CHAPTER 5

DATA ANALYSIS AND RESULTS

5.1 INTRODUCTION

This chapter elaborates on the results of the analysis conducted for this study. The first part of this chapter presents the data collection process and survey response, including the follow-up procedure to increase the response rate and detection of common method bias. The second section shows the data cleaning, including missing data, outliers, and suspicious response patterns. The third section explains the descriptive analysis, including sample background, interpreting the descriptive statistic level, and constructing analysis. The fourth section assesses the study's measurement model. The fifth section assesses the structural model of the study. Data analysis in this chapter uses the SPSS version 20.0 for data cleaning and the PLS-SEM version 3.0 for external and internal measurements.

5.2 RESPONSE RATE

In order to collect as much data to fit both sampling and statistical requirements, 231 questionnaires were distributed to ECF-funded firms across Malaysia from the year 2016 until 2019 in collecting data on the impact of financial management practices on the firm performance. A total of 101 questionnaires were returned, representing a response rate of 43.72%. Due to the movement control order (MCO), this study distributed the survey using "authority of the sender" and "plea for help" approach to

distribute the survey (Petrovčič *et al.*, 2016). As the "authority of the sender", the ECF platform provider is capable of reaching out to all the ECF recipients. The platform provider has been explained about the purpose of the survey and the importance of delivering the survey to the right respondent. In fact, Wright and Schwager (2008) discover that an invitation from a known person in charge (ECF platform provider) and a shorter introduction about the survey improve the levels of response quality and fastest response from the survey respondents.

The online survey has been widely used in data surveys (Liu & Inchausti, 2017; Wulandari *et al.*, 2020). Due to the pandemic and MCO, to improve the response rate, the survey questionnaire was modified to make it suitable for the online survey and ensure the response level is higher (Wright & Schwager, 2008).

According to Baruch and Holtom (2008), due to technological advancement, the response rate for online surveys has been improved. Previous studies claim that the electronic mail consistently shows a lower response rate than the postage-stamp survey (Crouch *et al.*, 2011; Mavis & Brocato, 1998). Due to Covid-19, most of the survey techniques use online surveying (Leigh *et al.*, 2020; Shafi *et al.*, 2020; Wulandari *et al.*, 2020). In fact, Ramayah *et al.* (2005) argue that most of the surveys conducted in Malaysia generated a response rate of between 10 to 20 percent. However, since the study investigated the factor of performance, only 92 respondents representing firms established three years and above were selected.

5.3 COMMON METHOD BIAS (CMB)

Common method bias is also known as common method variance. When the same respondent evaluates both the independent and the dependent variables, the researcher needs to investigate the common method bias (Podsakoff *et al.*, 2003;

Podsakoff, 2003). The bias happens when a single factor that emerges from the factor analysis accounts for most of the covariance among the measures. The most common remedy for CMB's issue is Harman's single factor test, as recommended by many authors (Lin *et al.*, 2015; Sharma *et al.*, 2009), used through a principal component analysis (Podsakoff & Organ, 1986).

In this study, the first factor only explains for 37.58%, which is below the CMB criteria of less than 50%. This indicates that the data do not have the issue of CMB (Appendix B2).

5.4 DATA SCREENING

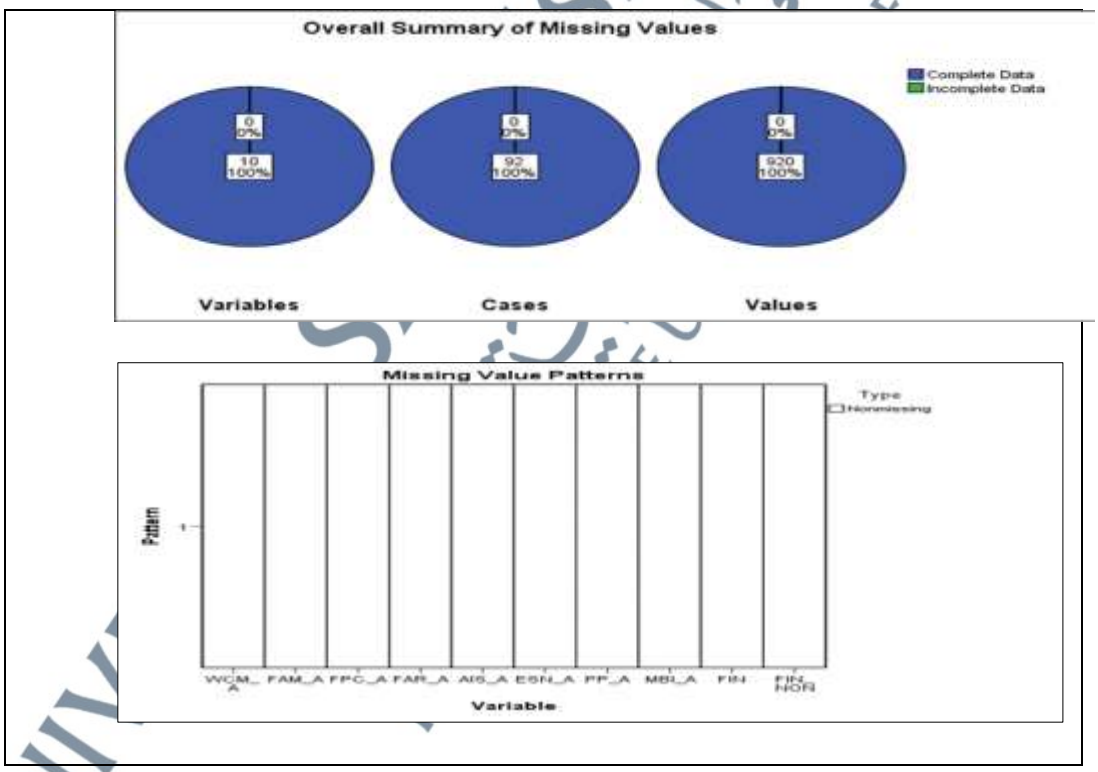
Preliminary research is needed before the first step for further statistical analysis. This includes data cleaning procedures that verify the accuracy of data, missing data, the pattern of the missing data, extreme responses, and whether the data meets the statistical assumptions as suggested by Tabachnick and Fidell (2007). The procedure ensures the data is clear from outliers, normality, linearity, homoscedasticity, and multicollinearity issues (Hair *et al.*, 2006, 2010). This study performed several steps to ensure data accuracy. The collected data were edited, coded, saved, and analyzed using SPSS. The following section discusses the data cleaning procedures mentioned above, including identifying the missing data and the existence of outliers (Appendix B1).

