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Effect of Technology Strategy on Organizational Performance of Manufacturing Companies: A note on how to conduct a Data Screening and Preliminary Analysis

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ABSTRACT

The increased awareness of technology strategy in contemporary firms has resulted in the postulation that associated behaviours would enable realistic advantage to be realised as a result of a firm's differentiation from competitors through such actions. Thus, the purpose of this study was to gather data and conduct a preliminary analysis of the influence of technology strategy on the performance of Malaysian manufacturing organizations. A total of 354 respondents were drawn from the Federation of Malaysian Manufacturers' (FMM) Directory. Probability sampling was used in this investigation. As a result, an assessment of missing data, identification of outliers, and finally, skewness and kurtosis were assessed. Additionally, Harman's technique was utilised to investigate solutions containing unrotated factors. Similarly, all exercises were developed using the Statistical Package for Social Science (SPSS) version 22 software, and preliminary analysis indicates that the data satisfy the criteria for multivariate analysis. The findings will serve as a springboard for additional investigation, with the goal of providing insight may be diversified in a fast changing environment

Keywords: technology strategy, organizational performance, data screening, preliminary analysis, manufacturing companies

1. INTRODUCTION

The value of preliminary data in analysis can not be overstated, as it is critical for social science research (Hair et al., 2013). Data missing occurs when a respondent fails to respond to questions intentionally or accidently (Hair et al., 2013). As a result, the value and clarity of the analysis are strongly dependent on the first data screening (Maiyaki & Mouktar, 2011). Regrettably, researchers usually ignore this critical first task, maybe due to the weight attached to it (Hair et al., 2010, 2013; Maiyaki & Mouktar, 2011).

One other point worth considering is that leaving this segment of data preliminary could affect the result value or the acceptability of the sort of analysis required. Although Tabachnick and Fidell (2007) assert that the most exact approach of verifying precision is to compare the original data to the electronic data file. On the other hand, proofreading becomes difficult, if not impossible, with large data sets (Maiyaki & Mouktar, 2011). As a result, descriptive statistics and computer tools are required to investigate data. This way, all undetected mistakes that are not readily apparent from experience would come to light (Hair et al., 2010, 2013).

Additionally, by conducting data analysis, researchers gain at the very least two critical benefits, which is 1) a complete understanding of the inter-associations between the constructs, which

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aids the clear explanation of the outputs; 2) being capable of satisfying the postulation of multivariate data analysis, which is more challenging than univariate data analysis. Finally, this study evaluated concerns with data screening and preliminary analysis in order to ensure that the data is error-free (Hair et al., 2010, 2013).

2. LITERATURE REVIEW

Technology strategy is one of the most essential parts in forming the organization's strategic posture (Zahra & Bogner, 2000a). While, Zhao et al. (2016) state there is only one fundamental key to cope with the poor performance challenges is technology improvement. It is a necessary precondition for a technology-enabled strategy since technology may serve as a basic tool for rivalry and the establishment of tangible physical alternative activities (Itami & Numagami, 1992). Meanwhile, organizations' core capabilities consider technology as a primary foundation (Itami & Numagami, 1992). Technology has become a key variable for profit or non-profit organisations seeking to leverage competitive edge and track changes in performance. Zahra (1996a) said that technology is a cornerstone of a company's competitiveness in many ways, among them as a barrier to entry, new markets and consumers, and even industry norms. Gillespie and Mileti (1977) expanded the significance of historical technology involving machine or equipment conceptualization to include subtle developments and usage of the characteristics of contemporary industry in their analysis.

Miles et al. (1978) and Porter (1985) advocated for a connection between technology and strategy, with technology thought to have a significant role in the development of various strategies. Additionally, an organization's technological strategy can influence both the current and future competitive position of an industry. In summary, businesses' performance and success are essentially determined by their technology strategy implementation. Thus, technology strategy is the process through which businesses leverage their technical assets and skills to accomplish organisational goals (Rieck & Dickson, 1993).

Technology strategy in this study is defined in such a way that despite the fact that the differences in the characteristics have suggested that technology strategy is considered a long-term plan that led companies to utilize the committed resources toward technology in order to provide manufacturing companies with a competitive edge.

This study aims to unravel some of the critical elements in the current manufacturing businesses. The manufacturing industry has encountered some critical decisions in the practice of its technology strategy. This study proposes the constructs of technology strategy to be: pioneer-follower posture, technological investments: internal R&D, the intensity of product upgrades, external technology sources and product and process technology.

There were several previous empirical studies conducted on the impact of technology strategy (Ngamkroeckjoti et al., 2005; Zahra & Bogner, 2000b). Most of the study listed organizational performance as the outcome of technology strategy. Organizational performance is a key construct in the discipline, and it is frequently utilised as the final dependent variable in a variety of fields. In a research conducted by Zahra and Bogner (2000b), organizational performance was listed as the outcome of technology strategy. Zahra (1996b) pointed out that organizational performance was often associated with technology strategy. Past research revealed that there were connections between technology strategy and organizational performance (Zahra & Bogner, 2000b). Dasgupta et al. (2011) opined that organizational performance depended on the technology strategy. In brief, most of the findings in previous research showed that technology strategy contributed to organizational performance. This was also demonstrated in Zahra and Bogner (2000a) technology strategy model, which demonstrated the relationship between technology strategy and organizational performance, as well as between resources and the competitive environment as sources of organizational performance (Bridoux, 2004).

