmad et al, 2002). The financial indicators mainly focus on evaluating a firm's financial performance, the results of which can be used as references for investors. For technological enterprises which possess intellectual capital and intangible assets as their critical resources, it would not be completely reliable and relevant to focus merely on financial performance, such as profitability, liquidity or solvency for measuring the performance and success of technology-based ventures. Moreover, it may not be appropriate to use the same set of indicators to evaluate the competitiveness and performance of ventures nurtured under technology clusters of different sizes and natures. In practice, the indictors and appraisal of traditional performance measurements may be assessed subjectively, based on experience, knowledge and the opinions of internal personnel within the institutional organization seeking legitimacy.

In addition, global science parks have difficulty in evaluating technological companies. It is a challenge to discover talented companies and provide them with resources and support. Investors largely rely on financial performance for evaluation, while some important components, such as R&D and technological capabilities, could be overlooked since they cannot be reflected in the near-term financial performance. As a result, a comprehensive assessment system must be developed so that science and technology parks can apply it for identifying potential technological companies.

In this paper, a cluster-based performance measurement system is proposed for assessing technology-based enterprises in a single assessment model within science parks. It argues that the traditional performance measurement systems, where one-size-fits-all approach is used, the indicators are too static and inflexible to be applied to different kinds of industries. Due to the rapid changing of emerging technology clusters, it is necessary to develop a performance measurement system that can customize the performance indicators based on the unique characteristics of the clusters. Different technology clusters need to be examined with a specific set of indicators and weightings. In this paper, multi-indicators with the coverage of financial and non-financial elements are adopted to identify the critical performance factors and determine overall company performance in a more objective manner. The weighting of the performance indicators can be automatically adjusted with respect to their significance within the measured cluster. The method focuses on indicator selection, weight allocation, and ranking model and result analysis so as to eliminate subjective judgment in measuring the performance of technology-based ventures.

In order to verify the assessment model, data are collected from the innovative technology-intensive enterprises in the Hong Kong Science and Technology Parks (HKSTP). Two groups of technology-based ventures are selected as samples from their respective clusters: the Information and Communications Technology (ICT) cluster and the Electronics cluster. The ICT cluster contains relatively virtual organizations that aim to pursue product and or service innovation through the exploitation of information and internet technologies, whereas the electronics cluster is composed largely of ventures that focus on the development of electronics products with prototype testing during their early stages. Based on the results, it is observed that there is a need for science parks to formulate a set of performance assessment indicators which should be dynamic in nature and be differentiated for the various emerging technology sectors. The variations between a traditional performance measurement method and the proposed performance measurement approach are examined as well.

2 Literature review

2.1 Performance measurement in science and technology parks

Performance measurement is defined as how organizations, public and private, measure the quality of their activities and services, the process by which the stakeholders examine certain indicators for determining the quality of their performance with reference to organizational goals (Nudurupati et al., 2011). Performance assessment is appraisal with a focus on observable results and standards, implemented through standards, tasks, indicators and scoring rubrics (Khattri et al., 2012). Based on the above definitions, measurement and assessment is to understand the goal of the organization, evaluate the current status of the company so as to identify any gaps and propose a framework for measurement. During the process, the key success factors can be identified as the performance measures are aligned with the objectives (Parmenter, 2015). In addition, it can pinpoint the strengths and weaknesses and can be useful in developing a strategic plan for performance enhancement.

Regions with well-developed high-tech industries have a positive impact on competitiveness. The stronger and more prosper the high-tech industries, the better it influences the traditional industries and further scientific development (Bielawska, 2010). As a result, the performance of technological industries needs to be assessed and monitored so that improvement can be made, and resources can be allocated effectively to foster the industry. In different regions and countries, performance measurements of high-tech firms are always undertaken to analyze their efficiency and growth prospects so that potential areas of improvement can be identified.

There have been studies that examined issues with performance measurement systems in science and technology parks in various countries. Six industries in Taiwan Hsin Chu Industrial Science Park were analyzed in a study for their operation efficiency and productivity growth (Sun, 2011). A Data Envelopment Analysis (DEA) was used to analyze the input and output variables of the industries and to identify the main factors of productivity growth. Based on the analysis, it was concluded that managerial skills and innovative performance should be improved. With this assessment, the Science Park suggested providing managerial training or support for the companies. Government can allocate more resources to scientific research for fostering innovative performance. In China, two kinds of business incubators: the university science parks as well as science and technology parks were compared by their performance to determine which one is better (Tang & Llerena, 2007). Indicators such as income and the number of high-tech products produced by the tenants were used to indicate the output variables of the parks. In Turkey, Murat Ar & Baki (2011) studied SMEs located in Turkish science and technology parks by investigating the relationships between R&D strategies, top management support, creative capability, products and processes, and firm performance. Their results showed that both product and process innovation have a strong and positive association with firm performance. In a study by Flor & Oltra (2004), companies in the ceramic tile industry in Spain were analyzed, and innovating firms were identified using several innovative indicators. It was found that indicators such as R&D budget, publications and patents can measure the innovative activities and screen out innovative firms within the industry. Consequently, the value of the indicators can be used as a benchmark for high performance technological firms, and other companies can use the benchmark to understand to what extent they can meet the standard.

The above case studies reveal the importance of performance measurement of technological firms, as well as science parks. However, organizations in general lack a structured approach to monitor and assess the ongoing development of science and technology. Expertise is needed to provide an in-depth and timely review of the technology clusters. There is an obvious need to develop an assessment tool for science parks and firms for self-understanding and quality enhancement.