5.4.1 Detection of Missing Data

According to Hair, Black, Babin, Anderson, Black and Tatham (2006), missing data is the information that is not available for a case about whom other information is available. In particular, missing data exists due to errors in data

collection or data entry or the omission of respondents' answers (Hair *et al.*, 2006, 2010; Pallant, 2020). Additionally, missing data must be addressed, regardless of the reason, since it can also seriously cause bias in the conclusions drawn from an empirical study (Byrne, 2010). Therefore, any incomplete questionnaires from the respondents are treated as unusable and disposed of (Hair *et al.*, 2006, 2010).

Upon performing the data screening, the researcher carried out the frequency distribution and missing value analysis for every variable to detect any missing responses. The results showed no missing responses. Therefore, the following step was the detection of outliers. Figure 5.1 depicts that all respondents have answered all items and cleared from missing data issues.



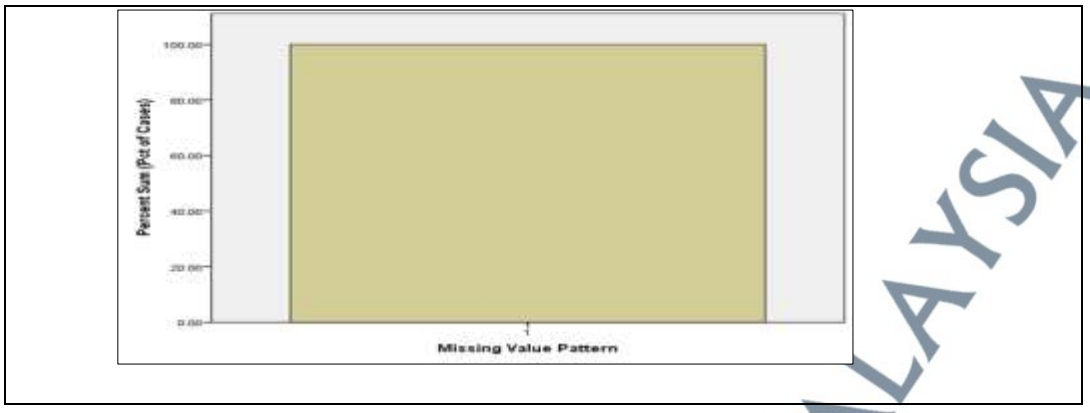


Figure 5.1: Data Clearing Through Multiple Imputation

5.4.2 Outliers

Outliers are observations that exist inconsistent with the remainder of the dataset (Ben-Gal, 2005). Therefore, the researcher needs to examine and treat outliers thoroughly to ensure that they are accurate or impact the results tremendously (Sekaran & Bougie, 2010). According to Tabachnick and Fidell (2007), the reasons of outliers are as follows:

- Incorrect data entry.
- Failure to specify missing values in the computer syntax, so missing values are treated as actual data.
- Outlier is not a member of the population that you intended to sample. Outliers represent the population you planned to test, but the population has more extreme scores than a normal distribution.

This study employed the Mahalanobis distance (D2) method to detect outliers, as suggested by Tabachnick and Fidell (2007). Mahalanobis D2 is a multidimensional version of a z-score that measures the distance of a case from the centroid (multidimensional mean) of distribution, given the covariance

(multidimensional variance) of the distribution. Hence, in this study, outliers were examined through Mahalanobis distance (D2) by looking into the box plots as suggested by Pallant (2020). In the findings, no outliers were detected.

5.4.3 Suspicious Response Patterns

When a respondent marks the same response for a high proportion of the questions, this leads to a suspicious response or unengaged response, also known as straight-lining. For instance, in a five-point scale questions, the response pattern is all the same 4s. The researcher should then remove the respondent from the data set. Likewise, if a respondent selects only 1s or only 2s, then that respondent should, in most cases, be removed (Hair *et al.*, 2013). However, in this current study, no suspicious response pattern was detected.