3. METHODS

The data were analysed in this section using descriptive and inferential statistics, both of which were implemented using SPSS 22 version software. For example, simple descriptive statistics, the Boxplots approach, and correlation analysis were used. Furthermore, this study's sample was drawn from Malaysian manufacturing firms. Data were collected by a probability sampling technique. As a result, 96 usable responses from Malaysian manufacturing firms were received.

4. DISCUSSION OF THE FINDINGS

This section contains the results and discussion. A total of 96 surveys were completed, representing a response rate of 53%. The response rate is deemed good, as the researcher comes from a culturally similar setting and has seen that responding to email and postal surveys is not a commonly recognised practise among Malaysian manufacturing organisations. In comparison to other research involving Malaysian firms, the response rate was rather high (Mohamad & Wheeler, 1996). Demographic data in this study explains gender, types of company and position in company of the respondents.

Table 1. Respondents' Profiles

Characteristics	Background Information	Frequency	Percentage
Gender	Male	71	74
	Female	25	26
Types of company	Multinational companies (MNCs)	22	22.9
	Joint venture (JV)	9	9.4
	Locally – owned (LO)	56	58.3
	Purely foreign – owned company (FO)	9	9.4
Position	CEOs	7	7.3
	Division or Group General Manager	12	12.5
	R&D/Technology Manager	7	7.3
	Financial Officer	13	13.5
	Strategist or Planner	9	9.4
	Human Resource Manager	5	5.2
	Managing Director	8	8.3
	Deputy Managing Director	2	2.1
	Factory Manager	11	11.5
	Others	22	22.9

A total of 96 usable responses were collected with 71 (74%) male and 25 (26%) female respondents. There are slightly more male than female in this study. Manufacturing companies were categorized to the types of company as follows (MNCs, JV, LO and FO) thus, a critical study of how different types of businesses apply technology strategy and how this can be linked to organisational performance should be conducted. This knowledge is considered useful because it is common for companies classified as MNCs to employ Technology Strategy in a manner consistent with their parent company's culture. It was discovered that 67.7% of manufacturing companies surveyed were predominantly locally-owned, comprising 56 companies and 9 joint ventures. Whereas, 22.9% are MNCs and 9.4% are purely foreign companies. This means that the majority of the type of company are locally – owned company which is 56 manufacturing companies.

The survey's objective was to analyse response from top management in manufacturing companies who make strategic decisions. While CEOs should complete the survey, responses from other senior managers would appropriate because they are a part of the team that is involved in the decision-making process. Furthermore, research from a broad sample of varied firms reveals that R&D managers at all levels were judged as less effective leaders than non-R&D managers. R&D executives were evaluated individually and found to be less productive than their non-R&D colleagues (Gritzo et al., 2017).

The survey sampled CEOs/GMs/MDs/Senior Managers of manufacturing companies. Although the survey was sent to CEOs, 13.5% (13) of those who completed the survey were Financial officers, 12.5% (12) were Division or Group General Managers, 11.5% (11) were Factory managers, 9.4% (9) were Strategist/planner, 8.3% (8) were Managing Directors, 7.3% (7) R&D/technology managers, 7.3% (7) were CEOs, 5.2% (5) were Human Resource managers, 4.2% (4) were Production managers, 3.1% (3) were Sales managers, 3.1% (3) were Senior managers, 2.1% (2) were Deputy Managing Directors, 2.1% (2) were Business Development managers, , 2.1% (2) were Operation managers, 2.1% (2) were Purchasing managers, 2.1% (2) were Programmer, 2.1% (2) were Senior engineer, 1% (1) were Quality managers, 1% (1) Engineering manager and 1% (1) were Service manager. Therefore, based on the percentage shows above the vast majority of responders in this research are Financial Officers (13.5%). This is an improvement over a study conducted by Sikander (2011) and Edler et al. (2002), in which only senior research and development managers were included in a benchmarking analysis of the world's most technology-intensive corporations from western Europe, North America, and Japan (see Table 1).

Table 2 Grouping According to Position Titles

	Frequency	**Percentage**
Group 1 Senior executive management		
CEOs	7	7.3
Division or Group General Manager	12	12.5
Managing Director	8	8.3
Total	**27**	**28.1**
Group 2 Second level management		
Deputy Managing Director	2	2.1
Factory Manager	11	11.5
Total	**13**	**13.6**
Group 3 Functional management		
R&D/Technology Manager	7	7.3
Financial Officer	13	13.5
Strategist or Planner	9	9.4
Human Resource Manager	5	5.2
Business Development Manager	2	2.1
Engineering manager	1	1
Operation manager	2	2.1
Production manager	4	4.2
Programmer	1	1
Purchasing manager	2	2.1
Quality manager	1	1
Sales manager	3	3.1
Senior engineer	2	2.1
Senior manager	3	3.1
Service manager	1	1
Total	**56**	**58.3**

According to Table 2, the majority of responders were in Group 3 functional management and within this group Financial Officers are predominant.

