

Extended Value Added Intellectual Coefficient in Manufacturing Companies: Technology Based Companies

Hamidreza Jafaridehkordi¹

National University of Malaysia, UKM Bangi, Selangor, Malaysia

Ruzita Abdul Rahim

National University of Malaysia, UKM Bangi, Selangor, Malaysia

Abstract

The main purpose of this study is to empirically compare of intellectual capital (IC) and its efficiency among manufacturing companies with different level of technology using a sample of 135 Malaysian listed manufacturing companies during the 2006-2012 period. The manufacturing companies are classified into different sectors based on their products and services (Standard Industrial Classification (SIC) code) on OSIRIS databases. Then, they are categorized into one of the four groups: high, medium-high, medium-low, and low technology. The results of ANOVA test indicate that investment in IC and its components, and efficiency of IC and its components vary with degree of technology of the manufacturing companies. It also can be concluded that more investment in IC components does not necessarily lead to more efficiency of IC.

Keywords: Intellectual Capital, Extended Value Added Intellectual Coefficient, Technology Based Companies

Cite this article: Jafaridehkordi, H., & Abdul Rahim, R. (2015). Extended Value Added Intellectual Coefficient in Manufacturing Companies: Technology Based Companies. *International Journal of Management, Accounting and Economics*, 2(7), 676-706.

¹ Corresponding author's email: hamidreza.jafari55@gmail.com

Introduction

According to Organisation for Economic Co-operation and Development (OECD) (2006), nowadays many firms are investing in employee training, job training programs, research and development (R&D), customer relations, computer and administrative systems, and so on. In some countries, investment in such business activities and items that are often referred to IC is growing and is competing with investment in physical and financial capital. In the U.S for instance, Apple company had been converted into the most invaluable company in the history with a share market value of above USD600 billion that is directly resulted from investment in IC and revenue from apps and its network (Edvinsson, 2013). Similarly, Google and Microsoft are included among the successful companies which are investing low in fixed assets, but a significant amount of capital in IC (Ong, Yeoh, & Teh, 2011). Leadbeater 2000) reports that merely about 7 percent of share market value of Microsoft is accounted for by tangible assets, while the remaining (93%) is derived from intangible assets such as patents, brands, and R&D.

Those world's top companies are not unique cases of IC success stories. Figure.1 indicates the percentage of the market value of tangible and intangible assets of S&P500 companies in different periods of time. There is a clear trend showing the growing importance that these 500 large-capitalization American companies place on intangible assets.

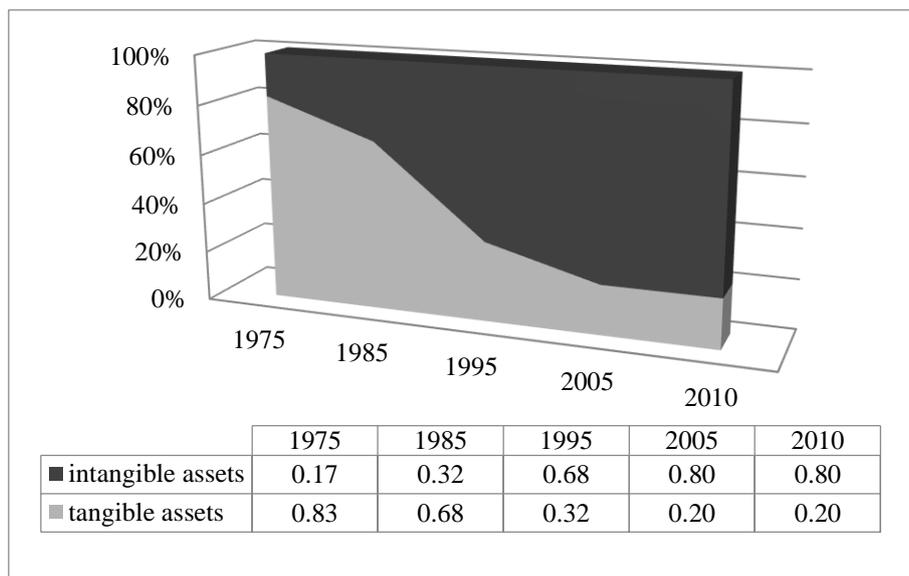


Figure.1 Components of market value (the U.S case)
 Source: Oceantomo (2013).

Malaysia has embarked on becoming a knowledge-based economy (K-economy) as its main vehicle to transform into a developed country by 2020. A K-economy is an economy where the creation and exploitation of knowledge act as the main factor in the process of value creation(Goh, 2005). Developing the K-economy was the focal point of the 2002 Economy Master Plan (EMP 2002) which was aimed at creating competitive advantages

among companies and communities. EMP 2002 was a plan summarizing the diverse strategies to speed up the transformation of Malaysia to the K-economy (Kim & Lee 2004). Without deemphasizing the importance of traditional physical and natural factors of production such as raw materials, labor, capital and entrepreneurship, the K-economy places intellectual capital (IC) as its nucleus. Emerged in the midst of the information age, the K-economy entrusts IC as the key driver of organizational performance, competitive advantage and value creation (Bontis, Keow & Richardson 2000; Mustapha & Abdullah 2004).

Table 1 illustrates the position of Malaysia relative to some other countries in term of the Knowledge Economy Index (KEI) in 2000 and 2012 as reported by the World Bank (2013). The KEI ranking for Malaysia relative to the U.S is good evidence that Malaysian companies need to invest more on intangible capital in general and knowledge capital in more specific. Focusing on the Asian region alone, it is rather obvious that Malaysia is catching up but still lagging behind the other developed countries such as Japan and other more develop countries such as Singapore. It is important to note that Malaysia's rank in term of its KEI has dropped in 2012 compared with 2000.

Table.1 Countries ranking on the Knowledge Economy Index (KEI)

Country/Economy	2012 Rank	KEI 2012	2000 Rank	Change from 2000
Sweden	1	9.43	1	0
Finland	2	9.33	8	6
Denmark	3	9.16	3	0
United States	12	8.77	4	-8
Taiwan, China	13	8.77	16	3
United Kingdom	14	8.76	12	-2
Japan	22	8.28	17	-5
Singapore	23	8.26	20	-3
Korea, Rep.	29	7.97	24	-5
Malaysia	48	6.1	45	-3
Thailand	66	5.21	60	-6
Indonesia	108	3.11	105	-3
India	110	3.06	104	-6

Source: <http://siteresources.worldbank.org>

K-economy places its focus on IC but Knowledge Economy Index (KEI) (Table 1) shows that Malaysian companies have not been investing enough on IC. If the K-economy is needed to transform Malaysia into a developed country status, then the nucleus of K-economy (i.e. IC) needs to be given a renewed energy. This study proposes that this can be done more efficiently by targeting on the companies that can optimize the IC. Past studies (Hayton 2005; Sáenz, Aramburu & Rivera 2009; Tseng & James Goo 2005) show that high technology is the sector which requires innovation the most and IC is the main input to fuel innovation. Therefore, this study proposes to examine the role of IC in manufacturing companies of different level of technology.

As one of the pioneers in the scope of defining, measuring and dealing with intellectual capital (IC), Edvinsson (1997:368) defines this concept as “the possession of knowledge,

applied experience, organizational technology, customer relationships and professional skills that provide a company (Skandia) with a competitive edge in the market”. Edvinsson (1997) believes that HC is the combined knowledge, skill of the firm's individual employees, culture and philosophy, and values of the firms. Edvinsson (1997) states that SC is organizational capability with the purpose of supporting the efficiency of the workforce and everything that are left in the company when the staff go home like trademarks, databases patents, hardware and software. Skandia (1994) and Edvinsson and Malone (1997) argue that SC can be subdivided into customer capital (CC) and organizational capital (OC). CC is association expanded with vital customers by acquisitions of information and knowledge concerning customers' tastes, required technology, new goods and services (Edvinsson, 1997). OC can be described as systems, equipments, and operational attitudes that speed up the stream of knowledge throughout the company. Edvinsson and Malone (1997) classify organizational capital (OC) further into innovation capital (InC) and process capital (PC). InC indicates the firm's revolutionary capability, innovative success, and potential accumulation of new product and service (Wang, 2008). Process capital (PC) represents working processes, standardized methods or schemes that can raise and enhance workers' efficiency and productivity. Figure. 2 display intellectual capital and its components. (Edvinsson & Malone, 1997)

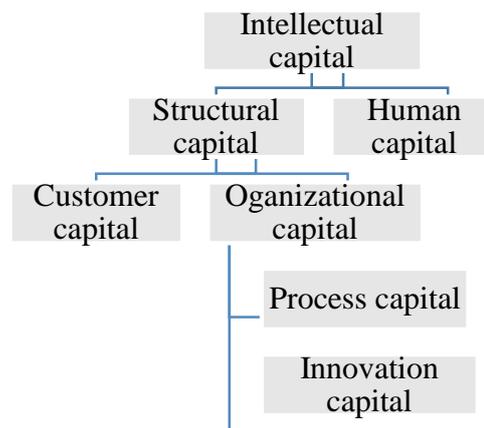


Figure.2 Skandia Navigator model: intellectual capital and its components

Manufacturing companies can be divided into four groups based on the technology that they are using: high technology, medium-high technology, medium-low technology, and low technology (Czarnitzki & Thorwarth, 2012; Hatzichronoglou, 1997; Kim & Lee, 2004; Mendonça, 2009). The literature shows that high technology companies have more investment on R&D expenditures as part of the IC than low technology companies (Czarnitzki & Thorwarth, 2012). Higher technology companies rely more heavily on the quality of human capital and the other components of IC because they operate in a more dynamic environment which forces them to be consistently on the innovative and creative mode to remain competitive. Consequently, it is expected that high technology companies present more efficiency than their low technology counterparts in using the IC and its components.