5.5 DEMOGRAPHIC, BUSINESS AND ECF BACKGROUND OF THE RESPONDENTS

This section only begins once the data is clean, with no missing data, outliers and suspicious response issues in the data set. It consists of a sample background of 92 respondents. The first part describes the respondent's profiles, the second part explains their firms' backgrounds, and the third part provides the ECF background of the respondents.

5.5.1 Founder-Manager Background Analysis

Findings in this section showed that in terms of gender, most of the respondents were male (79.3%) and the rest female (20.7% or 19 cases). As ECF has

a potential to increase the funds availability to the under-represented entrepreneurs (Venturelli *et al.*, 2019); i.e., female entrepreneurs, the Government and its agencies should play their roles in assisting more female-lead firms to approach the ECF platform. PwC's (2017) report shows that female-led firms accomplish their funding target better than their male counterparts. However, a study by Geiger and Oranburg (2018) discovered that, when the female-led firms solely have only females as signatories, their chances to get additional funding when asking more were slimmed.

In addition, during this Covid-19 period, it was found that female entrepreneurs have benefitted from the crises. In Italy's equity crowdfunding ecosystem, the researchers revealed that the equity crowdfunding campaigns managed by female entrepreneurs were more prone to succeed than their male counterparts throughout this time. Battaglia *et al.* (2020) opine that women entrepreneurs and their social capital significantly affect the campaign's success rate, perhaps due to the investors enhancing their preference and value towards the aspect of trust during crisis periods. Zhao, Xie and Yang (2020) also found that female issuers under ECF were more easily funded than male issuers in the ECF market. The study also confirmed the positive impact of leading investors in improving female issuers on ECF performance. However, the impact was reduced over time depending on the firm's business cycle.

In terms of age, the findings in this study showed that 76 cases or 82.6% of the respondents were between 30-49 years old, 13.0% were below 30 years old, and 4.3% were between 50-69 years old. It seems that ECF attracts millennial entrepreneurs to seek funding via the ECF platform. Levesque and Minniti (2006) argue that many studies had investigated the age effects on the firm's performance. According to them, the intention to become an entrepreneur weakens as the age

increases due to higher opportunity costs over time. In terms of opportunities, the higher the age, the higher the chances of penetrating the options due to accumulated networks, experiences, and physical capital (Lee & Vouchilas, 2016). There are mixed findings on the entrepreneurial tendency; decline (Parker, 2018) and increase (Fairlie *et al.*, 2015). According to Zhang & Acs (2018), it all depends on which stage the entrepreneurship is.

This study discovered that 63.0% of the respondents were undergraduate holders (diploma and bachelor degree), 31.5% were postgraduate (master degree and PhD), and 5.4% were secondary school leavers. They were the founders (56.5%), top management teams (37.0%), and the directors (6.5%) of the company.

The respondents have experience in both industrial and managerial scopes. 59.8% of the respondents had between 4 – 9 years of experience, 26.1% (10 – 15 years), 3.3% (above 15 years), and 10.9% (below four years) of industrial experience.

In terms of managerial experiences, 70.7% of the respondents had 4-9 years' worth of experience, 17.4% (10 – 20 years), 2.2% (above 15 years), and 9.8% (below four years). In addition, 81.5% of the respondents have attended entrepreneurial training or programs. In the ECF scenario, Cumming *et al.* (2019) argue that age does not significantly affect funding success. However, the experiences matter as they will positively increase investors' confidence and lead to the ECF campaign success rate (Piva & Rossi-Lamastra, 2018).

Robson and Obeng (2008) studied the demographic factors of entrepreneurs and their firms against elements called "business barriers". Their study showed that education greatly helped the growth of a company. Higher education levels increase the penetration of resources (human, financial), therefore, facing lesser business

barriers. Following training programs and investment in R&D can also open up more opportunities and the use of quality raw materials at a low cost. However, this study found that the gender and age of entrepreneurs were not significant to the rate of barriers encountered.

A recent study by Nigama, Benetti and Johan (2020) also argues human capital signals do not significantly affect the funding access process. Contrastly, Vrontis, Christofi and Battisti (2020) confirm that human capital within the firm's managerial personnel significantly influence the ECF campaigns success in Italy. They conducted a panel regression analysis. The independent variables were intellectual capital and knowledge sharing. The dependent variable was the ECF campaign success. Table 5.1 provides a summary of the firms' human demographic. Table 5.1 reports the frequencies and percentages among different categories of each variable.

Table 5.1 Summary of Owner-Manager Demographic

Variables	Categorization	Frequency	Percentage %
Gender	Female	19	20.7
	Male	73	79.3
Age	29 yrs and below	12	13.0
	30 - 49 yrs	76	82.6
	50 - 69 yrs	4	4.3
	> 69 years	-	-
Education	Secondary	5	5.4
	Undergraduate	58	63.0
	Postgraduate	29	31.5
	Others	-	-
Designation	TMT	34	37.0
	Director	6	6.5
	Founder	28	30.4
	Founder & TMT	20	21.7
	Founder & Dir	2	2.2
	Founder+BOD+TMT	2	2.2
Industrial experience	Less than 3 yrs	10	10.9
	4 - 9 yrs	55	59.8

Table 5.1 ***cont***

	10 - 15 yrs	24	26.1
	Above 15 yrs	3	3.3
Managerial experience	Less than 3 yrs	9	9.8
	4 - 9 yrs	65	70.7
	10 - 15 yrs	16	17.4
	Above 15 yrs	2	2.2
Attend entrepreneurship program	No	17	18.5
	Yes	75	81.5