Table 3 shows the business background of the respondents involved in this study. Most (74%) of the manufacturing companies between 50 and 3000 persons were employed by the companies covered in the study. There were only five manufacturing companies with more than 3000 employees while twenty manufacturing companies showed that they employed fewer than twenty people. The distribution of employees by firm size is shown in Table 3. The data shows that 33.3% of the manufacturing companies surveyed fell into electrical, electronic, computing machinery parts industry, 20.8% were non-metallic mineral products, basic metal and fabricated metal products, machinery and equipment and 11.5% were petroleum, chemical, rubber and plastic. This study used the Federation of Malaysian Manufacturers (FMM) Directory (2019) as a reference.

A total of 100% of all respondents stated that their company engages in research and development. Whereas, 30% of respondents indicated that their R&D department had less than 5 employees and 24% indicated that their R&D department had between 5 to 10 employees. Additionally, the findings show that the proportion of engineers with field experience more than 5 year was relatively high (62%). Additionally, 31% of respondents reported that their average sales turnover was between RM101 million and RM500 million. Only 8.3% of respondents recorded turnover between RM501 million and RM1000 million. Only one respondent stated that their business produced USD8 billion in turnover.

Table 3 Organization Background

Organization Background	**Background Information**	**Frequency**	**Percentage (%)**
Number of employees	< 50	20	20.8
	50 – 300	40	41.7
	301 – 1000	20	20.8
	1001 – 3000	11	11.5
	More than 3000	5	5.2
Main industry	Manufacture of food products, beverages and tobacco	10	10.4
	Textile, wearing apparel, leather and footwear	0	0
	Wood, furniture, paper products and printing	5	5.2
	Petroleum, chemical, rubber and plastic	11	11.5
	Non-metallic mineral products, basic metal and fabricated metal products, machinery and equipment	20	20.8
	Electrical, electronic, computing machinery parts	32	33.3
	Transport equipment and other manufacturers	8	8.3
	Other manufacturing activities	10	10.4
Number of workers in R&D Department	< 5	30	31.3
	Between 5 and 10	24	25.0
	Between 11 and 20	13	13.5
	More than 21	29	30.2
A engineers in R&D Department having field/R&D experience	1 – 3 years	28	29.2
	3 – 5 years	6	6.3
	More than 5 years	62	64.6
Average sales turnover	< RM25 million	25	26.0
	Between RM25 million and RM100 million	24	25.0
	Between RM101 million and RM500 million	30	31.3
	Between RM501 million and RM1000 million	8	8.3
	Between RM1001 million and RM2000 million	4	4.2
	> RM2000 million	1	1
	Between RM3 billion and RM4 billion	1	1
	RM1 billion	2	2.1

USD8 billion	1	1

The aforementioned research showed the following characteristics of the sample used in this study; it was slightly more males (74%) in this study; it consisted of 28.1% Senior executive management (CEOs, Division or Group General Manager, Managing Director), 13.6% Second level management (Deputy Managing Director, Factory Manager) and 58.3% Functional management; most (79.2%) companies having more than 50 workers; and about 31.3% of the companies had average sales turnover between RM101 million and RM500 million. These characteristics reflected the Malaysian industrial environment as a whole in early 2020. That responses came from top management, senior executive management, second level managers as well as functional managers contributed to the study's trust in the authenticity of the responses to strategy variables.

4.1 Non-Response Bias

Non-response bias is stated as the expectation of a researchers to make an error in estimating a sample characteristic as certain survey respondents groups are underrepresented owing to non-response (Berg, 2005). When there is a considerable disparity between survey responses and non-responses, the problem of non-response bias occurs (Lambert & Harrington, 1990). According to Singer (2006), a survey estimate is not always biased if the response rate is below a certain threshold. There is no response rate, on the other hand, at which it is never biassed. Whatever the degree of the non-response bias, a risk of bias needs to be examined (Pearl & Fairley, 1985; Sheikh & Mattingly, 1981). It is critical that this report includes a non-response bias analysis, as this condition jeopardises the survey's validity.

Henceforth, the Table 4 shows that respondents were divided into two large independent samples depending on their early and late responses to survey questionnaires with regards to seven main study constructs (Pioneer-Follower Posture, Technological Investments, The Intensity of Product Upgrades, External Technology Sources, Product and Process Technology, External Environments and Organizational Performance). The most popular and normal method for testing for non-response bias in this study is to use an independent samples t-test to compare the responses of those who responded to questionnaires distributed early before the end of September, 2019 (early responses) to those who responded to questionnaires distributed after September, 2019 (late responses). The range mean and standard deviation for early and late responses are clearly different, as shown in Table 4.

The organizational performance scores of early responses and late answers respondents were compared using an independent samples t-test. Table 5 presents the results of Levene's test for equality of variances. In this study given in the table below, a significance level for Levene's test is between 0.058 to 0.933. This is larger than the cut-off of 0.05. This means that the assumption of equal variances has not been violated; therefore, Equal variances assumed is referred.