Zéghal and Maaloul (2010) compare IC among high technology, traditional and services companies and their results indicate that IC and its component vary in these three groups. However, there is no research regarding the distinct IC and its efficiency among manufacturing companies with different levels of technology. Considering the important role of IC in developing the nation, investigating and comparing IC and its efficiency in manufacturing companies can help to identify the driving factors that the companies and government must emphasize on to realize the developed nation vision. Therefore, this research seeks to find credible answer(s) to this research questions: Is there a significant difference in intellectual capital and its efficiency among manufacturing companies with different levels of technology in Malaysia?

Most studies on IC have only focused on comparing IC among different companies in sectors such as banking or financial sector (Pal & Soriya, 2012; Sledzik, 2012; Zeghal & Maaloul 2010). Therefore, the main purpose of this study is to empirically compare of intellectual capital (IC) and its efficiency among manufacturing companies with different level of technology. This is a paradox given the argument that high-technology companies are more dependent on intellectual capital (Nunes, Serrasqueiro, Mendes, & Sequeira, 2010;Porrini, 2004; Wang & Chang, 2005) than their low-technology counterparts because these are the companies that rely mostly on innovation for its competitiveness.

One of the obstacles in examining IC empirically is the difficulty to quantify this variable, which could also explain why this item is not recorded explicitly in the financial statement. The difficulty to quantify IC is evident by the fact that the literature has not shown a commonly accepted definition and classification for IC (Pablos, 2004). To empirically test intellectual capital, this study adopts an extended version of the Pulic's model (Pulic, 2000). Referred as Value Added Intellectual Coefficient (VAICTM), Pulic's model is a composite index that disaggregates intellectual capital into two main components; human capital (HC) and structural capital (SC). The VAICTM model is proposed to measure the efficiency of intellectual capital in creating or adding value to the firms. The extent of acceptance of this model may be evidenced by a finding by Volkov (2012) who states that as of June 2012, VAICTM model of Pulic (2000) has been used in 46 researches and has been cited by 2373 researchers. This study takes a step further by adopting an extended version of the VAICTM model which is proposed by Nazari and Herremans (2007) (henceforth, *eVAIC*). This study proposes *eVAIC* to measure intellectual capital, which is introduced by Nazari and Herremans's (2007) because it disaggregates structural capital further into customer capital (CC) and organizational capital (OC). More importantly, *eVAIC* further segregates organizational capital into process capital (PC) and innovation capital (InC).

Literature review

Numerous studies have attempted to examine intellectual capital (IC) and intellectual capital efficiency (ICE) in different sectors. Kujansivu and Lönnqvist (2007) evaluate the efficiency of IC as measured by using VAICTM and the value of IC by using calculated intangible value (CIV) methods for 16 industries for 20,000 Finnish companies throughout the period of 2001-2003. The average IC is roughly half of the worth of tangible assets in these Finnish companies. The highest value of investment on IC is reported for the electronic industry (high technology) and the lowest value is seen in the

electricity, gas and water services, metal, and forest and construction sectors (low technology). Meanwhile, Ngwenya (2013) finds that among Zimbabwean companies, a lower level of IC is documented in information, communication and technology (ICT) companies (high technology) than other manufacturing companies. The highest value is reported for Agricultural sector and Ngwenya (2013) suggests that it could be because of small number of top managers is needed to create value in the Agriculture companies. Kujansivu and Lönnqvist (2007) argue that the competencies and stakeholder relationships are important factors in creating greater value for the electronics and chemical industries, while the value is mostly constructed on tangible assets in forestry and construction industries. The results of the study (Kujansivu & Lönnqvist 2007) show that the highest human capital efficiency (HCE), structural capital efficiency (SCE) and value added intellectual coefficient (VAIC) are related to commercial services (low technology) and the lowest for biochemical industries (high technology).

Pal and Soriya (2012) compare VAIC in 105 pharmaceutical companies and 102 textile companies in India. They argue that the pharmaceutical company is typically considered as ‘an innovative and knowledge intensive sector’ while textile industry is considered as ‘the labor-intensive’ industry. Despite the differences in the orientation, their findings indicate that VAIC is not much different in the two sectors. They explain that utilization IC is efficient for both groups.

Kamath (2007) analyzes the data from 98 commercial banks that are divided into four categories (state bank of India and its associates, national bank, foreign banks, and private sector domestic banks) for a five-year period from 2000 to 2004 in India. His results show that human capital (HC) and capital employed (CE) have significant positive effects on value added (VA), that is, increasing in HC and CE result in their efficiency. In addition, HCE is highest in foreign banks while capital employed efficiency (CEE) is highest in public sector banks whereas the overall VAIC is highest in foreign banks. Kamath (2007) argues that public banks employ a huge number of inefficient employees, which result in fewer added values. He also claims that the poor performance of private sector domestic banks is due to high infrastructure costs, high social obligations, enormous non-performing assets, inappropriate allocation of resources and weak investment decisions. These findings are similar to the results of Fayeze, Hameed and Ridha (2011) in 8 Kuwaiti commercials and non-commercial banks for the period of 1996–2006 where HCE is greater than CEE.

Kweh, Chan and Ting (2013) examine the intellectual capital performance (ICP) of small sample of Malaysian public-listed software companies (25 companies in only one sector) in the Main market and ACE market in 2010. The results show that investment in human capital is more than structural and employed capital in their sample and HCE and CEE in the Main market companies are more than ACE market companies while SCE in ACE market companies is more than Main market companies. Overall, efficiency of IC in ACE-market companies is more than Main-market companies. Kweh et al. (2013) believe that managers of 80 per cent of software firms are inefficient in managing and transforming intellectual capital into tangible and intangible values because of the technical problem. Reviewing the literature regarding IC and its efficiency indicates that prior studies have not compared the investment and efficiency of IC and its components

at different levels of technology of the manufacturing companies and results for the various industries from previous studies shows mixed results.

Hypotheses development

In line with resource-based view (RBV), different companies own different packages of resources and capabilities, and some companies within similar industry may do specific activities better than the others because of their different resources (Wernerfelt, 1995; Barney, 1991; Dierickx & Cool, 1989; Wernerfelt, 2010). Therefore, it can be concluded that IC as a resource (and thus, its efficiency) varies among different companies in term of theory. Based on RBV, this study proposes that human capital should be of more importance to companies of higher technology than lower technology. Drawing from these arguments, this study hypothesizes that:

H1: Intellectual capital investment varies with degree of technology of the manufacturing companies.

H1a: Investment in components of intellectual capital varies with degree of technology of the manufacturing companies.

H1b: Human capital is the most invested component of IC among high technology companies.

The second hypothesis is proposed based on the arguments that higher technology companies are more efficient than their low technology counterparts in using the IC and its components. Higher technology companies rely more heavily on the quality of human capital and the other components of IC because they operate in a more dynamic environment which forces them to be consistently on the innovative and creative mode to remain competitive. Of all components of ICE, this study focuses on the roles of HCE which are expected to be leveraged most efficiently by companies of higher technology than those of lower technology.

H2: Efficiency of intellectual capital varies with degree of technology of the manufacturing companies.

H2a: Efficiency of components of intellectual capital vary with degree of technology of the manufacturing companies.

H2b: Human capital is the most efficiently used component of IC among high technology companies.

Research methodology

This study selects its sample from manufacturing companies that are listed in Bursa Malaysia from 2006 to 2012. The sample manufacturing companies are classified into different sectors based on their products and services (or Standard Industrial Classification (SIC) code) in the OSIRIS databases. This study then follows researches of Czarnitzki and Thorwarth (2012), Mendonça (2009) and Hatzichronoglou (1997) to segregate manufacturing companies in different sectors into four groups of differing

technology intensity, that are: high technology, medium-high technology, medium-low technology, and low technology. The categorization of the sectors under each of the technology-based groups is as follows:

- i. High-technology industries: aerospace and defense, pharmaceuticals and biotechnology, technology hardware and equipment, mobile telecommunications, electricity, electronic and electrical equipment, and fixed line telecommunications,
- ii. Medium-high-technology industries: chemicals, automobiles and parts, health care equipment, industrial transportation, and oil equipment,
- iii. Medium-low-technology industries: general industrials, household goods, industrial metals and mining, leisure goods, construction and materials, and
- iv. Low-technology industries: beverages, food producers, forestry and paper, personal goods, and tobacco.