Under the RBV theory, the top manager is considered as a firm's resource. Thus, the manager's decision is crucial as it will affect the firm's performance. To illustrate, the TMT's decision to outsource innovation activities will help reduce the risk of failure and high innovation costs. Consequently, this promotes financial efficiency. TMT influences the relationship between the RBV and transaction costs economics (TCE) as well as outsourcing decisions that result in performance (Wang & Chen, 2016). In fact, different TMT's intelligent abilities provide several preferences for solving a problem or making a decision. In addition, while the TMT number in SMEs is relatively small, each of the TMTs' individual intelligence has larger weight than the TMT in big firms when deciding on highly risky projects (Rhodes *et al.*, 2018).

Greenberg and Mollick (2018) conducted a study on the Kickstarter platform. They found that firms led by an experienced and highly skilled solo founder getting funded via CF easier than firms led by a group of management teams. However, a recent study by Coakley, Lazos and Liñares-Zegarra (2021) investigates the Seedr, Syndicateroom and Crowdcube platforms found the opposite. Professional investors look to the human resource strength of the team founder as a key factor in the success of getting startup funds and the success of the company. The study also found that

the presence of professional investors increased firms' success and reduced moral hazard.

Piva and Rossilamastra (2018) conducted a study based on the signal theory as proposed by Spence (1973). They argue for the use of the ECF platform to raise capital. Indirectly, the ECF platform company shows the quality of human capital it owns. This study was supported by Barbi and Mattioli (2019). They proved that human capital is an important signal attracting investors' trust to invest in projects launched on the ECF platform.

5.5.2 Firm Demography

71.7% of the respondents were from technology-related industry and 28.3% from other industries; 4.3% (agriculture), 6.5% (consumer product), 2.2% (construction), 2.2% (transportation), 4.3% (food), 4.3% (manufacturing), and 4.3% (waste management).

Under the ECF, the most funded business activities are technology-related activities. Battaglia *et al.* (2020) add that technology-related and R&D industries are the most financed by investors during Covid-19. Calic and Shevchenko (2020) argue that technology projects are tangible as they have a clear business plan and expected delivery time. Investors are pleased and confident during the launching events on the ECF platform. In addition, Nasafi, Pangemanan and Sfenrianto (2020) statistically prove that firms with higher financial potential have a higher success rate in getting funded. In Malaysia, Kassim and Wahab (2021) explored PitchIN platform's activities during Covid-19. The study also determined that most of the ECF-funded firms were related to technology, such as online application features.

ECF in Malaysia provides funding not only to young firms but also to the mature firms. Most of the firms involved in ECF age between 3 – 9 years (87%), below three years (2.2%), 10 – 15 years (8.7%), and above 15 years (2.2%). This study shows that firms aged three years and above get the most ECF funding. According to Nasafi, Pangemanan and Sfenrianto (2020), in Indonesia, investors tend to support firms that have been established for quite some time.

In term of the firms' size, 70.6% (5 – 30 employees), 17.4% (31 – 75 employees), 8.7% (< 5 employees), and 3.3% (76 – 200 employees) were discovered. Most of the firms were located within the Klang Valley (91.3%) and outside the Klang Valley (8.7%). Table 5.2 shows the ECF-funded firms' profiles.

Table 5.2 Summary of Firm Demographic

Variable	Categorization	Frequency	Percentage %
Industry	Agriculture	4	4.3
	Consumer	6	6.5
	Construction	2	2.2
	Food	4	4.3
	Manufacturing	4	4.3
	Transportation	2	2.2
	Waste Management	4	4.3
	Technology	36	39.1
	Edu+Technology	8	8.7
	Food+Technology	8	8.7
	Consumeri+Technology	12	13.0
	Mfg+Technology	2	2.2
Firm Age	Below 3 yrs	2	2.2
	3 - 9 yrs	80	87.0
	10 - 15 yrs	8	8.7
	Above 15 yrs	2	2.2
Firm Size	Less than 5 employees	8	8.7
	5 - 30 employees	65	70.6
	31 - 75 employees	16	17.4
	76 - 200 employees	3	3.3
Location	Outside Klang Valley	8	8.7
	Within Klang Valley	84	91.3

5.5.3 ECF Background Analysis

60.9% of the respondents raised their campaigns on PitchIN Platform Sdn Bhd, 18.5% (Ata Plus Sdn Bhd), 14.1% (Crowdplus Sdn Bhd), and 6.5% (FBM Crowdtech Sdn Bhd). 9.8% of them were funded in 2016, 26.1% (2017), 44.6% (2018), and 19.6% (2019). Skirnevskiy, Bendig and Brettel (2017) opine that enhancing the creator-platform network significantly increases future campaign success. This network potential has been supported in research on post-crowdfunding event by Fan-Osuala, Zantedeschi and Jank (2018). The study examined the relationship between the creator and the investors. The outcome shows a positive relationship as the success of the previous campaign will help the issuer's future progress. On the other hand, when the issuer cannot deliver or completely abandon the promised project, the after-campaign interaction between the two actors will discontinue (Fan-Osuala *et al.*, 2018; Kuppuswamy & Roth, 2016; Skirnevskiy *et al.*, 2017).