The two-tailed t-test result (Table 5) indicates that there is no statistically significant difference between respondents with early and late responses based on Pioneer-Follower Posture (t -0.649, $p < 0.518$), Technological Investments (t -0.224, $p < 0.823$), Intensity of Product Upgrades (t 0.260, $p < 0.795$), External Technology Sources (t -1.748, $p < 0.084$), Product and Process Technology (t -0.250, $p < 0.804$), External Environment (t -0.304, $p < 0.762$) and Organizational Performance (t 0.051, $p < 0.959$). Due to the fact that this number is greater than the necessary cut-off of 0.05, the output determines that there is no difference in the mean that is statistically significant for both responses. The early responses respondent was not significantly different than late responses respondent. The t-test results indicate that there is no statistically significant difference between early and late responses, meaning that no issue of non-response bias exists (see Table 5).

Table 4 Group Descriptive Statistics for Early and Late Respondents

Variables	Response Bias	N	Mean	Std. Deviation	Std. Error Mean
Organizational Performance	Early responses	49	4.2357	0.94950	0.13564
	Late responses	47	4.2266	0.76101	0.11100
Pioneer-Follower Posture	Early responses	49	3.7800	1.16501	0.16643
	Late responses	47	3.9362	1.19328	0.17406
Technological Investments	Early responses	49	3.1352	1.20595	0.17228
	Late responses	47	3.1915	1.25943	0.18371
Intensity of Product Upgrades	Early responses	49	4.1973	1.07242	0.15320
	Late responses	47	4.1383	1.14805	0.16746
External Technology Sources	Early responses	49	2.7449	1.23479	0.17640
	Late responses	47	3.1968	1.29792	0.18932
Product and Process Technology	Early responses	49	3.9763	1.02628	0.14661
	Late responses	47	4.0320	1.16025	0.16924
External Environment	Early responses	49	3.2776	0.84415	0.12059
	Late responses	47	3.3312	0.88440	0.12900

Table 5 Independent Samples T-Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Organizational Performance	Equal variances assumed	3.671	.058	.051	94	.959	.00907	.17608	-.34055	.35868
	Equal variances Not assumed			.052	91.158	.959	.00907	.17527	-.33909	.35722
Pioneer-Follower Posture	Equal variances assumed	.007	.933	-.649	94	.518	-.15612	.24070	-.63404	.32179
	Equal variances not assumed			-.648	93.591	.518	-.15612	.24082	-.63431	.32206
Technological Investments	Equal variances assumed	.015	.904	-.224	94	.823	-.05629	.25162	-.55588	.44331
	Equal variances not assumed			-.223	93.319	.824	-.05629	.25185	-.55639	.44382
Intensity of Product Upgrades	Equal variances assumed	.008	.927	.260	94	.795	.05898	.22664	-.39102	.50898
	Equal variances not assumed			.260	92.875	.796	.05898	.22697	-.39174	.50970

External Technology Sources	Equal variances assumed	.272	.604	-1.748	94	.084	-.45191	.25849	-.96516	.06133
	Equal variances not assumed			-1.746	93.213	.084	-.45191	.25877	-.96575	.06193
Product Process Technology	Equal variances assumed	.146	.703	-.250	94	.804	-.05573	.22334	-.49917	.38771
	Equal variances not assumed			-.249	91.542	.804	-.05573	.22391	-.50047	.38901
External Environment	Equal variances assumed	.240	.625	-.304	94	.762	-.05365	.17642	-.40394	.29663
	Equal variances not assumed			-.304	93.268	.762	-.05365	.17659	-.40432	.29701

4.2 Data Preparation and Screening

Data screening is very crucial process that employs various method in helping the researcher to identify any potential violations of the fundamental principles underlying the application of multivariate data analysis techniques such as errors or missing data. Hence, initial data screening detects outliers and multicollinearity that requires some cleaning techniques in order to ensure its reliability, usability and trustworthiness. Therefore, it helps the researcher to better understand the data collected for further analysis because any error could lead to data reliability issues such as violating normality, linearity which leading to homoscedasticity assumption.

In this study, every questionnaire returned was assigned with the serial number at the top of each questionnaire. This prevent confusion and redundancy on respondent that return questionnaire late. In an effort to systematically manage the questionnaire, serial number were assigned on all questionnaire to track and trace each questionnaire before the data were transferred into the SPSS software accordingly. All 108 questionnaires were checked thoroughly and it was found that 12 questionnaires are incomplete in which be discarded. Due to the fact that these respondent were either purposefully or unintentionally failed to reply to one or more questions. Consequently, these questionnaire will not be used for the purpose of this analysis. Therefore, a number of 96 questionnaires remain for examination in this study.