In screening out the sample, companies are excluded if they report negative values of ICE and earnings or if they have missing data. The final composition of this sample is 30, 33, 31, and 35 of high, medium-high, medium-low, and low technology companies respectively. The sub-samples generate balanced panels of 210, 231, 217, and 245 year-company observations per variable for high, medium-high, medium-low and low technology companies, respectively. Data are sourced from DataStream and companies' annual reports. This study adopts extended version of the VAICTM model which is proposed by Nazari and Herremans (2007) for measuring the intellectual capital(IC) and the intellectual capital efficiency (ICE). That is, VAICTM can be dissected into;

$$e \text{VAIC}_i^{\text{TM}} = \text{ICE}_i + \text{CEE}_i = (\text{HCE}_i + \text{SCE}_i) + \text{CEE}_i = \text{HCE} + (\text{CCE} + \text{OCE}) + \text{CEE}$$

$$= \text{HCE} + (\text{CCE} + \text{PCE} + \text{InCE}) + \text{CEE}$$

Where $\text{HCE} = \text{VA}/\text{HC}$,

$\text{VA} = \text{OP} + \text{EC} + \text{D} + \text{A}$, OP = operating profit, EC = employee cost, D = depreciation, A = amortization, HC (human capital) = total salaries and wages for a company,

$\text{SCE} = \text{SC}/\text{VA}$,

SC (structural capital) = $\text{VA} - \text{HC}$,

$\text{CEE} = \text{VA}/\text{CE}$,

CE = book value of the net asset for a company.

$$\text{CCE} = \frac{\text{CC}}{\text{VA}}$$

Where, CCE = customer capital efficiency,

CC (customer capital) = marketing cost,

$$OCE = SCE - CCE$$

OCE = organizational capital efficiency,

$$InCE = \frac{Inc}{VA}$$

Where, InCE = innovation capital efficiency,

InC (innovation capital) = research and development expenditures

$$PCE = OCE - InCE$$

Where, PCE = process capital efficiency,

To compare the means of more than two groups or more than two variables, this study will be using the analysis of variance or ANOVA tests. In order to use ANOVA efficiently, there are two significant conditions: normality and having similar variances of data (Bland & Altman, 1995). If non-normal distribution of the data is seen, the Kruskal Wallis test should be employed as a non-parametric statistic test to the hypotheses (Shirley, 1977). To compare the mean of one variable with another variable of one sample (high technology companies) in sub-hypotheses of the first and second hypotheses (H1b, H2b) this study will be using the one sample tests.

Results and discussion

Table.2 displays descriptive statistics after the outlier treatment with improved range of skewness and kurtosis than original data. Replacements are made to extreme values identified as univariate outliers in accordance with Tabachnik and Fidell (2007). After replacing univariate outliers, companies with multivariate outliers also were omitted (Tabachnik and Fidell 2007). Figures .3 and 4 show the relative positions of intellectual capital (IC) and its components, and efficiency of intellectual capital and its components in the manufacturing companies of different technology levels are plotted in to simplify comparison.

As predicted, intellectual capital investment varies with degree of technology of the manufacturing companies. According to Figures.3 and 4, investment in IC and each of its elements is greater in medium-high technology companies than high technology companies, while the efficiency of IC and each of its elements is greater in high technology companies than medium-high technology companies. It can be deduced that more investment in IC and its components do not necessarily lead to more efficiency on IC and its components. Comparing the components of ICE, it can be seen that the HCE component is the dominant contributor of ICE, making up 84% (3.108/3.692), 82% (2.561/ 3.123), 81% (2.410/ 2.960), and 85% (2.399 / 2.813) of total ICE for high, medium-high, medium-low and low technology companies respectively. Aminiandehkordi, Ahmad, and Hamzeh (2014) report 80% of ICE comes from HCE for 110 companies listed on the ACE Market of Bursa Malaysia from 2009 to 2012. Thus, in

the context of this study, firms with higher HCE are most likely to have higher ICE. This finding is in line with that by Rehman, Zahid, Rehman, and Rehman (2011). According to Figure. 3, investment on the SC is greater than other elements of the IC, while according to Figure .4, efficiency of human capital is greater than efficiency of other elements of IC for all companies in four groups. Another interesting point that may be noted from Figure.4 is that high technology companies are benefiting the most from their human and structural capital investment compared to the other lower technology categories. The fact that the benefits of human and structural capital are combined with less advantage of physical capital correctly justify the importance of developing and encouraging human creativity and innovativeness in high technology companies. Even though high technology companies, due to its more complex nature, are more likely to hire highly qualified individuals (and thus high employee costs (EC)), the outputs that these individuals generate through their capabilities to effectively and efficiently use the companies' assets seem to generate operating profits (OP) that are high enough to more than offset their employee costs.

Since the sample size is large, normal distribution of data can be considered in this study. According to Hair, Black and Babin (2010), and Tabachnik and Fidell (2007), when the sample size is large ($N \geq 30$), a variable with statically significant skewness and kurtosis often does not make a substantive impact on the analysis result. Therefore, the analysis of variance (ANOVA) test was used to compare the means of more than two groups or more than two variables.¹ Table.3 shows the results from Levene's test for equality of variances as another prerequisite of ANOVA test. Levene's test is applied to evaluate the equality or similarity of variances of variable considered for two or more groups (homoscedasticity), before comparison of means. It examines the null hypothesis that the population variances are equal. According to Table 3, the p-value from the Levene's test is less than 0.05 (except for PCE). Therefore, the null hypothesis of equal variances is rejected and it is concluded that there is a difference between the variances in the population. Considering the equality of variances for PCE and inequality of variances for other variables, Tukey HSD and Tamhane's post-hoc tests have been used in order to compare the mean values, respectively.

Table.4 reports the results of ANOVA. The null hypothesis of ANOVA indicates that the variables are all equal among high, medium-high, medium-low, and low technology companies. Table.4 shows much difference between mean squares of between groups and within groups, resulting in a significant difference for IC and its components among high, medium-high, medium-low, and low technology companies. For instance, the mean squares of IC are reported MYR 94.32 billion between groups and MYR 5.09 billion within groups that resulting in a significant difference ($F = 18.523$; $P\text{-value} = 0.000$). Since the F statistic is larger than the critical value (critical value of $F = 1.96$), the null hypothesis is rejected and it is concluded that at least, there is a difference between IC and its components of one group than other groups. In other words, the average of investing on the IC and its components are not all equal among high, medium-high,

¹ In order to use ANOVA efficiently, there are two significant conditions: normality and having similar variances of data (Bland & Altman 1995). If non-normal distribution of the data is seen, the Kruskal Wallis test should be employed as a non-parametric statistic test to the hypotheses (Shirley, 1977). Appendix. A shows the results of Kruskal Wallis test as non-parametric test. The findings from Kruskal Wallis test are consistent with the findings of the ANOVA test.

medium-low, and low technology companies. Therefore, the first main hypothesis and the first sub-hypothesis (H1a) are supported. Appendix B presents the multiple comparisons in order to know whether one or more means vary from each other. Human capital investment is not the most invested components of IC among high technology companies. On the contrary, Figure.3 indicates that investment in structural capital (SC) is more than human capital (HC) for all group companies. Table. 5 shows the results of one sample test to find out whether investment of human capital is the most invested components of IC among high technology companies. The null hypothesis of one sample test indicates that the mean of investment in human capital (HC) is equal to the hypothesized mean of other components of IC among high technology companies. Since the t statistic is larger than the critical value (critical value of $t = 1.65$), the null hypothesis is rejected and it is concluded that mean of HC is not equal with mean of other components of IC. Table.5 indicates that the average investment in HC is less than that in SC (mean difference = -4607.7^{**}) in high technology companies. Therefore, HC is not the most invested component of IC among high technology companies and the second sub-hypotheses (H1b) is rejected.

The second hypothesis aims to test whether intellectual capital efficiency (ICE) varies in manufacturing companies with different levels of technology. Table. 4 proves that there is a difference between the mean squares between groups and within groups, resulting in a significant difference for ICE and its components among high, medium-high, medium-low, and low technology companies. Higher F statistics than the critical value (critical value of $F = 1.96$) for ICE and its components confirm at least a difference between ICE and its components of one group than other groups in Table .4. In other words, the average of ICE and its components are not all equal among technology groups. Therefore, the second main hypothesis (H2) and the first sub-hypothesis (H2a) are supported.

Figure.4 shows a summary of the average of intellectual capital efficiency (ICE) and its components among high, medium-high, medium-low, and low technology companies that helps to recognize whether ICE and its components vary with degree of technology of the manufacturing companies. As shown in Appendix. B (Results of multiple comparisons), the mean difference of ICE for high technology companies (group 1) with low technology companies (group 4) is significant (mean difference = 0.879). This result is consistent with the patterns shown in Figure.4 that the mean of ICE for high technology companies is higher than low technology companies. Therefore, it can be concluded that higher technology companies are more efficient than their low technology counterparts in using the IC. This is because high technology companies operate in a more dynamic environment which forces them to be consistently on the innovative and creative mode to remain competitive.

The second sub-hypothesis (H2b) proposes that human capital should be the most efficiently used components of IC among high technology companies. Table.5 shows the results of one sample test to find out whether human capital efficiency (HCE) is the most efficient components of intellectual capital efficiency (ICE) among high technology companies. The null hypothesis of one sample test demonstrates that mean of HCE is equal to the hypothesized mean of other components of ICE among high technology companies. According to Table.5, the p-value from the t test is less than 0.05 ($\alpha=0.05$) and the t statistic is larger than the critical value (critical value of $t = 1.65$). Therefore, the

null hypothesis of equal mean of HCE with other components of ICE is rejected and it is concluded that there is a significant difference between HCE of high technology group with other components of ICE. Table.5 shows that the average efficiency of HC is more than that in other components of ICE (the positive mean difference reported for HCE in compared with the hypothesized mean of other components of ICE) in high technology companies. Therefore, the second sub-hypotheses (H2b) is supported. As illustrated earlier in Figure.4, the efficiency of human capital is the highest (3.108) among components of IC in high technology companies. The mean of 3.108 for HCE suggests that about 84 percent of efficiency created by IC (3.692) is contributed by HCE. This finding suggests that the expertise and efficiencies of employees are important for generating the firm value. This result is also in line with the result of Kujansivu and Lönngqvist (2007) who document the highest average of HCE among ICE components for high technology companies (electronics industry) than low technology companies (food and forest industries) in Finland.