Nasafi, Pangemanan and Sfenrianto (2020) prove that the success of the ECF platform in securing investment in campaigns run on its platform, attracting more and more entrepreneurs in Jakarta to use the ECF platform as a vehicle to raise capital. Moreover, Barbi and Mattioli (2019) opine that the ECF platform's human capital also acts as a signal and plays an important role in bringing investors to their platforms.

This current study also determined the multiple objectives of raising the ECF. 56.5% raised ECF for working capital, 70.7% for marketing expenses, 69.6% for developing technology into their firms, 23.9% for renovation costs, 20.7% for product development, and 5.4% for R&D.

In ECF, the issuers are exchanging their firms' ownership to the funders. In this study, some of the firms offered ordinary shares (87%), preference shares (4.3%), and a combination of both (8.7%). However, in the case of ECF, if the founder offers high equity to the crowdfunders, this will less likely attract the potential backers to invest as it signals the quality of the founder's organization or the crowdfunded project (Vismara, 2016).

Table 5.3 shows that 53.3 per cent of these firms obtained additional funding after ECF. Kuppuswamy and Roth (2016) investigated the effect of the post-campaign towards additional external funding. They found that the first-round campaign outcomes significantly influence the additional funding via external sources, such as business angel (BA) and venture capital (VC) (Fili, 2014). Even though ECF funds are not an absolute funding for entrepreneurs, it will open to more opportunities in future funding, for instance, venture capital (Baumgardner *et al.*, 2017; Ljumovic & Pejovic, 2020; Strausz, 2017). According to Yang *et al.* (2021), being innovative, proactive and risk taker, the firm has actually inculcated the venture capitalists' trust at first glance. Such as in ECF, where the firms proactively approach the platform with new ideas about doing things, regardless of someone might stealing or copying their ideas.

The crowdfunding 'proof of concept' attracts potential investors to participate in the next campaign. The study conducted by Kuppuswamy & Roth, 2016 also shows that after the campaign successfully raises $75,000, the marginal effect of increasing additional funding decreases.

From the respondents' feedback in this study, 82.6% agreed that financing costs in ECF were cheaper (82.6%) and the processing time faster (77.2%) than the traditional banks. Other than that, 98.9% of the respondents' firms have an exit

strategy. In addition, 65.2% of the respondents agreed that ECF had assisted their performance. Three of the respondents' firms have successfully exited, which means they are being bought by or merged with other big companies.

Wulandari, Saeedi and Meskaran (2020) disclose that investors have more appetite on the return of their investment than the ownership offered, the social impact or the stress-free processing. In contrast with Wasiuzzaman, Chong and Ong (2021), they found that investors make decisions to invest in ECF not merely because of financial motive and to be part of the community, but more to aesthetic value, emotional value, novelty, trust, and willingness to support the ECF project. Table 5.3 depicts the ECF background of the respondents.

Table 5.3: Summary of ECF Background

Variable	Categorization	Frequency	Percentage %
ECF Platform	Ata Plus SB	17	18.5
	Crowdplus SB	13	14.1
	FBM Crowdtech SB	6	6.5
	PitchIN Platforms SB	56	60.9
Year funded	2016	9	9.8
	2017	24	26.1
	2018	41	44.6
	2019	18	19.6
ECF For working capital	No	40	43.5
	Yes	52	56.5
ECF for marketing	No	27	29.3
	Yes	65	70.7
ECF for tech. development	No	28	30.4
	Yes	64	69.6
ECF for renovation	No	70	76.1
	Yes	22	23.9
ECF for prod. development	No	73	79.3
	Yes	19	20.7
ECF for R&D	No	87	94.6
	Yes	5	5.4
Types of shares offered	Ordinary Shares	80	87.0
	Preference Shares	4	4.3
	Hybrid	8	8.7
Funding after ECF	No	43	46.7
	Yes	49	53.3

Table 5.3 ***cont***

Financing cost cheaper than traditional banks	No	16	17.4
	Yes	76	82.6
Processing time faster than traditional banks	No	21	22.8
	Yes	71	77.2
Have exit strategy	No	1	1.1
	Yes	91	98.9
ECF assist overall performance	No	32	34.8
	Yes	60	65.2
Experience exit	No	90	97.8
	Yes	2	2.2

In terms of size, location, type of enterprise, and innovation, there are various findings. Probably influenced by geographical factors such as Southern Africa, business size does not play a role in determining the survival ability of a firm (McPherson, 1996). However, a study in Britain conducted by Cosh and Hughes (2003) found that firm size was directly related to barriers in doing business. Large-sized firms can sustain business barriers because they have excess resources and assets and as collateral, while the advantage of small businesses is that they can identify problems and opportunities more quickly. For firms that innovate, the size and barriers of the business show mixed results. However, growing and family-oriented enterprises face more business barriers depending on the stage and type of the firms. Hence, firms must encounter obstacles such as lack of funding, managerial matters, market issues, regulatory disputes, materials difficulties, infrastructure problems, and social-cultural concerns that slow down their growth.