4.2.1 Data Coding and Detection of Entry Error

Coding is a vital process, to code all the responses either before or after the data collected and it is an easier way to enter into a database (Hair et al., 2007). The aim of coding is to make it simple to identify items. As a consequence, every item on the questionnaire was assigned a number to facilitate data input. The number and the variable's unique name are used to determine the coding. This study employs 6-point Likert scale and it has been coded with 6 or 1 from high to strongly agree and low to strongly disagree. Following that, the code will be entered into a Microsoft Office Excel document that contains all of the questionnaire's constructs: organizational performance containing financial and non-financial are labeled as OP_F1 – OP_F7 and OP_NF1 – OP_NF3, respectively. Technology strategies are labeled accordingly: pioneer-follower posture as TS_PFP1 – TS_PFP9, technological investments: internal R&D as TS_TI10 – TS_TI17, the intensity of product upgrades as TS_IPU18 – TS_IPU23, external technology sources as TS_ETS24 – TS_ETS27, and product and process technology as

TS_PPT28 – TS_PPT33. Consequently, external environments comprise dysfunctional competition, institutional support, environment turbulence, strategic alliance for product development and political networking strategy are labelled separately as TCE_DC1 – TCE_DC4, TCE_IS1 – TCE_IS4, TCE_ET1 – TCE_ET4, TCE_SA1 – TCE_SA6 and TCE_PN1 – TCE_PN4. See Table 6 of data coding. Fortunately, no error has been found after keyed-in the data to check frequency. Moreover, questionnaire screening has been performed and it was confirmed no error was detected.

Table 6 Data Coding

Variables	Code of items
Technology strategy	TS_PFP1 – TS_PFP9
	TS_TI10 – TS_TI17
	TS_IPU18 – TS_IPU23
	TS_ETS24 – TS_ETS27
	TS_PPT28 – TS_PPT33
External environments	TCE_DC1 – TCE_DC4
	TCE_IS1 – TCE_IS4
	TCE_ET1 – TCE_ET4
	TCE_SA1 – TCE_SA6
	TCE_PN1 – TCE_PN4
Organizational performance	OP_F1 – OP_F7
	OP_NF1 – OP_NF3

4.3 Missing Data Analysis

Missing data is one of the most frequent issues in data analysis (Tabachnick & Fidell, 2007). Given the potential consequences of missing data, the researcher implemented preventive steps beginning with the data collection process in order to reduce their frequency. The completed surveys have been quickly reviewed from beginning to end to ensure that all questions were adequately addressed. The data were then entered into SPSS software, and a preliminary round of descriptive statistics was conducted to assess whether or not this report had any missing data. Unfortunately, missing value was found for twelve respondents after the process of keyed–in the data was conducted. These kind of occurrence always happen when a respondent refused to answer certain items in the questionnaire (Hair et al., 2014). Therefore, the missing data had been treated by using SPSS and were removed for further analysis. This is consistent with Hair et al. (2010) recommendation to exclude cases with more than 50% missing data to the extent that the sample data remain acceptable. Additionally, a method for dealing with missing data entails dropping the missing case. According to Tabachnick and Fiddel (2007), missing data occurs when an insignificant missing value of 1 is disclosed in statistical information. For this purpose SPSS were used to treate the value of replaced data for the purpose of further analysis in the Smart-PLS. Similarly, data inspection and replacement are crucial since PLS-SEM is particularly responsive to missing data, signalling that it was evaluated well (Maiyaki & Moktar, 2011). Additionally, data with missing values is not processed by the PLS software. Therefore, only 96 questionnaires were used in the following step of analysis using PLS software.

4.4 Analysis of Outliers

In addition to missing data, it is a crucial aspect of data cleaning to detect outliers. These findings imply that high case scores are likely to have a major negative effect on outcomes (Maiyaki & Moktar, 2011). Typically, outlier examples exhibit an excessive reaction to a single question or to all questions (Hair et al., 2017). These extremes of a construct's high or low value, or a unique mix of values across many constructs, are what set the analysis apart from the others (Byrne, 2010). Outlier is a case which the values are well above or below the majority of other cases. The outliers can be detected using boxplot which particularly useful to identify skewness and outliers (Zikmund et al., 2013). Outliers are defined by IBM SPSS as values that are more than 1.5 box-lengths from the box's edge. Extreme points (marked by an asterisk, *) extend beyond three box-lengths from the box's edge. A number of techniques have been proposed in dealing with outliers, either to correct data entry errors with mean values if missing value less than 5 percent or throw it out only the uncommon respondent from the data set (Hair et al., 2010; Hair et al., 2014). In this study, the researcher had found that there are no extremes, although six outliers exist for the case 25, 36, 87 and 89 in three variables, namely intensity of product upgrades, product and process technology and organizational performance as illustrated in Figure 1. Therefore, the researcher had decided to replace with mean values for these three variables to 4.1684 (intensity of product upgrades), 4.0035 (product and process technology) and 4.2894 (organizational performance) for the data of 25, 36, 87 and 89.