Conclusion and implications

This study compares investing in intellectual capital and its components, and efficiency intellectual capital and its components among manufacturing companies with different level of technology. The findings of this study show that investment in IC and its components, and efficiency of IC and its components vary with degree of technology of the manufacturing companies. The results of this study are consistent with resource-based view (RBV) and the “new economy” literature, which indicate that manufacturing companies are showing greater awareness on the importance of investment in IC in creating value and economic wealth in a knowledge-based economy and a competitive business world, including in low technology companies (Ze'ghal & Maaloul 2010). The results of a research done by Libo, Xin, and Su (2011) confirm somewhat the result of this study. They document that the average of IC and its components in the total manufacturing industry is more than those in high technology companies in China. Meanwhile, Ngwenya (2013) finds that the mean IC for information communication and technology companies is lower than that for manufacturing companies in Zimbabwe. The results indicate that 60% of investment in IC is related to SC not HC in medium-high technology companies. SC is the infrastructure of a company that can store information, knowledge and permit staff access to information, knowledge and the necessary resources (Chang, Chen, Hsing, & Huang, 2006). When a firm uses the accurate information system, integration between individual intelligence and scattered information will increase and that helps data, information, knowledge and awareness exchanges more efficiently within firms (Chen et al. 2006). The results of this study confirmed that human capital is the most efficiently used components of IC among high technology companies. High technology companies require manpower (HC) with specialized expertise and skills and state-of-the-art technology to remain competitive in the industry. When properly managed, this costly human capital should be more efficient. Less efficiency of human capital (HC) than amount of investment in it in low technology companies may be due to inefficient employees who could have been hired without considering their competencies, knowledge, experiences, skills, behavior, intelligent, creative, cognitive abilities in order to generate value added. Meanwhile, low efficiency of structural capital than its invested amounts may be due to high infrastructure expenditures, poor usage of technology and structural capital, inefficient management process, and machine inefficiency (Calabrese,

Costa, & Menichini, 2013). From the results, it can be concluded that more investment in IC components does not necessarily lead to more efficiency of IC especially in low technology companies. Weakness of the management of intellectual capital is one of the most important factors in the inefficiency of intellectual capital (Bontis, 1999). The result of this study is important for policy makers to provide incentive for all companies to pay attention to intellectual capital investment that can lead to intellectual capital efficiency. The government can offer tax exemptions and incentives for investing in IC, especially R&D activities (such as the US), or help the manufacturing companies financially (grant) in order to provide R&D expenditure that contribute to innovations and inventions and new products in manufacturing companies in Malaysia. Considering the invested amounts in IC, high technology companies earn more intellectual capital efficiency than low technology ones. Therefore, more of the country's monetary and non-monetary IC-related resources should be placed on these companies to optimize its values.

References

Aminiandehkordi, P., Ahmad, A., & Hamzeh, N. (2014). The Moderating Effect of Management Ownership on the Relationship between Intellectual Capital Performance and Market Value of Company. In *Proceedings of 5th Asia-Pacific Business Research Conference 17 - 18 February, 2014, Hotel Istana, Kuala Lumpur, Malaysia, ISBN: 978-1-922069-44-3* (pp. 1–13).

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120.

Bland, J. M., & Altman, D. G. (1995). Multiple significance tests: the Bonferroni method. *BMJ: British Medical Journal*, 310(6973), 170.

Bontis, N. (1999). Managing organisational knowledge by diagnosing intellectual capital: framing and advancing the state of the field. *International Journal of Technology Management*, 18(5), 433–462.

Bontis, N., Chua, W., Keow, C., & Richardson, S. (2000). Malaysian industries Intellectual capital and business performance in Malaysian industries. *Journal of Intellectual Capital*, 1(1), 58–100.

Calabrese, A., Costa, R., & Menichini, T. (2013). Using Fuzzy AHP to manage Intellectual Capital assets: An application to the ICT service industry. *Expert Systems with Applications*, 40(9), 3747–3755.

Chang, S.-C., Chen, S.-S., Hsing, A., & Huang, C. W. (2006). Investment opportunities, free cash flow, and stock valuation effects of secured debt offerings. *Review of Quantitative Finance and Accounting*, 28(2), 123–145. <http://doi.org/10.1007/s11156-006-0007-6>

Czarnitzki, D., & Thorwarth, S. (2012). Productivity effects of basic research in low-tech and high-tech industries. *Research Policy*, 41(9), 1555–1564.

Dierickx, I., & Cool, A. K. (1989). Asset Stock Accumulation And Sustainability Of Competitive Advantage. *Management Science*, 35(12), 1504–1512.

Edvinsson, L. (1997). Developing intellectual capital at Skandia. *Long Range Planning*, 30(3), 366–373.

Edvinsson, L. (2013). IC 21: reflections from 21 years of IC practice and theory. *Journal of Intellectual Capital*, 14(1), 163–172.

Edvinsson, L., & Malone, M. S. (1997). *Intellectual capital: Realizing your company's true value by finding its hidden brainpower*. New York, NY: HarperBusiness New York.

Fayez, A., Hameed, A.-Q., & Ridha, A.-K. (2011). The Intellectual Capital Performance of Kuwaiti Banks: An Application of VAIC?1 Model. *iBusiness*, 03(01), 88–96.

Goh, P. C. (2005). Intellectual capital performance of commercial banks in Malaysia. *Journal of Intellectual Capital*, 6(3), 385–396.

Hair, J. F., Black, W. C., & Babin, B. J. (2010). *RE Anderson Multivariate data analysis: A global perspective*. New Jersey, Pearson Prentice Hall,).

Hatzichronoglou, T. (1997a). *Revision of the High- Technology Sector and Product Classification*. Retrieved from <http://dx.doi.org/10.1787/134337307632>

Hatzichronoglou, T. (1997b). *Revision of the High- Technology Sector and Product Classification*.

Hayton, J. C. (2005). Competing in the new economy: the effect of intellectual capital on corporate entrepreneurship in high-technology new ventures. *R&D Management*, 35(2), 137–155.

Kamath, G. B. (2007). The intellectual capital performance of the Indian banking sector. *Journal of Intellectual Capital*, 8(1), 96–123.

Kim, S., & Lee, H. (2004). Organizational factors affecting knowledge sharing capabilities in e-government: an empirical study. In *Knowledge Management in Electronic Government* (pp. 281–293). Springer Berlin Heidelberg.

Kujansivu, P., & Lönnqvist, A. (2007). Investigating the value and efficiency of intellectual capital. *Journal of Intellectual Capital*, 8(2), 272–287.

Kweh, Q. L., Chan, Y. C., & Ting, I. W. K. (2013). Measuring intellectual capital efficiency in the Malaysian software sector. *Journal of Intellectual Capital*, 14(2), 310–324.

Leadbeater, C. (2000). *New measures for the new economy*. Wales, England.: Institute of Chartered Accountants in England & Wales.

Libo, F. A. N., Xin, Y., & Su, W. (2011). Research on the Relationship Between Intellectual Capital and Company Performance — An Empirical Analysis Based on Panel Data.

Mendonça, S. (2009). Brave old world: Accounting for “high-tech” knowledge in “low-tech” industries. *Research Policy*, 38(3), 470–482.

Mustapha, R., & Abdullah, A. (2004). Malaysia transitions toward a knowledge-based economy. *The Journal of Technology Studies*, 30(3), 51–61.

Nazari, J. a., & Herremans, I. M. (2007). Extended VAIC model: measuring intellectual capital components. *Journal of Intellectual Capital*, 8(4), 595–609.

Ngwenya, B. (2013). Intellectual Capital’s Leverage on Shareholder Value Growth: A Lesson for Developing Economies. *American Journal of Educational Research*, 1(5), 149–155.

Nunes, P. M., Serrasqueiro, Z., Mendes, L., & Sequeira, T. N. (2010). Relationship between growth and R&D intensity in low-tech and high-tech Portuguese service SMEs. *Journal of Service Management*, 21(3), 291–320.

Oceantomo. (2013). tomo. Retrieved from <http://www.oceantomo.com/productsandservices/investments/intangible-market-value>[1 Sep2013]

Ong, T. S., Yeoh, L. Y., & Teh, B. H. (2011). Intellectual Capital Efficiency in Malaysian Food and Beverage Industry. *International Journal of Business and Behavioral Sciences*, 1(1), 16–31.

Organisation for Economic Co-operation and Development. (2006). *Innovation and knowledge-intensive service activities*. OECD Publishing. Retrieved from <http://www.oecd.org/sti/inno/innovationandknowledge-intensiveserviceactivities.htm>[4June2013].