2.2 Conventional financial performance measurement

Business performance measurement is often carried out with a focus on financial indicators. Income statements, balance sheets and cash flow statements are the financial documents a company would produce at the end of a financing period, usually quarterly or yearly. There are three common methods to analyze the financial status: Profitability evaluation, Liquidity evaluation and Solvency evaluation. Profitability evaluation reflects whether the company can achieve a satisfactory income. The general indicators used in analyzing the profitability of companies includes Profit Margin, Asset turnover, Return on assets (ROA), Return on common equity (ROE), Earnings per share (EPS), Price/ Earnings Ratio (PE), Payout ratio, and Sales Growth (Weygandt et al., 2008). Profit Margin provides an indication of efficiency in that it captures the amount of surplus generated per unit of the product or service sold. Return on assets (ROA) represents the pay back for shareholders' assets. Sales Growth is a profitability indicator which measures the percentage increase (or decrease) in sales over the defined period. Liquidity evaluation illustrates whether the company can repay loans when they are due, and unanticipated cash demand in the short-term. The related ratios are useful in identifying the cash flow status and are of wide interest to investors in the belief that "Cash is King". The common indicators used in computing the liquidity of companies include Current Ratio, Acid-test ratio/ Quick ratio, Receivable turnover, Average collection period, Inventory turnover, Average days to sell inventory, and Average payment period (Weygandt et al., 2008). Solvency evaluation looks into a company's ability to fulfill its financial commitments in a longer term considering its overall level of debt composed of both short-term and long-term liabilities. Debt to total asset ratio, Times Interest earned, and Financial Leverage Ratio are some common solvency indicators for solvency evaluation (Weygandt et al., 2008). By gathering financial data from a group of companies, their performances can be compared and the industry averages of the ratio can be used to determine a firm's relative performance within the industry cluster.

2.3 Performance indicators for technology-based ventures

Other than the financial indicators, there are other aspects, including scientific or technological activities, research and development unit input and output, personnel, customer perspective, and business process efficiency, which were commonly used in previous studies on technology-based firms. In particular, Black et al. (2009) noted that technology-based venture firms that are able to improve their products and or services with innovation, while meeting the long-term needs of the customer, would increase their sales as well as gain better access to capital. The degree of market penetration or sales growth was also found to be value relevant to startup ventures in general (Gavious & Schwartz, 2009).

Brown & Gobeli (1992) and Bapna et al (2013) focused on R&D related inputs, such as human capital and investment, outputs, such as products, patents and journal publications, as well as outcomes, such as sales improvement. R&D expenditure is considered the resource allocated by central management for developing new innovative technologies and products. Average R&D expenditure (R&D spending) reveals the overall scale of a company's technical activity. Such expenditure affects R&D intensity (Ratio of R&D expenditure to a firm's sales) and reveals the effectiveness of R&D expenditure in company competitiveness in generating sales (Schoenecker & Swanson, 2002). Pegels & Thirumuethy (1996) and García-Manjón & Romero-Merino (2012) suggested that using R&D spending per employee can also be a measure of R&D intensity.

Personnel productivity can be measured by computing the revenue or sales generated per employee. It is an important indicator for measuring efficiency in people-oriented industries such as the service industry, high-tech or high product-value manufacturing. A high value of this ratio can be the result of good personnel management or efficient equipment (Huselid et al., 1997). Indicators for personnel include quality and quantity perspectives. The former one can be indicated by the academic background and industrial experience of an employee, and the latter one is revealed by the number of R&D workers within the company (Geisler, 1995). These R&D human resource inputs can affect the output of the R&D unit as well as the overall financial performance of an entity Ganotakis, 2012).

2.4 Multiple Attribute Decision Making (MADM)

Multiple Attribute Decision Making (MADM) refers to "making preference decisions (e.g., evaluation, prioritization and selection) over the available alternatives that are characterized by multiple, usually conflicting attributes" (Hwang & Yoon, 1995). It has been widely applied to projects, supplier selection and inter-company comparisons since it can deal with several conflicting indicators (Wang & Lee, 2009). Among the quantitative methods of MADM, the Simple Additive Weighting Method (SAW), Weighted Product Method, Elimination et Choice Translating Reality (ELECTRE) method, and Technique for Order Preference by Similarity to Ideal Solution Method (TOPSIS) are used in the literature (see Table 1).

Table 1: Comparison of multiple attribute decision making methods

SAW (by Fishburn, 1967)	**Weighted Product (by Bridgman, 1922)**	**ELECTRE (by Benayoun & Sussman, 1966)**	**TOPSIS (by Hwang & Yoon, 1981)**
+ Simple + Widely Used + Applicable in MADM problems	+ Applicable in MADM problems	+ Measurement of satisfaction and dissatisfaction of alternatives by decision maker + Applicable in MADM problems	+ Easy to understand + Applicable in MADM problems +A scalar value that accounts for both the best and worst alternatives simultaneously +Simple computation process + Fewer rank reversal
- Attributes are preferentially independent	- Not widely used - Alternative value do not have upper bound → no true meaning to decision maker	- Massive work with pairwise comparison - Threshold might be arbitrary for eliminating worst alternatives than ranking	- Not widely used

As shown in Table 1, SAW introduced by Fishburn (1967) obtains a score by the addition of normalized attribute values after multiplying them with the respective important weight assigned (Kontos et al., 2005). The attributes are preferentially independent. The Weighted Product Method introduced by Bridgman (1922) is applied through multiplying attribute values with their weights as exponents. A positive power for benefit attributes and a negative power for cost attributes. A standard value can be calculated to achieve the purpose of comparing attribute values to ideal alternative values. It is not so widely used in MADM compared with SAW, and the alternative values do not have upper bounds, so that it has no true meaning to a decision maker.