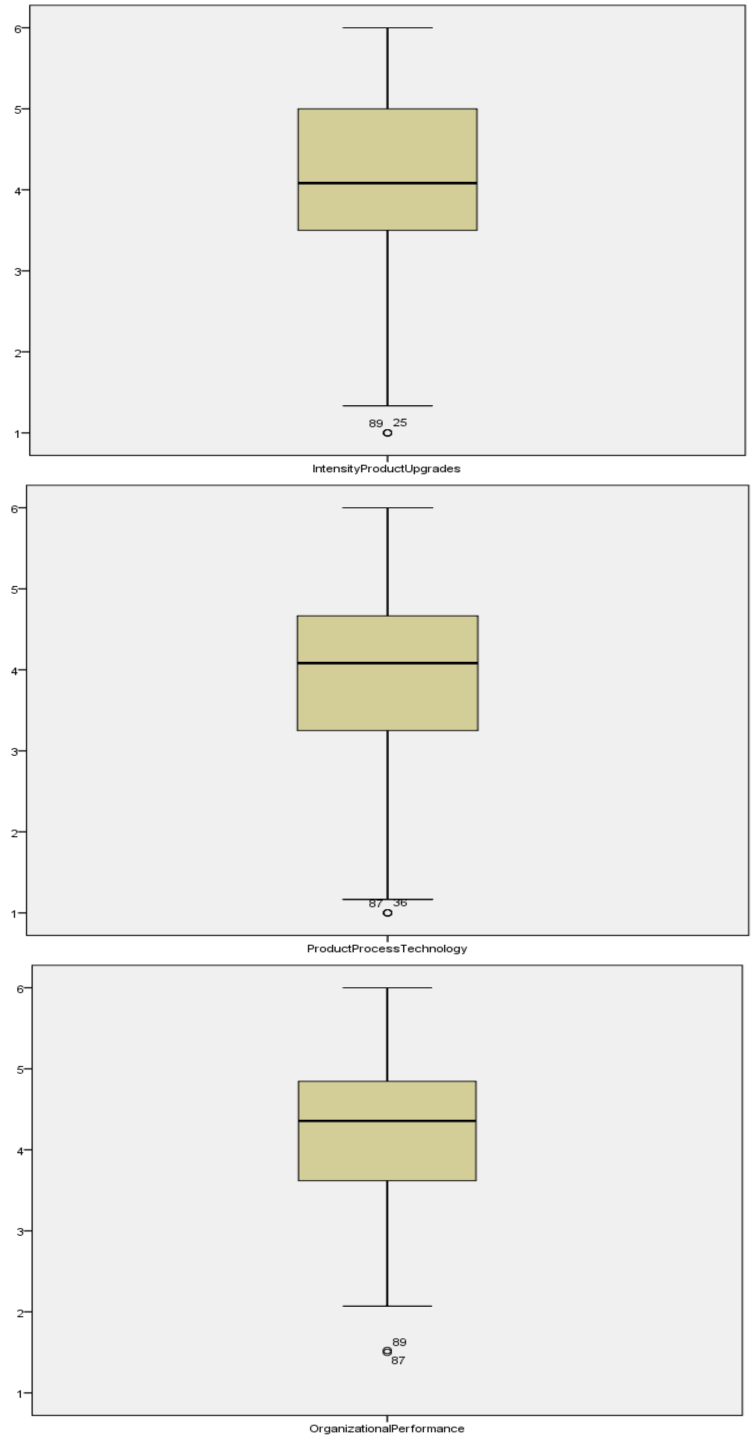

Figure 1. Boxplot of Outliers

4.5 Normality Test

Often time in research it is important to know if the distribution is normal. Moreover, this study observed most statistical procedure to fulfil the assumption of normality. Parametric statistical analysis is the best indication that the study is conform to the normality assumption. Studies is considered as within parametric domain when the data distribution is normal. However, there are instances where the presumption of normality is violated, and as an outcome, result interpretation and inference can introduce biases or, in extreme cases, render the study invalid. As a result, these critical measures must be thoroughly tested to ensure that this presumption is met prior to conducting any further applicable statistical procedures. Fundamentally, there are three widely accepted rules of thumb for determining the validity of the normality assumption. Using graphic approaches is the most convenient method. Another often used tool for detecting data normality is the normal quantile-quantile plot (Q-Q plot). Although histograms, box plots, and stem-and-leaf plots are widely employed to test for normality.

Additionally, there are other formal approaches that extend beyond graphical approaches by utilising numerical methods and formal normality tests to provide robust and conclusive evidence prior to reaching any conclusive decision on the normality of the data. By using a normal distribution, the numerical approaches incorporate the skewness and kurtosis coefficients. The normality test, on the other hand, is a more rigorous process for determining if the data follows a normal distribution. The Shapiro-Wilk and Kolmogorov-Smirnov tests are the two most frequently used normality tests available in statistical software.

Pearson (1895) initiated the attempt to develop techniques for detecting deviations from normality by focusing on the skewness and kurtosis coefficients (Althouse et al., 1998). Normality tests vary in their focus on the skewness and kurtosis values of the normal distribution. Whereas, between the variable's distribution or characteristic function and the standard normal variable Z, a linear relationship exists. Skewness is a measure of a distribution's asymmetry, while kurtosis is a measure of its peakiness. In order to identify a normal distribution is when both skewness and kurtosis is zero (Hair et al., 2014; Tabachnick & Fidell, 2013). Any values are considered normal, if skewness and kurtosis are within +/- 1.96. Thus, the needed value has been extracted using SPSS and it can be seen from the result of the skewness and kurtosis analysis revealed that the computed z-values demonstrated in Table 7. The skewness and kurtosis measures of normality in SPSS output should be as near to zero as feasible. However, in actuality, statistics are frequently skewed and kurtotic. All z-values are within +/- 1.96. In this study, organizational performance should be approximately normally distributed for each category of the independent variable. In conclusion, the data are somewhat skewed and kurtotic, but do not significantly deviate from normalcy in terms of skewness and kurtosis. As a result, skewness and kurtosis values can be presumed to be nearly normal.