Pablos, P. O. De. (2004). Measuring and reporting structural capital: Lessons from European learning firms. *Journal of Intellectual Capital*, 5(4), 629–647. <http://doi.org/10.1108/14691930410567059>

Pal, K., & Soriya, S. (2012). IC performance of Indian pharmaceutical and textile industry. *Journal of Intellectual Capital*, 13(1), 120–137.

Porrini, P. (2004). Alliance experience and value creation in high-tech and low-tech acquisitions. *The Journal of High Technology Management Research*, 15(2), 267–292.

Pulic, A. (2000). VAICTM—an accounting tool for IC management. *International Journal of Technology Management*, 20(5), 702–714.

Rehman, H., Zahid, A., Rehman, C. A., & Rehman, W. ul. (2011). Intellectual Capital Performance And Its Impact On Corporate Performance : An Empirical Evidence From

Modaraba Sector Of Pakistan . *Australian Journal of Business and Management Research*, 1(5), 8–16.

Sáenz, J., Aramburu, N., & Rivera, O. (2009). Knowledge sharing and innovation performance: a comparison between high-tech and low-tech companies. *Journal of Intellectual Capital*, 10(1), 22–36.

Shirley, E. (1977). A non-parametric equivalent of Williams' test for contrasting increasing dose levels of a treatment. *Biometrics*, 33(2), 386–389.

Skandia. (1994). Visualizing Intellectual Capital in Skandia, intellectual capital supplement.

Śledzik, K. (2012). *The Intellectual Capital Performance Of Polish Banks : An Application Of VAICTM*. University of Gdansk Faculty of Management Department of Banking ul. Retrieved from Electronic copy available at: <http://ssrn.com/abstract=2175581>[20Jun 2013]

Tabachnik, B. G., & Fidell, L. S. (2007). *Using Multivariate Statistics*. CALIFORNIA STATE UNIVERSITY: Pearson.

Tseng, C., & James Goo, Y. (2005). Intellectual capital and corporate value in an emerging economy: empirical study of Taiwanese manufacturers. *R&D Management*, 35(2), 187–201.

Volkov, A. (2012). Value Added Intellectual Co-efficient (VAICTM): A Selective Thematic-Bibliography. *Journal of New Business Ideas & Trends*, 10(1), 14–24.

Wang, J.-C. (2008). Investigating market value and intellectual capital for S&P 500. *Journal of Intellectual Capital*, 9(4), 546–563.

Wang, W.-Y., & Chang, C. (2005). Intellectual capital and performance in causal models: Evidence from the information technology industry in Taiwan. *Journal of Intellectual Capital*, 6(2), 222–236.

Wernerfelt, B. (1995). The Resource-Based View of the Firm: Ten Years After. *Strategic Management Journal*, 16(3), 171–174.

Wernerfelt, B. (2010). The Use of Resources in Resource Acquisition. *Journal of Management*, 37(5), 1369–1373.

World bank. (2013). Retrieved from <http://data.worldbank.org/indicator>

Zéghal, D., & Maaloul, A. (2010). Analysing value added as an indicator of intellectual capital and its consequences on company performance. *Journal of Intellectual Capital*, 11(1), 39–60.

Table.2 Descriptive statistics

Level of technology		HC	SC	IC	CC	OC	PC	InC
High	Mean	21492981	26100681	47593662	9587424	16513257	14353352	2312543
	Min	199000	523000	1331000	90000	58000	24000	20000
	Max	92183000	108679000	173280000	53172000	95223000	65573000	12349000
	S. Deviation	26482	26577	50057	13689	17537	16347	3198
	Skewness	1.473	1.121	1.205	2.044	1.521	1.473	1.901
	Kurtosis	0.856	0.138	0.252	3.453	2.255	1.368	2.777
Medium-high	Mean	36049550	53407957	89457506	13581424	39826532	35379251	4443654
	Min	215000	265000	713000	35000	149000	12000	17000
	Max	155828000	233457000	382416000	65615000	209782000	195945000	22201000
	S. Deviation	39983	62836	101155	17257	51249	48287	5954
	Skewness	1.715	1.588	1.669	1.743	1.813	1.87	1.552
	Kurtosis	2.369	1.64	2.055	2.387	2.668	2.767	1.346
Medium-low	Mean	17157083	27505258	44662341	2648129	24582880	23962779	612267
	Min	115000	230000	345000	25000	28000	6000	0
	Max	78301000	153844000	216869000	13046000	129588000	128474000	2388000
	S. Deviation	18995	36548	54445	3740	33505	33332	577
	Skewness	1.735	1.92	1.816	1.746	1.897	1.893	0.601
	Kurtosis	2.608	3.107	2.741	1.806	2.857	2.837	-0.75
Low	Mean	24136441	35904135	60040576	6753053	29151082	28714514	439016
	Min	1143000	166000	3367000	100000	25000	25000	0
	Max	98560000	163534000	236395000	25708000	148027000	148027000	3038000



	S. Deviation	25176	42003	65921	6969	38168	37890	969
	Skewness	1.843	1.684	1.729	1.395	1.749	1.758	2.108
	Kurtosis	2.462	1.711	1.851	1.193	1.922	1.933	2.776
Level of technology		HCE	SCE	ICE	CCE	OCE	PCE	InCE
High	Mean	3.108	0.583	3.692	0.181	0.402	0.328	0.079
	Min	1.402	0.287	1.689	0.008	0.019	0.007	0.001
	Max	8.119	0.877	8.996	0.462	0.851	0.778	0.4
	S. Deviation	1.816	0.179	1.981	0.11	0.215	0.195	0.098
	Skewness	1.206	0.109	1.115	0.35	0.19	0.243	1.787
	Kurtosis	0.251	-1.234	0.052	-0.671	-0.92	-0.912	2.472
Medium-high	Mean	2.561	0.562	3.123	0.157	0.405	0.345	0.068
	Min	1.1	0.091	1.191	0.003	0.013	0.002	0.001
	Max	4.634	0.784	5.418	0.465	0.759	0.735	0.293
	S. Deviation	0.826	0.158	0.975	0.116	0.195	0.2	0.073
	Skewness	0.304	-0.983	0.108	0.773	-0.337	-0.136	1.379
	Kurtosis	-0.582	0.332	-0.632	-0.213	-0.943	-1.037	1.073
Medium-low	Mean	2.41	0.549	2.96	0.081	0.467	0.424	0.044
	Min	1.117	0.104	1.221	0.001	0.007	0.007	0
	Max	4.08	0.757	4.835	0.302	0.754	0.753	0.292
	S. Deviation	0.7048	0.147	0.834	0.073	0.171	0.194	0.064
	Skewness	0.311	-0.988	0.074	1.281	-0.68	-0.547	1.965
	Kurtosis	-0.41	0.397	-0.461	1.051	-0.187	-0.655	3.554
low	Mean	2.399	0.541	2.813	0.155	0.386	0.378	0.009
	Min	1.009	0.009	1.019	0.001	0.001	0.001	0
	Max	3.821	0.738	4.408	0.552	0.719	0.698	0.088



	S. Deviation	0.6563	0.1627	0.848	0.125	0.191	0.186	0.02
	Skewness	-0.311	-1.438	-0.3	1.035	-0.345	-0.376	2.449
	Kurtosis	-0.657	1.448	-0.945	0.621	-0.908	-0.887	4.872

Note: HC is human capital = sum of total salaries and wages. SC is structural capital = VA-HC. VA is value added = operating profit + employee cost + depreciation + amortization. IC is intellectual capital= HC + SC. CC is customer capital = sum of total marketing cost. OC is organizational capital= SC - CC. PC is process capital = OC - InC. InC is innovation capital = sum of total research and development expenditure (R&D). HCE is human capital efficiency = $\frac{VA}{HC}$. SCE is structural capital efficiency = $\frac{SC}{VA}$. ICE is intellectual capital efficiency = HCE +SCE. CCE is customer capital efficiency = $\frac{CC}{VA}$. OCE is organizational capital efficiency = SCE - CCE. PCE is process capital efficiency = OCE - InCE. InCE is innovation capital efficiency = $\frac{R\&D}{VA}$. MBVA is ratio of market value to book value of assets = $\frac{\text{market value assets}}{\text{book value of assets}}$. Market value asset = book value of debt + market value equity. Market value equity = number share outstanding* share closing price. Book value of assets = book value of debt + book value of equity. MBVE is ratio of market value to book value of equity = $\frac{\text{market value equity}}{\text{book value of equity}}$. GPPEMVA is ratio of gross plant, property and equipment to market value assets = $\frac{\text{gross plant,property and equipment}}{\text{market value assets}}$. Gross plant, property and equipment =cost of plant, property and equipment - accumulated depreciation of plant, property and equipment. DMVA is ratio of depreciation of property, plant and equipment to market value assets = $\frac{\text{depreciation of property,plant and equipment}}{\text{market value assets}}$. ROA is return on assets = $\frac{\text{earnings before interest and tax}}{\text{book value of assets}}$. LEV is financial leverage = $\frac{\text{book value of total debt}}{\text{book value of assets}}$. FF is financial flexibility = $\frac{\text{cash and cash equivalents}}{\text{book value of the net asset}}$. DP is dividend payout ratio = $\frac{\text{dividend paid}}{\text{net income}}$. R&DS is ratio of R&D expenditures to net sales and calculates = $\frac{\text{R\&D expenditures}}{\text{total net sales}}$. Total net sales = value of goods sold - discounts and returns. SIZ is company size = \log^{10} of total assets.