Benayoun & Sussman (1966) developed the ELECTRE method and it has been modified since then. It concerns the decision maker's satisfaction with the alternatives, and formulates concordance and disconcordance indexes so that the outranking relationships are determined (Vahdani et al., 2013). Sets of data are normalized and expressed in a decision matrix, and weights are then assigned to each attribute. However, it creates a massive workload with pairwise comparison. Moreover, threshold might be arbitrary for eliminating worst alternatives than ranking. Hwang & Yoon (1981, 1995) developed TOPSIS. It suggests that the best alternative would have the shortest distance to the positive ideal solution and the longest distance to the negative ideal solution. As the ideal solution is always unattainable and infeasible, a similarity index to the positive ideal solution is defined by combining the proximity to the positive-ideal solution and remoteness from negative-ideal solution (Wan et al., 2015).

In this study, by considering the MADM with information on the attributes given, TOPSIS is a relatively suitable choice for comparing and ranking companies. From the research of Deng et al. (2000), TOPSIS is a rational and comprehensible approach for solving the cardinal preference of alternatives. It is easy to adapt as it transforms multiple indicators in all dimensions in a simple mathematical form for computation, and is capable of applying objective weightings into the ranking process.

3 Proposed methodology

By comparing with the traditional approaches of MADM, the proposed methodology selects multiple indicators and assigns dynamic weightings based on the significance of each indicator. Hence, the weightings of the indicators can objectively reflect the relative importance among companies in the measured technology cluster. A schematic diagram of the cluster-based performance measurement system is shown in Figure 1. It is composed of data collection, data analysis and performance representation.

Please insert Figure 1

Multiple indicators are selected as the performance indicators based on the literature review discussed in Section 2. A list of proposed performance indicators is shown in Table 2. Inter-dependence between indicators might result in double counting of the performance rating in similar means. As a result, correlation analysis and statistical analysis are performed for eliminating indicators that are inter-correlated with other indicators most. TOPSIS is then applied to determine the performance of the companies within the assessed cluster based on the selected indicators. A performance matrix is generated by normalizing the values of the selected indicators of the companies, as shown in Table 3.

The weightings are determined by the distances between the best and worst indexes in the indicators measured (see Equation 1). The distance to the best performer is computed by multiplying the square of the distance between the company index and best performer index with the objective weight, and takes the square root of the summation of the distance in all indicators (see Equation 2). The distance to the worst performance is calculated vice versa. Objective weighting is used as there is no reliable subjective weighting provided by decision makers. In particular, entropy weighting (Shannon & Weaver, 1947) is used in this study since it is suitable when reliable weighting cannot be obtained from decision makers (Wang & Lee, 2009; Sen & Yang, 2012). After that, the overall performance of the company is calculated as Equation 3. The larger the value of P, the further the distance it is from the worst solution, and the higher the ranking of the company. A list of performance ranking of the companies can be obtained.

Table 2: Proposed performance indicators

Performance	Indicators	Research Method
Financial	1. Profitability Ratios 2. Liquidity Ratios 3. Solvency Ratios	Provided by tenants

R&D	1. Number of Patents 2. Citation of Patents 3. New Product Release 4. New Product Under-Development	Researched by Patents Office of Unite State, Europe, China and Hong Kong Press Release
Publication	1. National Publications 2. International Publications	Provided by tenants and researched by web searching
Customer/Market	1. Customers Retention Rate 2. Customer Acquisition Rate/ Pace of Market Penetration	Provided by tenants
Business Process	1. Time to Market	Provided by tenants
Learning and Growth	1. Employee Retention 2. Academic Background Ratio	Provided by tenants
Experience, Awards and Standards	1. Number of Years in the Industry 2. Number of Awards Received 3. Number of ISO Standard Passed	Provided by tenants
Diversification	1. Geographical 2. Product	Provided by tenants

$$w_j = \frac{d_j}{\sum_{k=1}^{m} d_k}$$ Equation (1)

where w_j is the weighting of indicators j, d_j is the degree of divergence of the indicators j, and m is the total number of indicators

$$d_i^+ = \left[\sum_{j=1}^{m} w_j \left(d_{ij}^+\right)^2\right]^{\frac{1}{2}}, \quad d_i^- = \left[\sum_{j=1}^{m} w_j \left(d_{ij}^-\right)^2\right]^{\frac{1}{2}}, \text{ i = 1, 2, …, n}$$ Equation (2)

where $d_i^+ =$ Distance to best performer for company i; $d_i^- =$ Distance to the worst performer for company i

Table 3: Performance matrix

Weight	w_1	w_2	…	w_n		
	Indicators 1	**Indicators 2**	…	**Indicators n**	**Distance to best performer**	**Distance to worst performer**
Company 1	p_{11}	p_{12}	…	p_{1m}	d_1^+	d_1^-
Company 2	p_{21}	p_{22}	…	p_{2m}	d_2^+	d_2^-
Company 3	p_{31}	p_{32}	…	p_{3m}	d_3^+	d_3^-
⋮	⋮	⋮	⋱	⋮	⋮	⋮
Company n	p_{n1}	p_{n2}	…	p_{nm}	d_n^+	d_n^-
Best index	p_1^+	p_2^+	…	p_m^+		
Worst index	p_1^-	p_2^-	…	p_m^-		

$$P_i = \frac{d_i^-}{d_i^+ + d_i^-}$$ Equation (3)

where P_i is the performance value of company i

4 Evaluation and discussions

4.1 Data collection

In order to verify the proposed methodology, a pilot study was conducted during the period 2010 to 2011. The tenants of Hong Kong Science and Technology Parks (HKSTP) were selected as the subjects of this study. HKSTP was established in 2001 by the Hong Kong Science and Technology Corporation. It is dedicated to transforming innovation and technology into value creation to benefit Hong Kong, Mainland China and even the world by providing facilities, service and a dynamic environment to tenants. HKSTP organizes 3 to 4 years incubation programmes for start-up companies. It provides support to techno-entrepreneurs, including financial funding, office subsidies, promotion service, legal service, business matching services, and technical and management assistance. Incubatees are assessed by HKSTP so as to evaluate the performance of graduated incubatees for consideration as potential tenants in HKSTP. This forms the research motivation of the present performance measurement system study.