5.6 DESCRIPTIVE STATISTICS OF THE STUDY VARIABLES

The following data interpretation table is made for setting the level to measure the level of distributive financial management practices, social network, platform providers, business intelligence, firm financial and non-financial

performance. This is because the study data were collected through a questionnaire using 5 Likert scales, so it is considered very appropriate if a mean interval from the descriptive analysis is used to measure the firm performance. Table 5.4 shows a mean value of the five Likert scales is divided into five points according to the following levels:

Table 5.4: Mean for Likert Scale of 5 points

Mean Value	Interpretation
1.00 – 1.80	Very Low
1.81 – 2.60	Low
2.61 – 3.40	Moderate
3.41 – 4.20	High
4.21 – 5.00	Very high

Source: Tschannen-Moran, M. & Gareis, C.R., (2004). Principle's sense of efficacy: Assessing a promising construct. *Journal of Educational Administration, 42*(5), 573-585

The descriptive statistics in Table 5.5 show all indicators have mean values of above 3.41 and the standard deviation values of near to one, indicating that on average, the respondents agree with the statements in the questionnaire. All of the indicators were measured by Likert scale from 1 to 5 with 5 being strongly agree.

Table 5.5: Summary of Descriptive Statistics of the Study Variables

Variables	N	Minimum	Maximum	Mean	Std Deviation
FMP-Accounting Info. System	92	2.00	5.00	4.032	0.8849
FMP-Fin. Analysis & Reporting	92	2.00	5.00	4.217	0.8232
FMP-Fin. Planning & Control	92	3.00	5.00	3.950	0.7514
FMP-Working Capital Management	92	1.75	5.00	4.193	0.8333
Social networks	92	2.25	5.00	4.530	0.6524
ECF platform	92	2.50	5.00	4.372	0.7531
Business Intelligence	92	3.00	5.00	3.962	0.5096
Financial performance	92	2.67	5.00	4.014	0.8057
Non-financial performance	92	2.67	5.00	4.199	0.7215

5.7 MEASUREMENT MODEL ASSESSMENT

The measurement model identifies how each construct is measured. It is essential to ensure reliability and validity before assessing the structural model (Hair *et al.*, 2017). Prior to assessing the measurement models, one needs to differentiate between the reflective and formative constructs as each of them has special consideration for evaluation measures (Becker *et al.*, 2012). This study uses a reflective measurement model. Reflective measurement models assess on their internal consistency, reliability, and validity. The specific measures used are the composite reliability that assesses the internal consistency reliability, the convergent validity, and discriminant validity. However, assessing the formative models requires further steps (Hair *et al.*, 2017).

After identifying the types of the constructs (i.e., reflective or formative), the first step in PLS-SEM analysis is to evaluate the measurement model (or outer model). It is to reveal how good the items (questions) load on the hypothetical-defined construct. According to Hair, Ringle and Sarstedt (2011), analyzing the outer model involves unidirectional predictive relationships between each of the latent constructs linked with the observed indicator.

Hair *et al.* (2016) explain that assessing the reflective outer model involves;

- the examining of reliabilities of the individual items (indicator reliability),
- reliability of each latent variables, internal consistency (Cronbach alpha and composite reliability),
- construct validity (loading and cross-loading),
- convergent validity (average variance extracted, (AVE)) and

- the discriminant validity - Fornell-Larcker criterion, cross-loading, HTMT criterion

5.7.1 Indicator Reliability (Factor Loading)

The researcher used factor loading to examine the indicator reliability. High loading on a construct shows that the related indicators appear to have much in common, captured by the construct (Hair *et al.,* 2017). According to Hair *et al.* (2010), factor loadings greater than 0.50 are considered very significantly. Table 5.6 displays that the loadings for all the items surpass the recommended value of 0.50. Meaning, the loadings for all items in the model fulfil all the requirements. WCM1 was deleted from the scale due to low loadings.

Table 5.6: Results of Loadings for all Items

Latent Constructs		Factor Loading (> 0.50)
Accounting Information System	AIS1	0.791
	AIS3	0.918
	AIS4	0.896
	AIS2	0.928
Financial analysis & reporting	FAR1	0.825
	FAR2	0.836
	FAR3	0.834
	FAR4	0.888
Financial planning & control	FPC1	0.916
	FPC2	0.846
	FPC3	0.789
	FPC4	0.882
Working capital management	WCM1	Deleted
	WCM2	0.863
	WCM3	0.852
	WCM4	0.926
Social networks	ESN1	0.884
	ESN2	0.867
	ESN3	0.880
	ESN4	0.871
ECF platform provider	PP1	0.850
	PP2	0.888
	PP3	0.845

Table 5.6 ***cont***

	PP4	0.786
Business intelligence	MBI1	0.839
	MBI2	0.747
	MBI3	0.812
	MBI4	0.874
Financial performance	FP1	0.862
	FP2	0.925
	FP3	0.933
Non-financial performance	NFP1	0.954
	NFP2	0.880
	NFP3	0.875

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FP: financial performance; NFP: non-financial performance; MBI: business intelligence (mediator)

5.7.2 Construct Reliability (Composite Reliability and Cronbach's Alpha)

By testing the consistency and stability, the researcher can measure the reliability. Reliability refers to how reliable the measurement model is in measuring the proposed latent constructs (Awang *et al.*, 2015). The researcher has to fulfil the below criteria to assess the measurement model's reliability;

1) Internal reliability: This is achieved when the Cronbach's alpha value is 0.7 or greater (Nunnally & Bernstein, 1994). Cronbach's alpha is a reliability coefficient. It indicates how good the items in a set positive correlate to one another. It is computed in terms of the average intercorrelations among the items measuring the concept (Sekaran & Bougie, 2012). However, Cronbach's alpha has its own limitation in the population. Thus, to overcome this issue, a different measure of internal consistency reliability, which known as composite reliability, can be applied (Hair *et al.*, 2017).