Table.3 Results of Levene’s test

Test of Homogeneity of Variances									
Variable	Levene Statistic	df1	df2	P-value	Variable	Levene Statistic	df1	df2	P-value
HC	25.266	3	899	0.000	HCE	110.933	3	899	0.000
SC	31.934	3	899	0.000	SCE	6.650	3	899	0.000
IC	27.763	3	899	0.000	ICE	90.039	3	899	0.000
CC	74.023	3	899	0.000	CCE	19.757	3	899	0.000
InC	185.479	3	899	0.000	InCE	71.472	3	899	0.000
PC	32.284	3	899	0.000	PCE	.704	3	899	0.550
OC	34.009	3	899	0.000	OCE	5.991	3	899	0.000

Note: HC is human capital = sum of total salaries and wages. SC is structural capital = VA-HC. VA is value added = operating profit + employee cost + depreciation + amortization. IC is intellectual capital= HC + SC. CC is customer capital = sum of total marketing cost. InC is innovation capital = sum of total research and development expenditure (R&D). PC is process capital = OC - InC. OC is organizational capital= SC - CC. HCE is human capital efficiency= $\frac{VA}{HC}$. HC is human capital = sum of total salaries and wages. VA is value added = operating profit + employee cost + depreciation + amortization. SCE is structural capital efficiency = $\frac{SC}{VA}$. SC is structural capital = VA-HC. ICE is intellectual capital efficiency = HCE +SCE. CCE is customer capital efficiency = $\frac{CC}{VA}$. CC is customer capital = sum of total marketing cost. InCE is innovation capital efficiency = $\frac{R\&D}{VA}$. PCE is process capital efficiency = OCE - InCE. OCE is organizational capital efficiency = SCE - CCE.

Table.4 ANOVA results

variable		Sum of Squares	df	Mean Square	F	P-value	variable		Sum of Squares	df	Mean Square	F	P-value
HC	Between Groups	44306344707	3	14768781569	17.778	0.000	HCE	Between Groups	72.263	3	24.088	20.454	0.000
	Within Groups	746848079102	899	830754259				Within Groups	1058.69	899	1.178		
	Total	791154423809	902					Total	1130.953	902			
SC	Between Groups	106235597886	3	35411865962	17.938	0.000	SCE	Between Groups	0.223	3	0.074	2.847	0.037
	Within Groups	1774757172447	899	1974145909				Within Groups	23.504	899	0.026		
	Total	1880992770334	902					Total	23.727	902			
IC	Between Groups	282960365743	3	94320121914	18.523	0.000	ICE	Between Groups	97.231	3	32.41	21.356	0.000
	Within Groups	4577707034741	899	5091998926				Within Groups	1364.369	899	1.518		
	Total	4860667400484	902					Total	1461.6	902			
CC	Between Groups	14294850207	3	4764950069	34.96	0.000	CCE	Between Groups	1.219	3	0.406	34.58	0.000
	Within Groups	122532767124	899	136298962				Within Groups	10.565	899	0.012		
	Total	136827617332	902					Total	11.784	902			
OC	Between Groups	62854580382	3	20951526794	14.874	0.000	OCE	Between Groups	0.857	3	0.286	7.651	0.000
	Within Groups	1266310971179	899	1408577276				Within Groups	33.549	899	0.037		



variable		Sum of Squares	df	Mean Square	F	P-value	variable		Sum of Squares	df	Mean Square	F	P-value
	Total	1329165551561	902					Total	34.406	902			
InE	Between Groups	2411634962	3	803878321	68.222	0.000	InCE	Between Groups	0.673	3	0.224	47.827	0.000
	Within Groups	10593175991	899	11783288				Within Groups	4.216	899	0.005		
	Total	13004810953	902					Total	4.889	902			
PC	Between Groups	51508888894	3	17169629631	13.054	0.000	PCE	Between Groups	1.146	3	0.382	10.187	0.000
	Within Groups	1182405671522	899	1315245463				Within Groups	33.708	899	0.037		
	Total	1233914560416	902					Total	34.854	902			



Table .5 Results of one-sample test

Variable	Hypothesized mean of	t	p-value	Mean Difference	Variable	Hypothesized mean of	t	p-value	Mean Difference
HC	SC	-2.521	0.006	-4607.7	HCE	SCE	20.151	0.000	2.525
HC	CC	6.515	0.000	11905.6	HCE	CCE	23.359	0.000	2.927
HC	OC	2.725	0.003	4979.7	HCE	OCE	21.596	0.000	2.706
HC	PC	3.907	0.000	7139.6	HCE	PCE	22.186	0.000	2.780
HC	InC	10.496	0.000	19180.4	HCE	InCE	24.173	0.000	3.029
InC	SC	-107.800	0.000	-23788.1	InCE	SCE	-74.325	0.000	-.504
InC	CC	-32.967	0.000	-7274.9	InCE	CCE	-15.056	0.000	-.102
InC	OC	-64.353	0.000	-14200.7	InCE	OCE	-47.639	0.000	-.323
InC	PC	-54.565	0.000	-12040.8	InCE	PCE	-36.729	0.000	-.249
InC	HC	-86.919	0.000	-19180.4	InCE	HCE	-446.648	0.000	-3.029

Note: HC is human capital = sum of total salaries and wages. InC is innovation capital = sum of total research and development expenditure (R&D). $HCE = \frac{VA}{HC}$. HC is human capital = sum of total salaries and wages. VA is value added = operating profit + employee cost + depreciation + amortization. $InCE = \frac{R\&D}{VA}$. P-value of one-tailed reported. The critical t with 209 degrees of freedom, $\alpha=0.05$ and one-tailed is 1.65. The sample is high technology manufacturing companies.

Appendix A: Non-parametric test

Null hypothesis	Chi-Square	df	P-value	Decision
The distribution of HC is the same across categories of groups	50.439	3	0.000	Reject the null hypothesis
The distribution of SC is the same across categories of groups	36.251	3	0.000	Reject the null hypothesis
The distribution of IC is the same across categories of groups	44.984	3	0.000	Reject the null hypothesis
The distribution of CC is the same across categories of groups	119.198	3	0.000	Reject the null hypothesis
The distribution of OC is the same across categories of groups	20.975	3	0.000	Reject the null hypothesis
The distribution of InC is the same across categories of groups	301.347	3	0.000	Reject the null hypothesis
The distribution of HCE is the same across categories of groups	4.690	3	0.046	Reject the null hypothesis
The distribution of SCE is the same across categories of groups	3.737	3	0.031	Reject the null hypothesis
The distribution of ICE is the same across categories of groups	11.979	3	0.007	Reject the null hypothesis
The distribution of CCE is the same across categories of groups	107.415	3	0.000	Reject the null hypothesis
The distribution of OCE is the same across categories of groups	23.118	3	0.000	Reject the null hypothesis
The distribution of InCE is the same across categories of groups	318.227	3	0.000	Reject the null hypothesis
The distribution of PCE is the same across categories of groups	31.365	3	0.000	Reject the null hypothesis

HC is human capital and calculates through sum of total salaries and wages. SC is structural capital and calculates through [VA-HC]. IC is intellectual capital and computes by sum of HC and SC. CC is customer capital and calculates through sum of total marketing cost. OC is organizational capital and calculates through [SC-CC]. InC is innovation capital and calculates through sum of total research and development expenditure (R&D). PC is process capital and computes by [OC-InC]. HCE is human capital efficiency and calculates through value added (VA) over human capital (HC). HC is human capital and calculates through sum of total salaries and wages. VA is [operating profit+ employee cost+ depreciation +amortization]. SCE is structural capital efficiency and calculates through SC /VA. SC is structural capital and calculates through [VA-HC]. ICE is intellectual capital efficiency and computes by sum of HCE and SCE. CCE is customer capital efficiency and computes by CC /VA. CC is customer capital and calculates through sum of total marketing cost. OCE is organizational capital efficiency and calculates through [SCE-CCE]. InCE is innovation capital efficiency and computes by R&D/VA. PCE is process capital efficiency and computes by [OCE-InCE].