Tenants of different sizes in HKSTP belong to different clusters. There are six clusters in HKSTP, in which the Information & Communications Technology (ICT) cluster and the electronics cluster are the top two clusters in HKSTP in terms of the number of tenants. During the period of data collection of this study, the population of the two clusters was obtained, as shown in Table 4. Quantitative data was provided by the management office of HKSTP. Since some of the tenants did not provide complete data, they were eliminated before the data analysis. The filtered population of ICT and Electronics companies is shown in the bracketed numbers of Table 4.

Table 4: Population of ICT and electronics clusters in HKSTP

Cluster	**Number of Local Companies (After filtering out missing data)**	**Number of Non- Local Companies (After filtering out missing data)**	**Total Number of Companies (After filtering out missing data)**
ICT	33 (30)	12 (11)	45 (41)
Electronics	38 (24)	20 (17)	58 (41)

Quantitative data was collected from the HKSTP's tenant admission form. As discussed in the literature review, the reviewed indicators belong to 8 major areas, namely Financial; R&D; Publication; Customer/Market; Business Process; Learning and Growth; Experience; Awards and Standards; and Diversification. However, due to the limitation of compliance with institutional policy (i.e. HKSTP does not disclose the names of its tenants) and data available in the HKSTP, only 3 areas of the proposed indicators can be made available, which include Financial, R&D, and Customer/Market. The linkage of the performance areas of the proposed framework and the indicators available from the data set are shown in Table 5.

These indicators include Number of R&D and Non-R&D Employee, R&D Budget of Current Year (i.e. 2010) and Estimation of Next Year (i.e. 2011), Annual Turnover of Current Year (i.e. 2010) and Estimation of Next Year (i.e. 2011), Country of Origin of Companies and the Cluster of companies. Based on the collected data, 8 indicators were devised. As shown in Table 5, indicator 1 "Annual Turnover per Employee" aims to indicate the overall employee productivity and commercialization success of the companies. Indicator 2 "Annual Turnover per R&D Employee" aims to indicate the productivity of R&D employees. Indicator 3 "R&D Personnel Percentage" aims to measure the human resource input on R&D. Indicator 4 "R&D Expenditure per Employee" aims to indicate company effort on R&D in general. Indicator 5 "R&D Expenditure per R&D Employee" aims to indicate company effort on R&D based on the size of the R&D team. Indicator 6 "R&D Intensity" aims to indicate company effort on continuous reinvestments and momentum for innovation. Indicator 7 "R&D Spending" aims to indicate the overall scale of company's R&D activities. Indicator 8 "Sales Growth" aims to indicate the profitability and growth rate of the company.

Table 5: Indicators available from the data set

Indicator Number	Indicators	Performance	Implication	Definition
1	Annual Turnover per Employee	Financial	Employee Productivity / Commercialization success	$\frac{Annual\ Turnover}{Total\ Employee}$
2	Annual Turnover per R&D Employee	Financial R&D	R&D employee Productivity	$\frac{Annual\ Turnover}{R\&D\ Employee}$
3	R&D Personnel Percentage	Financial R&D	R&D human resource input	$\frac{R\&D\ Employee}{Total\ Employee}$
4	R&D Expenditure per Employee	Financial R&D	R&D effort of Company (per employee)	$\frac{R\ \&\ D\ Expenditure}{Total\ Employee}$
5	R&D Expenditure per R&D Employee	Financial R&D	R&D effort of Company (per R&D employee)	$\frac{R\ \&\ D\ Expenditure}{R\&D\ Employee}$
6	R&D Intensity	Financial R&D	Extent of R&D is in the company's competitive strategy / Continuous Reinvestments / Momentum for innovation	$\frac{R\ \&\ D\ Expenditure}{Annual\ Turnover}$
7	R&D Spending	Financial R&D	Overall scale of company's R&D activities	$Average\ R\&D\ Expenditure$
8	Sales Growth	Customer/Market Financial	1. Profitability 2. Measures of company growth rate 3. Momentum in Commercialization success	$\frac{2011\ AT - 2010\ AT}{2010\ AT}$ (AT = Annual Turnover)

4.2 Performance Ranking Analysis

For the ICT cluster, the 8 indicators are tested by correlation and statistical analysis. Annual Turnover per R&D Employee (Indicator 2), R&D Expenditure per Employee (Indicator 4), and R&D Intensity (Indicator 6) have the highest correlation among the indicators, and hence, they are indicators for preventing double counting. For the electronics cluster, Annual Turnover per R&D Employee (Indicator 2), R&D Expenditure per R&D Employee (Indicator 5), and R&D Intensity (Indicator 6) are removed due to their high correlation with other indicators. Hence, the five most significant indicators for the two selected clusters are obtained through the TOPSIS method. The performance matrix and objective weights are obtained by the method as discussed in Section 3. The list of top 10 ventures of the ICT cluster and electronics cluster is shown in Tables 6 and 7, respectively.

As shown in Table 6, the results indicate that ICT ventures with no more than 100 employees have the advantage of committing to high R&D Spending (Indicator 7), and also have a high overall ranking. Some companies have a higher ranking in Annual Turnover per Employee (Indicator 1) also have a higher ranking in the overall ranking. Some of the companies in top ten also have top ranking in R&D Expenditure per R&D Employee (Indicator 5) and Sales Growth (Indicator 8). However, not many companies with high ranking in R&D Personnel Percentage (Indicator 3) are included in the top-ten list. Three of the top ten ranking companies are non-local companies.