2) Composite reliability: It measures the reliability and internal consistency for a latent construct. A Cronbach alpha value of greater than 0.70 is needed (Gefen

et al., 2000; Kline, 2011). Composite reliability is calculated using the following formula:

$$CR = \left(\sum K\right)^2 / \left(\left(\sum K\right)^2 + \left(\sum 1 - K^2\right)\right)$$

Where K - is factor loading of every item.

The composite reliability fluctuates between 0 and 1, where the higher values represent the higher level of reliability. Generally, composite reliability is interpreted in the same manner as Cronbach's alpha. However, in specific, composite reliability values of 0.60 to 0.70 are acceptable in exploratory research. Meanwhile, values below 0.60 show a lack of internal consistency (Hair *et al.*, 2013). Table 5.7 shows the results of composite reliability with values higher than 0.70 and Cronbach's alpha also higher than 0.70. It indicates that the construct reliability is fulfilled. Thus, it claims that there are both consistency and stability in the model.

Table 5.7: Result of Cronbach's Alpha and Composite Reliability

Latent construct	Cronbach Alpha (>0.70)	Composite Reliability (>0.70)
AIS	0.906	0.935
FAR	0.868	0.910
FPC	0.881	0.919
WCM	0.855	0.912
SN	0.899	0.929
PP	0.867	0.908
BI	0.836	0.891
FP	0.892	0.933
NFP	0.887	0.930

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FP: financial performance; NFP: non-financial performance; MBI: business intelligence (mediator)

5.7.3 Average Variance Extracted (AVE)

AVE is a standard measure to establish convergent validity on the construct level. This principle is defined as the grand mean value of the squared loadings of

the indicators associated with the construct (i.e., the sum of the squared loadings divided by the number of indicators). Thus, the AVE is equal to the commonality of a construct. Using the same reason as to the individual indicators, an AVE value of 0.50 or greater shows that, on average, the construct explains more than half of the variance of its indicators. On the contrary, an AVE value less than 0.50 indicates that, on average, more error lingers in the items than the variance explained by the construct (Hair *et al.*, 2017). The AVE is calculated using the given formula:

$$AVE = \sum K^2 \; / \; n$$

Where K= factor loading of every item, and n= number of items in a model.

Table 5.8 shows the result of the AVE for the current study. All the AVE values were greater than 0.50. As such, all the convergent validity components of the full model of the construct have been fulfilled.

Table 5.8: Result of Average Variance Extracted (AVE)

Latent Construct	AVE (> 0.50)
AIS	0.783
FAR	0.716
FPC	0.739
WCM	0.776
SN	0.767
PP	0.711
BI	0.671
FP	0.823
NFP	0.817

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FP: financial performance; NFP: non-financial performance; MBI: business intelligence (mediator)

Carlson and Herdman (2012) explain that when the constructs in the research satisfy the requirement of the Cronbach's alpha (> 0.50), CR (> 0.70), factor

loadings (> 0.5) and AVE (> 0.50), then next is checking the discriminant validity as per the following subsection.

5.7.4 Discriminant Validity: Fornell-Larcker Criterion, Cross Loading and Heterotrait-Monotrait Ratio

Discriminant validity refers to the extent to which items differentiate among constructs or measure-distinct concepts. It is checked using three criteria: the cross-loadings, Fornell-Larcker, and Heterotrait-Monotrait ratio (HTMT). Based on Hair, Babin and Krey (2017), cross-loadings are usually the first attempt to measure the discriminant validity of the indicators. As shown in Table 5.9, the cross-loadings' criterion fulfils the requirements as the indicator's outer loadings on a construct are greater than all its cross-loadings with other constructs (italic and bold values).

Table 5.9: Result of Discriminant Validity by Cross-Loadings

Construct	AIS	SN	FAR	FP	FPC	MBI	NFP	PP	WCM
Items									
AIS1	***0.791***	0.410	0.455	0.030	-0.076	0.039	0.287	0.077	0.339
AIS3	***0.918***	0.235	0.285	0.068	-0.022	-0.017	0.290	0.159	0.076
AIS4	***0.896***	0.332	0.240	-0.053	-0.158	-0.106	0.348	0.244	0.093
AIS2	***0.928***	0.282	0.220	0.067	-0.003	0.019	0.266	0.188	0.043
ESN1	0.252	***0.884***	0.427	-0.054	-0.109	0.012	0.352	0.610	0.405
ESN2	0.288	***0.867***	0.340	-0.021	-0.074	0.083	0.280	0.508	0.350
ESN3	0.400	***0.880***	0.376	0.005	-0.089	0.115	0.367	0.441	0.477
ESN4	0.306	***0.871***	0.278	0.028	-0.045	0.001	0.399	0.717	0.323
FAR1	0.198	0.282	***0.825***	-0.052	-0.195	0.064	0.453	0.146	0.667
FAR2	0.286	0.324	***0.836***	-0.056	-0.160	-0.095	0.351	0.159	0.368