Table 7. Skewness and Kurtosis Analysis

				Skewness			**Kurtosis**		
	N	**Mean**	**SD**	**S**	**SE**	**z-value**	**S**	**SE**	**z-value**
Pioneer-Follower Posture	96	3.8565	1.16120	-.247	.246	-1.004	-.543	.488	-1.113
Technological Investments	96	3.1628	1.22624	-.108	.246	-0.440	-.450	.488	-0.922

Intensity Product Upgrades	96	4.1649	1.10488	-.472	.246	-1.920	-.012	.488	-0.025
External Technology Sources	96	2.9661	1.27971	.267	.246	1.085	-.915	.488	-1.875
Product Process Technology	96	4.0035	1.08848	-.305	.246	-1.240	.055	.488	0.113
External Environment	96	3.2936	0.86198	.306	.246	1.244	-.206	.488	-0.422
Organizational Performance	96	4.2833	0.81830	-.298	.246	-1.211	-.167	.488	-0.342
Valid N (listwise)	96								

The following Table 8 summarises the findings of two widely used normality tests, the Kolmogorov-Smirnov Test and the Shapiro-Wilk Test (Hair et al., 2017) to verify that data are not too far from normal. Normality tests compare the data set to the null hypothesis, which states that the data originate from a normally distributed population. Non-significant results mean that it is rational to behave as if the data set is normally distributed (or sufficiently close to it). The Shapiro-Wilk Test is better ideal for small sample sizes (<50 samples), although it is also capable of handling sample sizes up to 2000.

The Kolmogorov-Smirnov statistic is used to determine the normality of a score distribution. Table 8 shows non-statistical significant finding for pioneer-follower posture, intensity product upgrades, product process technology, external environment and organizational performance but for technological investments and external technology sources shows statistical significant finding. A non-significant result (Sig. value greater than 0.05) shows that the data are normal. So, pioneer-follower posture, intensity product upgrades, product process technology, external environment and organizational performance are normally distributed but for technological investments and external technology sources are not normally distributed.

Originally, the Shapiro and Wilk (1965) was required a sample size of less than 50 for the test. This test was the first to detect deviations from normality caused by skewness, kurtosis, or both (Althouse et al., 1998). Due to its superior power properties, it has become the preferred test (Mendes & Pala, 2003). As a result, this study use the Shapiro-Wilk test as a numerical method of determining normalcy. Generally, if the Sig. value of the Shapiro-Wilk Test is larger than 0.05, the data is deemed normal. If it is less than 0.05, the data deviate considerably from the normal distribution. For this normality test, the null hypothesis is that the data are normally distributed. If the p-value is less than 0.05, the null hypothesis is rejected.

According to the Shapiro-Wilk's test ($p > 0.05$) (Shapiro & Wilk, 1965; Razali & Wah, 2011) as numerical means of assessing normality and a visual examination of the histograms, Q-Q plots and boxplots are normal. This indicates that organizational performance were normally distributed for the respective independent variable. The skewness of -0.247 (Standard Error = 0.246) and a kurtosis of -0.543 (Standard Error = 0.488) for pioneer-follower posture, skewness of -0.305 (Standard Error = 0.246) and a kurtosis of 0.055 (Standard Error = 0.488) for product process technology, skewness of 0.306 (Standard Error = 0.246) and a kurtosis of -0.206 (Standard Error = 0.488) for external environment and skewness of -0.298 (Standard Error = 0.246) and a kurtosis of -0.167 (Standard Error = 0.488) for organizational performance are normally distributed but for technological investments, intensity product upgrades, and external technology sources are not normally distributed. Therefore, it is recommended to use PLS-SEM as a statistical tool for further analysis as pointed out by Henseler et al. (2016). Fundamentally, PLS technique does not requires the assumption of normality to be fulfilled in order to use the SEM technique.

Table 8. Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Pioneer-Follower Posture	.079	96	.162	.982	96	.206
Technological Investments	.093	96	.040	.968	96	.020
Intensity Product Upgrades	.077	96	.188	.971	96	.031
External Technology Sources	.111	96	.005	.958	96	.004
Product Process Technology	.072	96	.200*	.981	96	.172
External Environment	.082	96	.115	.986	96	.405
Organizational Performance	.078	96	.185	.987	96	.472

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction
*. The distribution which the data was sampled from is not significantly different from normal.

4.6 Test of Multicollinearity

Multicollinearity arises when the independent variables are strongly connected, showing a value of r = 0.90 or above (Tabachnick & Fidell, 2007). When two or more of the above constructs are too interconnected, they encompass extraneous features and hence are not required in the same analysis. Consequently, these cause an increase in the size of error terms while weakening the analysis (Maiyaki & Moktar, 2011). However, there are instance where multicollinearity problem persist. This problem can be fixed by removing the offending variables. Hence, multicollinearity can be easily detected by analyzing the correlation matrix using SPSS and according to Hair et al., (2010) if the correlation value of r = 0.90 or above, this indicates the presence of multicollinearity. In this study evidenced that all the highlighted values are in the range between 0.328 to 0.718 which is less than 0.90 as in Table 9. Therefore, all variables will be retained and it shows that the subject of multicollinearity does not existed in this study.