Table 6: Top ten ranking of ICT cluster's ventures with reference to company size, country of origin and indicators ranking

Rank	Company Code	Performance Score	Company Size	Country of Origin	Indicator 1	Indicator 3	Indicator 5	Indicator 7	Indicator 8
1	ICT001	0.425	640	Local	16	6	11	1	38
2	ICT006	0.419	10	Local	39	10	21	12	1
3	ICT003	0.402	40	Non-local	1	21	29	7	39
4	ICT027	0.307	27	Local	41	17	32	8	2
5	ICT037	0.158	110	Non-local	2	27	2	2	40
6	ICT033	0.078	9	Local	4	5	1	3	28
7	ICT036	0.064	8	Local	40	29	35	18	3
8	ICT042	0.048	19	Local	3	23	14	9	34
9	ICT013	0.034	39	Non-local	6	37	9	5	23
10	ICT025	0.033	10	Local	5	10	8	13	10

As shown in Table 7, more top performers in electronics ventures are non-local companies in comparison with ICT ventures. However, large size electronics ventures with no more than 100 employees, similar to ICT, had an advantage in having high R&D Spending (Indicator 7) and a high overall ranking. Companies have a higher ranking in Annual Turnover per Employee (Indicator 1) also have a relatively higher overall ranking. Moreover, companies with good performance in Sales Growth are also listed in the overall ranking. Furthermore, more than half of the top ten companies are non-local companies. The best performers in both clusters received the highest rank in R&D spending (Indicator 7) and the largest company size. The second and third top performers in both clusters top rank in Annual Turnover per Employee (Indicator 1) and Sales Growth (Indicator 8) respectively.

Table 7: Top ten ranking of electronics cluster's ventures in with reference to company size, country of origin and indicators ranking

Rank	Company Code	Performance Score	Company Size	Country of Origin	Indicator 1	Indicator 3	Indicator 4	Indicator 7	Indicator 8
1	E039	0.582	916	Non-local	11	40	10	1	38
2	E036	0.377	25	Non-local	1	4	3	5	22
3	E047	0.299	225	Local	15	10	17	2	1
4	E022	0.232	8	Non-local	41	25	38	24	2
5	E010	0.181	6	Non-local	2	20	20	26	29
6	E009	0.147	11	Local	30	16	7	3	3
7	E037	0.094	64	Non-local	5	32	12	4	40
8	E011	0.087	11	Non-local	3	36	4	10	24
9	E034	0.081	4	Local	4	11	13	29	10
10	E057	0.071	5	Local	40	8	35	34	4

Correlation Analysis is applied to identify the relevance of the indicators in assessing the overall performance of the companies. The results of Correlation Analysis between Multi-Indicator Ranking and Single Indicator Ranking of ICT Companies Assessment Model in Table 8 showed that R&D Spending (Indicator 7) is highly correlated with the overall ranking of the company. Annual Turnover per Employee (Indicator 1) and R&D Expenditure per R&D Employee (Indicator 5) are moderately correlated to the overall ranking. This information can facilitate decision makers to recognize important indicators.

Table 8: Spearman's rank correlation analysis between Multi-Indicator Ranking and Single Indicator Ranking of ICT and Electronics companies assessment model

	Productivity	**R&D Personnel %**	**R&D Effort**	**R&D Spending**	**Sales Growth**
ICT	0.532	0.111	0.546	0.801	0.169
Electronics	0.452	-0.069	0.543	0.635	0.062

From the results of the electronics cluster shown in Table 8, it is observed that R&D Spending (Indicator 7) has the highest correlation coefficient among all the other indicators. Both annual Turnover per Employee (Indicator 1) and R&D Expenditure per Employee (Indicator 4) are moderately correlated to overall ranking. R&D Personnel Percentage (Indicator 3) and Sales Growth (Indicator 8) do not correlate to the overall rank, implying that the high performance indexes in these two indicators do not have a strong influence on the overall ranking.

It is concluded that R&D Spending (Indicator 7) contributes the most to the overall ranking as it has the highest value. R&D Spending reveals the overall scale of a company's activities in technological innovation. Increasing the investment in R&D can improve the overall performance rating which results in a higher rank level.

4.3 Comparison between ICT and Electronics clusters

To further analyze the data represented in the two clusters, t-tests are utilized to test the underlying relationships in their respective emphases on the 8 Indicators. The results are shown in Table 9. Based on the results, one can see that the means of Indicators 1, 2, 4, 5 and 6 are significantly different between the two clusters, while the mean of Indicators 3, 7 and 8 are not significantly different between the two clusters.

Table 9: t-test on indicators between the two Clusters

	ICT cluster	**Electronics cluster**
t-test: Paired two sample for means of Indicator 1 (Annual Turnover per Employee)		
Mean	2240.586	26598.804
Variance	63317001.970	5374015285.000
Pearson Correlation	-0.068	
t Stat	-2.100	
P(T<=t) one-tail	0.021	
t Critical one-tail	1.684	
P(T<=t) two-tail	0.042	
t Critical two-tail	2.021	
t-test: Paired two sample for means of Indicator 2 (Annual Turnover per R&D Employee)		
Mean	3236.148	37699.502
Variance	129404651.100	7527903500.000
Pearson Correlation	-0.083	

t Stat	-2.495	
P(T<=t) one-tail	0.008	
t Critical one-tail	1.684	
P(T<=t) two-tail	0.017	
t Critical two-tail	2.021	

t-test: Paired two sample for means of Indicator 3 (R&D Personnel Percentage)

Mean	0.711	0.689
Variance	0.021	0.021
Pearson Correlation	0.143	
t Stat	0.748	
P(T<=t) one-tail	0.229	
t Critical one-tail	1.684	
P(T<=t) two-tail	0.459	
t Critical two-tail	2.021	

t-test: Paired two sample for means of Indicator 4 (R&D Expenditure per Employee)