Appendix B. Results of multiple comparisons

Dependent Variable			Mean Difference (I-J)	P-value	95% Confidence Interval		Dependent Variable			Mean Difference (I-J)	P-value	95% Confidence Interval	
					Lower Bound	Upper Bound						Lower Bound	Upper Bound
HC	1	2	-14556.569*	.000	-23025.81	-6087.33	OC	1	2	-23313.275*	.000	-32804.32	-13822.23
		3	4335.898	.280	-1579.52	10251.32			3	-8069.623*	.011	-14889.30	-1249.94
		4	-2643.460	.859	-9077.90	3790.98			4	-12637.824*	.000	-19840.48	-5435.17
	2	1	14556.569*	.000	6087.33	23025.81		2	1	23313.275*	.000	13822.23	32804.32
		3	18892.467*	.000	11138.20	26646.73			3	15243.652*	.001	4488.94	25998.37
		4	11913.109*	.001	3758.35	20067.87			4	10675.451	.062	-324.38	21675.28
	3	1	-4335.898	.280	-10251.32	1579.52		3	1	8069.623*	.011	1249.94	14889.30
		2	-18892.467*	.000	-26646.73	-11138.20			2	-15243.652*	.001	-25998.37	-4488.94
		4	-6979.358*	.005	-12427.24	-1531.48			4	-4568.201	.676	-13379.57	4243.16
	4	1	2643.460	.859	-3790.98	9077.90		4	1	12637.824*	.000	5435.17	19840.48
		2	-11913.109*	.001	-20067.87	-3758.35			2	-10675.451	.062	-21675.28	324.38
		3	6979.358*	.005	1531.48	12427.24			3	4568.201	.676	-4243.16	13379.57
SC	1	2	-27307.276*	.000	-39282.05	-15332.50	InC	1	2	-2131.111*	.000	-3320.70	-941.52
		3	-1404.577	.998	-9563.04	6753.88			3	1700.276*	.000	1105.31	2295.24
		4	-9803.454*	.016	-18395.79	-1211.12			4	1873.527*	.000	1265.53	2481.52
	2	1	27307.276*	.000	15332.50	39282.05		2	1	2131.111*	.000	941.52	3320.70
		3	25902.699*	.000	13149.24	38656.16			3	3831.386*	.000	2786.66	4876.11
		4	17503.822*	.003	4470.97	30536.67			4	4004.637*	.000	2952.44	5056.84
	3	1	1404.577	.998	-6753.88	9563.04		3	1	-1700.276*	.000	-2295.24	-1105.31



Dependent Variable	Mean Difference (I-J)	P-value	95% Confidence Interval		Dependent Variable	Mean Difference (I-J)	P-value	95% Confidence Interval					
			Lower Bound	Upper Bound				Lower Bound	Upper Bound				
	2	-25902.699*	.000	-38656.16	-13149.24		2	-3831.386*	0.000	-4876.11	-2786.66		
	4	-8398.877	.125	-18056.07	1258.32		4	173.251	.106	-20.49	366.99		
	4	1	9803.454*	.016	1211.12		18395.79	4	1	-1873.527*	.000	-2481.52	-1265.53
		2	-17503.822*	.003	-30536.67		-4470.97		2	-4004.637*	0.000	-5056.84	-2952.44
		3	8398.877	.125	-1258.32		18056.07		3	-173.251	.106	-366.99	20.49
IC	1	2	-41863.845*	.000	-61707.13	-22020.56	1	2	-21025.899*	.000	-29957.86	-12093.94	
		3	2931.321	.993	-10441.16	16303.80		3	-9609.426*	.001	-16303.37	-2915.48	
		4	-12446.914	.129	-26841.71	1947.89		4	-14361.162*	.000	-21428.48	-7293.84	
	2	1	41863.845*	.000	22020.56	61707.13	2	1	21025.899*	.000	12093.94	29957.86	
		3	44795.165*	.000	24653.87	64936.46		3	11416.472*	.021	1104.39	21728.56	
		4	29416.931*	.001	8589.43	50244.43		4	6664.737	.454	-3892.06	17221.54	
	3	1	-2931.321	.993	-16303.80	10441.16	3	1	9609.426*	.001	2915.48	16303.37	
		2	-44795.165*	.000	-64936.46	-24653.87		2	-11416.472*	.021	-21728.56	-1104.39	
		4	-15378.234*	.037	-30184.82	-571.65		4	-4751.735	.629	-13507.49	4004.02	
	4	1	12446.914	.129	-1947.89	26841.71	4	1	14361.162*	.000	7293.84	21428.48	
		2	-29416.931*	.001	-50244.43	-8589.43		2	-6664.737	.454	-17221.54	3892.06	
		3	15378.234*	.037	571.65	30184.82		3	4751.735	.629	-4004.02	13507.49	
CC	1	2	-3994.000*	.042	-7897.98	-90.02	HCE	1	2	.5475622*	0.000	0.186	0.909
		3	6939.295*	.000	4344.16	9534.43			3	.6980380*	0.000	0.342	1.054
		4	2834.371*	.041	68.43	5600.31			4	.7092730*	0.000	0.359	1.060
	2	1	3994.000*	.042	90.02	7897.98		2	1	-.5475622*	0.000	-0.909	-0.186
		3	10933.295*	0.000	7848.03	14018.56			3	0.1504758	0.209	-0.041	0.342
		4	6828.371*	.000	3598.22	10058.52			4	0.1617109	0.108	-0.020	0.343



Dependent Variable			Mean Difference (I-J)	P-value	95% Confidence Interval		Dependent Variable			Mean Difference (I-J)	P-value	95% Confidence Interval			
					Lower Bound	Upper Bound						Lower Bound	Upper Bound		
SCE	3	1	-6939.295*	.000	-9534.43	-4344.16	OCE	1	3	1	-.6980380*	0.000	-1.054	-0.342	
		2	-10933.295*	0.000	-14018.56	-7848.03			2	2	-0.1504758	0.209	-0.342	0.041	
		4	-4104.924*	.000	-5460.50	-2749.35			4	4	0.0112351	1.000	-0.157	0.179	
	4	1	-2834.371*	.041	-5600.31	-68.43	2	2	4	1	-.7092730*	0.000	-1.060	-0.359	
		2	-6828.371*	.000	-10058.52	-3598.22			2	2	-0.1617109	0.108	-0.343	0.020	
		3	4104.924*	.000	2749.35	5460.50			3	3	-0.0112351	1.000	-0.179	0.157	
	ICE	1	2	0.0210069	0.724	-0.022	0.064	PCE	1	2	2	-0.0028767	1.000	-0.055	0.049
			3	0.0338799	0.184	-0.008	0.076			3	3	-.0651632*	0.004	-0.115	-0.015
			4	.0420568*	0.045	-0.001	0.085			4	4	0.0161239	0.954	-0.035	0.067
2		1	-0.0210069	0.724	-0.064	0.022	2	2	1	1	0.0028767	1.000	-0.049	0.055	
		3	0.012873	0.938	-0.025	0.051			3	3	-.0622865*	0.002	-0.108	-0.017	
		4	0.02105	0.629	-0.018	0.060			4	4	0.0190006	0.864	-0.028	0.066	
3		1	-0.0338799	0.184	-0.076	0.008	3	3	1	1	.0651632*	0.004	0.015	0.115	
		2	-0.012873	0.938	-0.051	0.025			2	2	.0622865*	0.002	0.017	0.108	
		4	0.0081769	0.994	-0.030	0.046			4	4	.0812871*	0.000	0.037	0.126	
4		1	-.0420568*	0.045	-0.085	0.001	4	4	1	1	-0.0161239	0.954	-0.067	0.035	
		2	-0.02105	0.629	-0.060	0.018			2	2	-0.0190006	0.864	-0.066	0.028	
		3	-0.0081769	0.994	-0.046	0.030			3	3	-.0812871*	0.000	-0.126	-0.037	
ICE	1	2	.5685690*	0.001	0.169	0.968	PCE	1	2	2	-0.0169935	0.794	-0.065	0.031	
		3	.7319179*	0.000	0.340	1.124			3	3	-.0954202*	0.000	-0.144	-0.047	
		4	.8790850*	0.000	0.489	1.269			4	4	-.0493730*	0.034	-0.096	-0.003	
	2	1	-.5685690*	0.001	-0.968	-0.169	2	2	1	1	0.0169935	0.794	-0.031	0.065	
		3	0.1633488	0.296	-0.063	0.389			3	3	-.0784267*	0.000	-0.126	-0.031	



Dependent Variable			Mean Difference (I-J)	P-value	95% Confidence Interval		Dependent Variable			Mean Difference (I-J)	P-value	95% Confidence Interval	
					Lower Bound	Upper Bound						Lower Bound	Upper Bound
		4	.3105160*	0.001	0.089	0.532			4	-0.0323795	0.263	-0.078	0.013
	3	1	-.7319179*	0.000	-1.124	-0.340		3	1	.0954202*	0.000	0.047	0.144
		2	-0.1633488	0.296	-0.389	0.063			2	.0784267*	0.000	0.031	0.126
		4	0.1471671	0.315	-0.060	0.354			4	0.0460472	0.053	0.000	0.093
	4	1	-.8790850*	0.000	-1.269	-0.489		4	1	.0493730*	0.034	0.003	0.096
		2	-.3105160*	0.001	-0.532	-0.089			2	0.0323795	0.263	-0.013	0.078
		3	-0.1471671	0.315	-0.354	0.060			3	-0.0460472	0.053	-0.093	0.000
CCE	1	2	0.0238836	0.149	-0.004	0.052	InCE	1	2	0.0113107	0.683	-0.011	0.033
		3	.1000241*	0.000	0.076	0.124			3	.0352786*	0.000	0.014	0.057
		4	0.0259329	0.109	-0.003	0.055			4	.0702722*	0.000	0.052	0.089
	2	1	-0.0238836	0.149	-0.052	0.004		2	1	-0.0113107	0.683	-0.033	0.011
		3	.0761405*	0.000	0.052	0.100			3	.0239679*	0.001	0.007	0.041
		4	0.0020493	1.000	-0.027	0.031			4	.0589614*	0.000	0.046	0.072
	3	1	-.1000241*	0.000	-0.124	-0.076		3	1	-.0352786*	0.000	-0.057	-0.014
		2	-.0761405*	0.000	-0.100	-0.052			2	-.0239679*	0.001	-0.041	-0.007
		4	-.0740912*	0.000	-0.099	-0.049			4	.0349935*	0.000	0.023	0.047
	4	1	-0.0259329	0.109	-0.055	0.003		4	1	-.0702722*	0.000	-0.089	-0.052
		2	-0.0020493	1.000	-0.031	0.027			2	-.0589614*	0.000	-0.072	-0.046
		3	.0740912*	0.000	0.049	0.099			3	-.0349935*	0.000	-0.047	-0.023