Table 9. Correlation among Variables

	PFP	TI	IPU	ETS	PPT	EE	OP
Pioneer-Follower Posture	1.000	0.706	0.718	0.450	0.617	0.459	0.636
Technological Investments	**0.706**	1.000	0.607	0.483	0.478	0.381	0.520
The Intensity of Product Upgrades	**0.718**	**0.607**	1.000	0.342	0.573	0.446	0.644
External Technology Sources	**0.450**	**0.483**	**0.342**	1.000	0.328	0.549	0.391
Product and Process Technology	**0.617**	**0.478**	**0.573**	**0.328**	1.000	0.472	0.362
External Environments	**0.459**	**0.381**	**0.446**	**0.549**	**0.472**	1.000	0.519

Organizational Performance	**0.636**	**0.520**	**0.644**	**0.391**	**0.362**	**0.519**	1.000

Furthermore, SPSS was used for collinearity diagnostics in order to identify problems with multicollinearity that may not be seen in the correlation matrix. The Variance Inflation Factor (VIF) and the Tolerance Level were also explored. The typical rule of thumb for detecting the presence of multicollinearity is a VIF value greater than 10 or a Tolerance value less than 0.10. (Pallant, 2013; Hair et al., 2010). The inverse of the Tolerance value is used to calculate VIF (1 divided by Tolerance). The presence of multicollinearity is indicated by values greater than 10. Tolerance values less than 0.10 (extremely small) show a strong propensity of multiple correlation among variables, implying a higher likelihood of multicollinearity. Collinearity diagnostics from the Table 10 clearly demonstrate that tolerance ranges between 0.108 and 0.689 are significantly > 0.10. Similarly, a VIF range of 1.452 - 9.233 is acceptable since the value is 10 (Tabachnick & Fidell, 2007), indicating that multicollinearity is not a significant issue (Yong & Pearce, 2013). As a result, it is concluded that there is no issue of exogenous variable multicollinearity.

Table 10. Tolerance Level and VIF Value

Exogenous Variables	**Collinearity Statistics**	
	Tolerance	**VIF**
Pioneer-Follower Posture	.137	7.306
Technological Investments	.206	4.861
Intensity Product Upgrades	.108	9.233
External Technology Sources	.155	6.453
Product Process Technology	.167	5.970
External Environment	.689	1.452

4.7 Common Method Variance

Common method variance (CMV) or so-called common method bias usually occurs when responses systematically vary due to similarities in measurement methods derived from a single source data collection which could result in inflated relationships between variables (Green et al., 2016; Fuller et al., 2016; Conway & Lance, 2010). CMV can be a problem when a single component emerges through factor analysis or when a single component contributes for the majority of the covariance between measurements (Podsakoff et al., 2003). Although the questionnaire of this study was adapted from several sources, but it seems that this study using the standard type of scale for all constructs and items that will make things the same which also have been addressed by Chang et al. (2010) and Podsakoff et al. (2003). Therefore, CMV is expected to happen in this study and might be a threat to the validity of the result. Consequently, to avoid any problems in the future, it is an essential to identify any issues related to CMV.

Typically, it can be avoided if not using the measurement from the same person, similar item context and characteristics (Podsakoff et al., 2003). There are few procedural remedy to reduce CMV by the following four techniques; i) Separating independent variable and dependent variable data collection in different timing (physical separation). This could help respondent to focus on what they are answering at that particular time; ii) Asking respondent something in between the independent variable and dependent variable first before asking dependent variable (psychological separation); iii) Employing different scale for independent variable and dependent variable because standardization of the scale will make things the same and; iv) Not grouping items in the questionnaire by giving a header for the context and respondent will answer more consistently.

Harman's single factor test was used in this study (Yeap et al., 2016) to determine the level of bias inherent in the variance proportional distribution of items. Harman's approach was used to examine unrotated factor solution by taking all items in *exploratory factor analysis* (EFA) including dependent variable and check for unrotated first factor should be less than 50% (Podsakoff & Organ, 1986) on all the observed indicators (including dependent variable). The result had discovered that unrotated the first factor is 41.65%, which is less than the threshold level of 50% of total variance explained. This indicates that in this analysis, common method variance is not a concern.

5. CONCLUSION

This analysis indicates that missing data were replaced using mean value replacement. Similarly, outliers were eliminated in accordance with (Hair et al., 2010; Tabbannik & Fidell, 2007). As a consequence, no risk of non-response bias existed, and the data could be validated as being thoroughly screened and cleansed for multivariable analysis (Hair et al., 2010; Tabbannik & Fidell, 2007). To be sure, all the individual factors have converged into components with substantial factor loading, therefore the variables must be measuring different constructs. This follows the findings on multicollinearity, which proved to be missing (Hair et al., 2010; Tabbannik & Fidell, 2007). The above results show that the data are deserving of the most compelling hypotheses and demand multivariate analysis. It is our aim that by understanding how and why this is diverse, we will gain further insights into the findings.

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