Mean	325.944	448.456
Variance	136131.902	100594.780
Pearson Correlation	0.186	
t Stat	-1.785	
P(T<=t) one-tail	0.041	
t Critical one-tail	1.684	
P(T<=t) two-tail	0.082	
t Critical two-tail	2.021	

t-test: Paired two sample for means of Indicator 5 (R&D Expenditure per R&D Employee)

Mean	446.050	676.645
Variance	175368.461	261230.276
Pearson Correlation	0.372	
t Stat	-2.804	
P(T<=t) one-tail	0.004	
t Critical one-tail	1.684	
P(T<=t) two-tail	0.008	
t Critical two-tail	2.021	

t-test: Paired two sample for means of Indicator 6 (R&D Intensity)

Mean	10.117	52.721
Variance	1941.442	10995.400
Pearson Correlation	-0.090	
t Stat	-2.325	
P(T<=t) one-tail	0.013	
t Critical one-tail	1.684	
P(T<=t) two-tail	0.025	
t Critical two-tail	2.021	

t-test: Paired two sample for means of Indicator 7 (R&D Spending)

Mean	14789.244	25207.5122
Variance	2942500002.000	9114512048.000
Pearson Correlation	-0.0579	
t Stat	-0.593	
P(T<=t) one-tail	0.278	
t Critical one-tail	1.684	
P(T<=t) two-tail	0.557	
t Critical two-tail	2.021	

t-test: Paired two sample for means of Indicator 8 (Sales Growth)

Mean	2.990	1.113
Variance	125.530	7.555
Pearson Correlation	-0.090	
t Stat	1.021	
P(T<=t) one-tail	0.157	
t Critical one-tail	1.684	
P(T<=t) two-tail	0.313	
t Critical two-tail	2.021	

4.4 Comparison between Local and Non-Local Companies

Statistical analysis between local and non-local companies is performed since it may generate useful information for identifying the critical areas for companies to improve. The results are shown in Tables 10 and 11 for the ICT cluster and electronics cluster respectively.

Table 10: Statistical results of ICT Local and Non-Local Companies

	Performance Score	Productivity	R&D Personnel %	R&D Effort	R&D Spending	Sales Growth
Local Companies mean	0.055	834	0.741	445	15683	3.893
Non-local Companies mean	0.066	6077	0.631	448	12351	0.528
F-Test	0.8052	1.445E-24	0.3885	0.0595	0.00683	3.770E-13
T-Test	0.782	0.277	0.028	0.985	0.810	0.169

Table 11: Statistical results of electronics Local and Non-Local Companies

	Performance Score	Productivity	R&D Personnel %	R&D Effort	R&D Spending	Sales Growth
Local Companies mean	0.042	8921	0.701	309	10060	1.277
Non-Local Companies mean	0.113	51555	0.673	646	46592	0.943
F-Test	0.000141	1.309E-12	0.1395	0.000895	8.77E-13	0.988
T-Test	0.086	0.129	0.543	0.002	0.320	0.704

The results show that local companies perform similarly to non-local companies in the ICT cluster. Non-local companies perform better than local companies in the electronics cluster. R&D Personnel Percentage (Indicator 3) of ICT local companies is significantly higher than that of ICT non-local companies. It implies that the human resource inputs of local companies are higher. In the electronics cluster, non-local companies notably had higher R&D effort as opposed to local companies.

4.5 Comparison between SAW and the proposed method

The traditional ranking method based on SAW and the proposed model are significantly different from each other in terms of indicator selection. The ranking model with results is shown in Figures 2 and 3 for the two respective clusters. For the ICT cluster, the top ranked companies in the SAW ranking method appear to have relatively high ranking in the proposed ranking method. However, top performers identified by the proposed ranking method, such as ICT001, ICT006, ICT027 and ICT036, have relatively low ranking in the SAW method. Besides, the correlation analysis showed that Annual Turnover per Total Employee and Annual Turnover per R&D Employee (Indicators 1 and 2) are strongly correlated with the Overall Rank in the SAW method, as shown in Table 12.

Please insert Figures 2 and 3

Table 12: Spearman’s Rank Correlation Analysis between Multi- Indicator Ranking and Single Indicator Ranking of SAW method for ICT and Electronics clusters

Overall Rank	**Productivity 1**	**R&D Effort 1**	**Productivity 2**	**R&D Effort 2**	**R&D Personnel Percentage**
ICT	0.986	0.603	0.992	0.686	-0.086
Electronics	0.995	0.441	0.998	0.518	-0.329

As shown in Figure 3, the top ranking companies identified by the SAW method have relatively high ranking in the proposed ranking method for the electronics cluster. The best company in the proposed ranking method, E039, also has a relatively high rank in the SAW method. However, other performers among the best, such as E047, E022, E009 and E057, are not recognized as relatively high ranked in the SAW method. The correlation analysis between the Multi-Indicator Ranking and Single Indicator Ranking of SAW method for the electronics cluster is shown in Table 12. Similar to the ICT cluster, the Annual Turnover per Total Employee and Annual Turnover per R&D Employee (Productivity 1 & 2) have a strong correlation with Overall Rank.

Although the SAW method considers both Productivity and R&D Effort, it is observed that the assessment tends to favor the option of Annual Turnover per Total Employee and Annual Turnover per R&D Employee (Productivity 1 & 2) instead of R&D Expenditure per Total Employee and R&D Expenditure per R&D Employee (R&D Effort 1 & 2). It is because most of the companies have a higher value in Annual Turnover than in R&D Expenditure. This phenomenon reflects that the ranking is almost solely based on the Employee Productivity of the Companies and neglects the R&D Effort, which is an important factor in R&D output. On the other hand, a high correlation is found between Annual Turnover per Total Employee and Annual Turnover per R&D Employee. It is unnecessary to include both indicators which basically have similar implications in the ranking model.