*. The mean difference is significant at the 0.05 level. 1, 2, 3 and 4 indicate high, Medium-high, Medium-low and low technology companies respectively. HC is human capital and calculates through sum of total salaries and wages. SC is structural capital and calculates through [VA-HC]. IC is intellectual capital and computes by sum of HC and SC. CC is customer capital and calculates through sum of total marketing cost. OC is organizational capital and calculates through [SC-CC]. InC is innovation capital and calculates through sum of total research and development expenditure (R&D). PC



is process capital and computes by $[OC - InC]$. HCE is human capital efficiency and calculates through value added (VA) over human capital (HC). HC is human capital and calculates through sum of total salaries and wages. VA is $[operating\ profit + employee\ cost + depreciation + amortization]$. SCE is structural capital efficiency and calculates through SC / VA . SC is structural capital and calculates through $[VA - HC]$. ICE is intellectual capital efficiency and computes by sum of HCE and SCE. CCE is customer capital efficiency and computes by CC / VA . CC is customer capital and calculates through sum of total marketing cost. OCE is organizational capital efficiency and calculates through $[SCE - CCE]$. InCE is innovation capital efficiency and computes by $R\&D / VA$. PCE is process capital efficiency and computes by $[OCE - InCE]$.

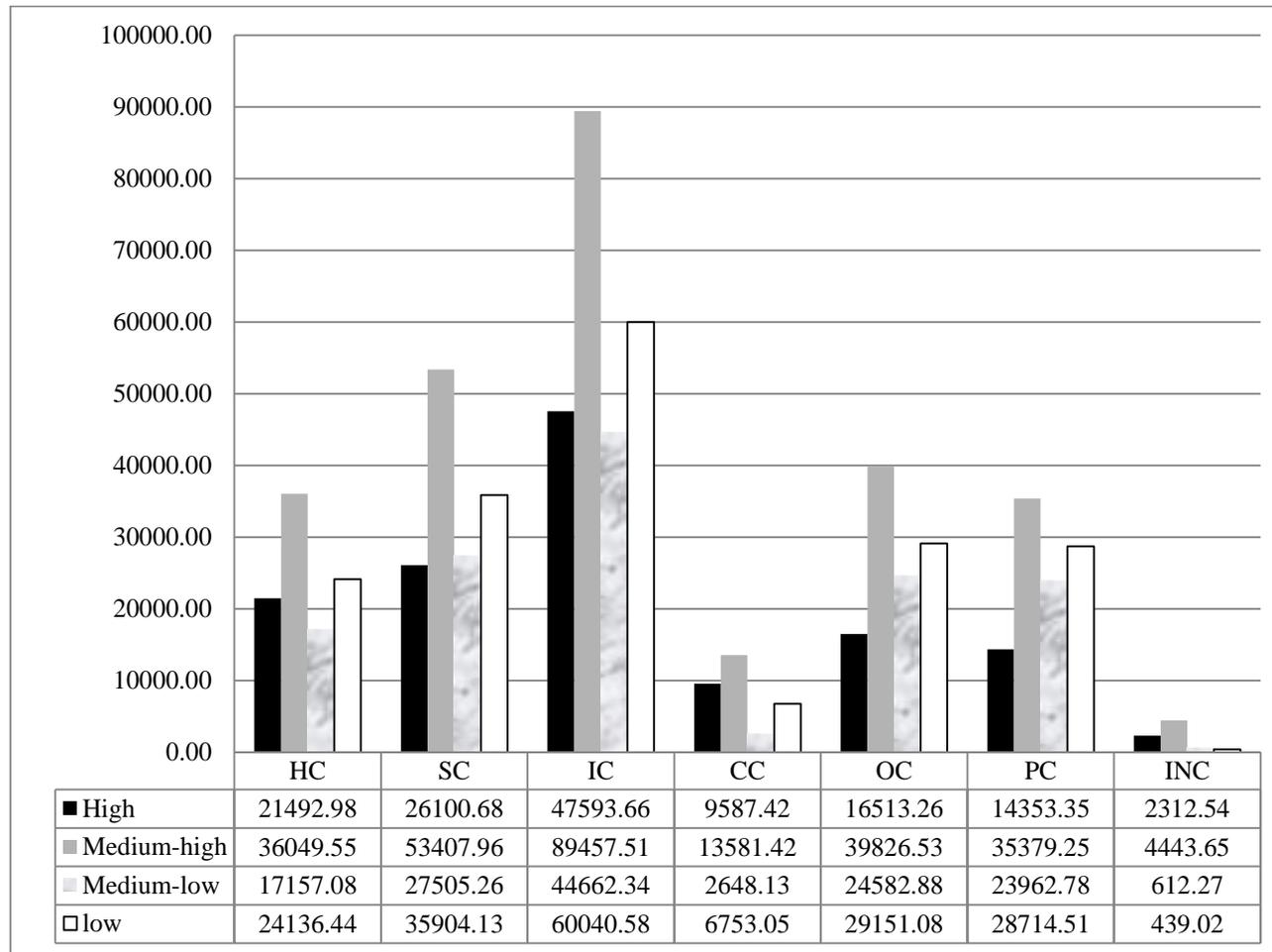


Figure.3 Investment in intellectual capital and its components among groups of different technology levels (MYR'000)

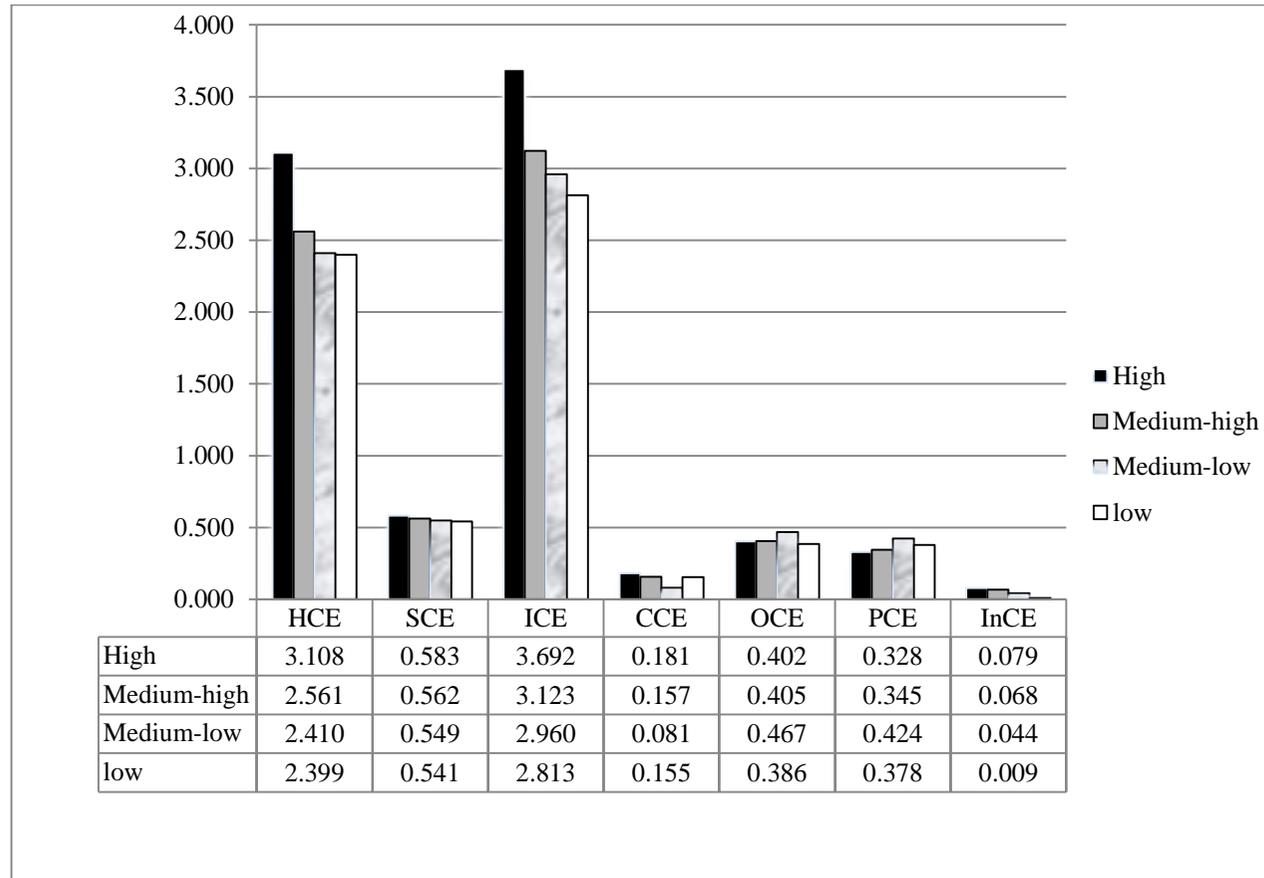


Figure.4 Efficiency of intellectual capital and its components among groups of different technology levels