As shown in Figure 2 and Figure 3, it is observed that gaps between the SAW method and the proposed method are relatively smaller and approximately the same order, while some of the low ranking companies in the SAW method are ranked higher in the proposed ranking list. The reason is that high ranking companies in the SAW list are distinctive and truly top performers and had high ranking as well in other indicators in achieving top overall rank in the proposed method. In addition, Figure 3 for the electronics cluster showed that relatively more companies with low rank in the SAW list are ranked higher in proposed ranking list. To sum up, gap analysis indicates that gap between the traditional rank and proposed rank is larger in the electronics cluster than that of the ICT cluster.

By investigating the data, all of the increased rankings of ventures from both clusters are pertinent to the influence of R&D Spending (Indicator 7) and Sales Growth (Indicator 8). As R&D Spending implies the overall scale of company’s technical activity and Sales Growth is the profitability and measure of the growth of companies, this situation implies that the SAW system cannot reflect the potential of large scale investment of larger organization and growth of companies. In contrast, the new ranking system can meet the objectives of identifying potential ventures based on the indicators.

In terms of ranking-decreased ventures in the two Clusters, they score lower in the proposed ranking system because of the lower value in R&D Expenditure per Employee (Indicator 4) or R&D Expenditure per R&D Employee (Indicator 5) R&D Spending (Indicator 7) and Sales Growth (Indicator 8). This phenomenon also reveals that the traditional rank is relying overly on the measure of employees' productivity and neglects other important variables.

5 Concluding remarks

To assess the competitiveness and performance of technology-based ventures, this study reveals that the traditional performance measurement approach appears to have emphasized heavily on financial parameters and unduly on historical data related to resource allocation with static weightings. Such seemingly standardized assessment factors and weightings may lead to a double rating and bias in the assessment of their competitiveness and the prospects for their future performance. The existing approach of focusing on performance outcomes is inadequate in identifying and predicting performers for sustainable growth and development in an emerging technology sector. Resource allocation in R&D expenditure is an important consideration, in combination with other performance indicators, such as sales growth (Black et al. 2009; Gavious & Schwartz, 2009). However, the effectiveness and efficiency of a company in converting R&D resources into commercialization success needs to be understood as part of the overall performance monitoring and management processes. As such, there is a need for a more dynamic assessment method which is able to identify the key success factors and the potential outperformers in an emerging technology sector.

In this paper, a cluster-based performance measurement method is developed which makes use of the performance matrix and objective weighting. To verify the technical feasibility of the proposed method, a pilot study was conducted between 2010 and 2011 in the Hong Kong Science and Technology Parks (HKSTP). The results showed that the proposed performance measurement approach provides an alternative assessment approach that looks into relevant performance indicators and their weightings in order to unveil potential outperformers. Various weightings of the performance indicators were estimated for the two technology clusters in HKSTP in this study. This particular phenomenon should be taken into consideration in the differentiation within emerging technology clusters as well as customization for the unique characteristics of their performance indicators. Different technology clusters need to be examined for their specific sets of indicators and respective weightings, as a venture may be undergoing a specific stage of development, which would impose unique resource requirements, for instance, for the development of prototypes and related testing.

Based on the results of the present study, they infer that there is a need for science and technology parks to formulate a set of performance assessment indicators which are dynamic to the various emerging technology sectors. Given the other variables associated with the externalities, the effectiveness and efficiency of a company in converting R&D resources into commercialization success also needs to be attuned in the overall performance monitoring and management processes. Such process of evaluation should involve expert inputs for a particular cluster in order to obtain insights about forthcoming product innovation and commercialization. With dynamic interactions with the externalities, stakeholders with concerns about future competitiveness should assess carefully, and in a timely manner, how technology-ventures within a cluster are able to respond to their external challenges. As time goes by, with the evolution of an emerging technology sector, a comprehensive performance measurement system can be evolved with reconfigured indicators to augment competitiveness and performance assessment for the technology-based ventures within a cluster. Such dynamic development of a performance measurement system is also consistent with prior studies on the need to revise in response to externalities over time (Kennerley &Neely, 2002, 2003; Zairi, 2012).

Currently in the trial implementation, due to the limitation of the data availability of the organizations, only 3 out of 8 proposed areas could be addressed. Although the data collected covers the R&D area which has received relative little concern in the literature and the aim of this paper is to demonstrate the significance of providing automatically adjusted weighting of the performance indicators for performance measurement, this study can only be considered as a pilot study. Further work should be done with a larger coverage of relevant indicators. Moreover, a more comprehensive performance measurement system can be developed with the input of cluster-specific experts to proactively augment performance assessment within an emerging technology cluster. Through such an interactive monitoring mechanism, a science and technology park would be able to make timely strategic decisions concerning resource allocation to nurture the growth and development of technology-based ventures.

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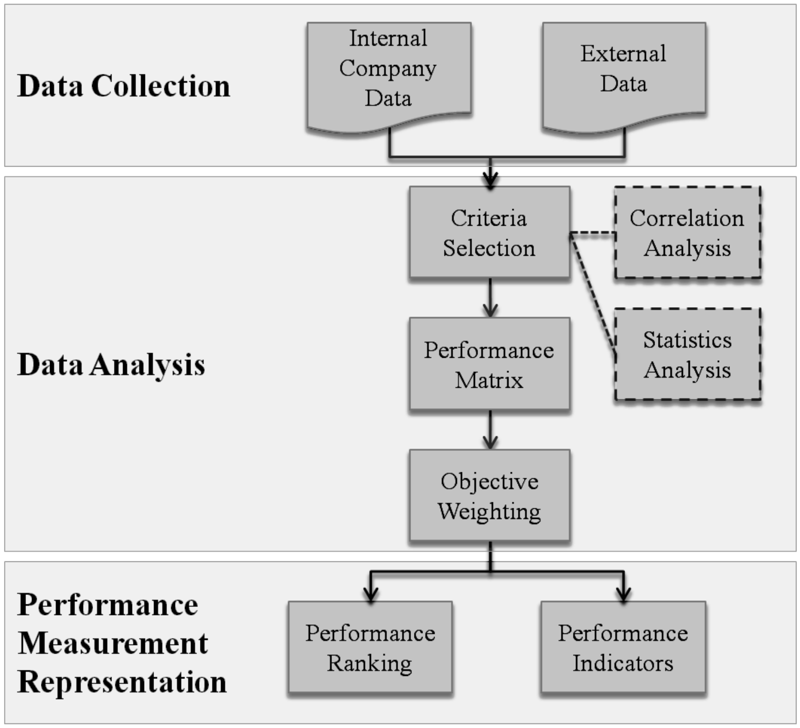

Figure 1: A schematic diagram of the cluster-based performance measurement system

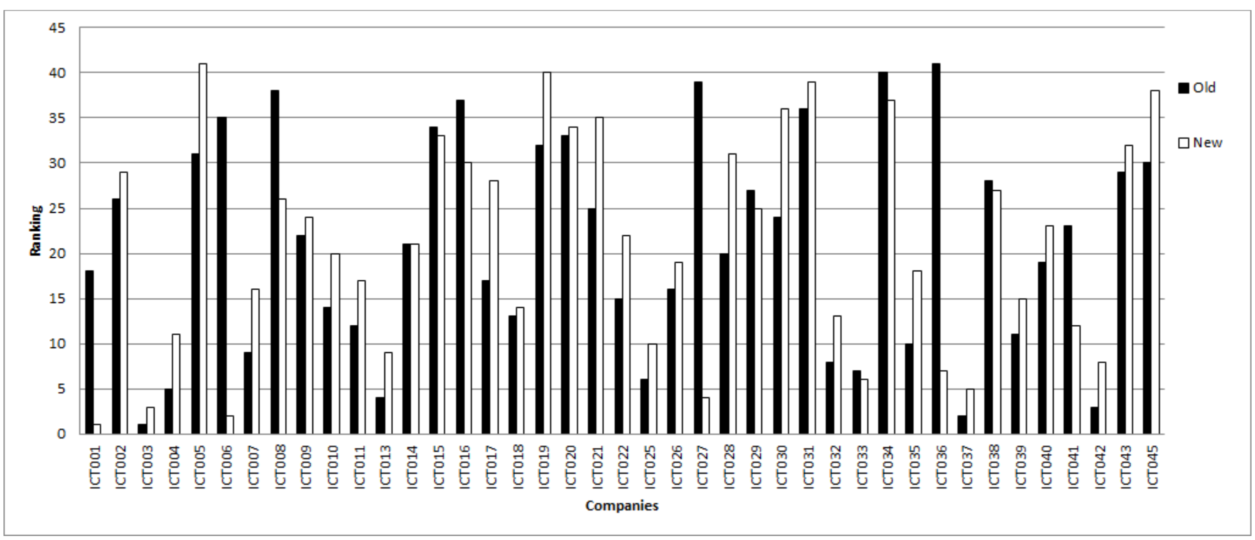

Figure 2: Gap analysis between SAW (Old) and proposed (New) ranking of ventures of ICT cluster

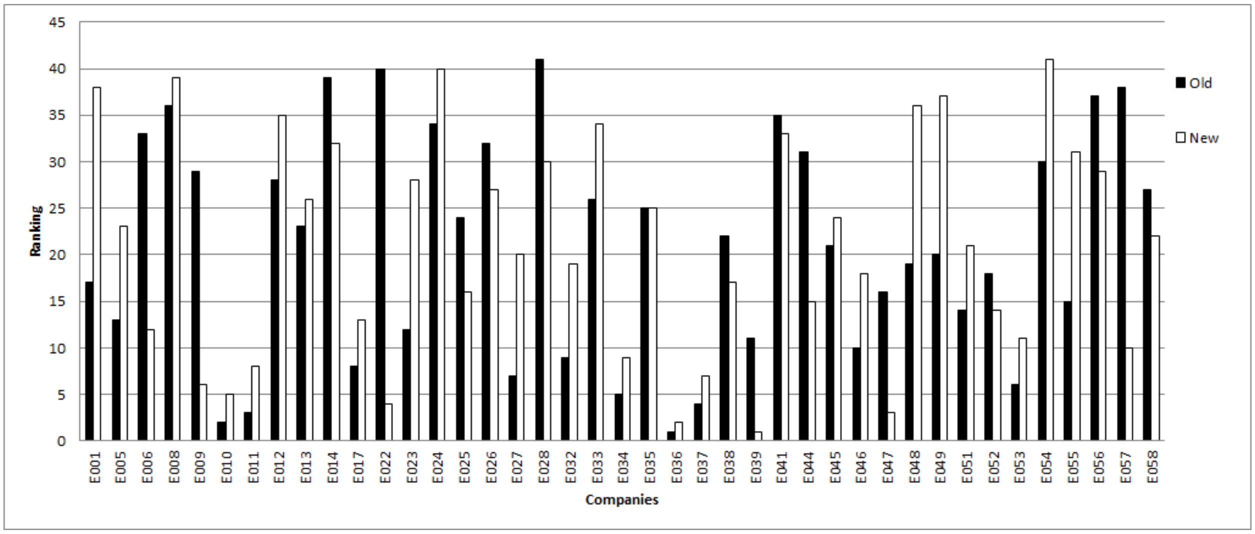

Figure 3: Gap analysis between SAW (Old) and proposed (New) ranking of ventures of electronics cluster