Table 5.9 ***cont***

FAR3	0.341	0.275	***0.834***	-0.043	-0.054	0.119	0.408	0.190	0.408
FAR4	0.327	0.488	***0.888***	-0.007	-0.158	-0.022	0.419	0.253	0.453
FP1	0.054	0.041	0.001	***0.862***	0.490	0.421	-0.093	-0.167	0.032
FP2	0.001	-0.036	-0.077	***0.925***	0.559	0.486	-0.199	-0.130	-0.102
FP3	0.022	-0.025	-0.046	***0.933***	0.601	0.487	-0.269	-0.236	-0.092
FPC1	-0.047	-0.107	-0.049	0.626	***0.916***	0.458	-0.397	-0.302	-0.071
FPC2	-0.032	-0.035	-0.209	0.467	***0.846***	0.303	-0.276	-0.083	-0.089
FPC3	-0.131	-0.048	-0.239	0.427	***0.789***	0.487	-0.322	-0.092	-0.171
FPC4	-0.062	-0.105	-0.115	0.548	***0.882***	0.482	-0.243	-0.208	-0.120
MBI1	0.091	0.093	0.060	0.380	0.375	***0.839***	0.037	-0.085	0.050
MBI2	0.015	-0.012	-0.008	0.336	0.400	***0.747***	0.099	-0.132	0.057
MBI3	-0.156	0.065	-0.014	0.462	0.412	***0.812***	-0.084	-0.116	0.002
MBI4	-0.011	0.039	0.046	0.486	0.474	***0.874***	-0.084	-0.211	-0.033
NFP1	0.395	0.416	0.530	-0.159	-0.284	-0.037	***0.954***	0.489	0.491
NFP2	0.294	0.305	0.391	-0.277	-0.359	-0.089	***0.880***	0.495	0.330
NFP3	0.222	0.374	0.388	-0.142	-0.354	-0.007	***0.875***	0.461	0.395
PP1	0.030	0.551	0.101	-0.187	-0.168	-0.154	0.488	***0.850***	0.191
PP2	0.019	0.478	0.185	-0.279	-0.267	-0.253	0.496	***0.888***	0.247
PP3	0.354	0.637	0.228	-0.139	-0.174	-0.148	0.400	***0.845***	0.181
PP4	0.352	0.595	0.266	-0.004	-0.064	-0.038	0.393	***0.786***	0.190
WCM2	-0.148	0.306	0.473	-0.108	-0.134	-0.050	0.339	0.160	***0.863***
WCM3	0.185	0.393	0.495	0.058	-0.088	0.061	0.413	0.124	***0.852***
WCM4	0.084	0.460	0.538	-0.118	-0.123	0.028	0.432	0.337	***0.926***

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FP: financial performance; NFP: non-financial performance; MBI: business intelligence (mediator)

The result of the discriminant validity by Fornell-Larcker in Table 5.10 shows that the square root of the AVEs on the diagonals represented by the bold and italic values are greater than the correlations between constructs (corresponding row and column values). It indicates that the constructs are strongly related to their respective indicators compared to other model constructs (see Chin, 1998; Fornell & Larcker, 1981), thus suggesting a good discriminant validity (see Hair *et al.*, 2017). Additionally, the correlation between exogenous constructs is less than 0.85 (see Awang *et al.*, 2015). Therefore, in this study, the discriminant validity of all constructs is fulfilled.

Table 5.10: Result of Discriminant Validity by Fornell-Larcker Criterion

	Latent Constructs	**1 AIS**	**2 MBI**	**3 FAR**	**4 FIN**	**5 FIN_NON**	**6 FPC**	**7 PP**	**8 SN**	**9 WCM**
1	AIS	***0.885***								
2	MBI	-0.024	***0.819***							
3	FAR	0.338	0.025	***0.846***						
4	FIN	0.027	0.514	-0.046	***0.907***					
5	FIN_NON	0.340	-0.020	0.486	-0.212	***0.904***				
6	FPC	-0.079	0.510	-0.169	0.609	-0.364	***0.860***			
7	PP	0.193	-0.170	0.221	-0.198	0.533	-0.211	***0.843***		
8	SN	0.358	0.059	0.404	-0.010	0.405	-0.090	0.655	***0.876***	
9	WCM	0.155	-0.018	0.571	-0.064	0.452	-0.130	0.242	0.446	**0.881**

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems;
ESN: social network; PP: ECF platform provider; FIN: financial performance; FIN_NON: non-financial performance; MBI: business intelligence (mediator)

There are some criticisms over the Fornell-Larcker criterion. According to Henseler, Ringle and Sarstedt (2015), the Fornell-Larcker criterion does not correctly disclose the lack of discriminant validity in common research situations. Thus, they

propose an alternative technique called the Heterotrait-Monotrait ratio (HTMT) of correlations based on the multitrait-multimethod matrix. This study assesses the discriminant validity through the HTMT. The discriminant validity has a problem when the HTMT value is greater than the HTMT value of 0.90 (Gold, Malhotra & Segars, 2001) or the HTMT value of 0.85 (Kline, 2011). However, according to Henseler, Ringle and Sarstedt (2015), the HTMT value must be below the 1.00 threshold to pass the test. Table 5.11 shows that all values are far below the suggested value of less than the threshold, indicating the discriminant validity has been determined in this study.

Table 5.11: Result of Discriminant Validity by HTMT

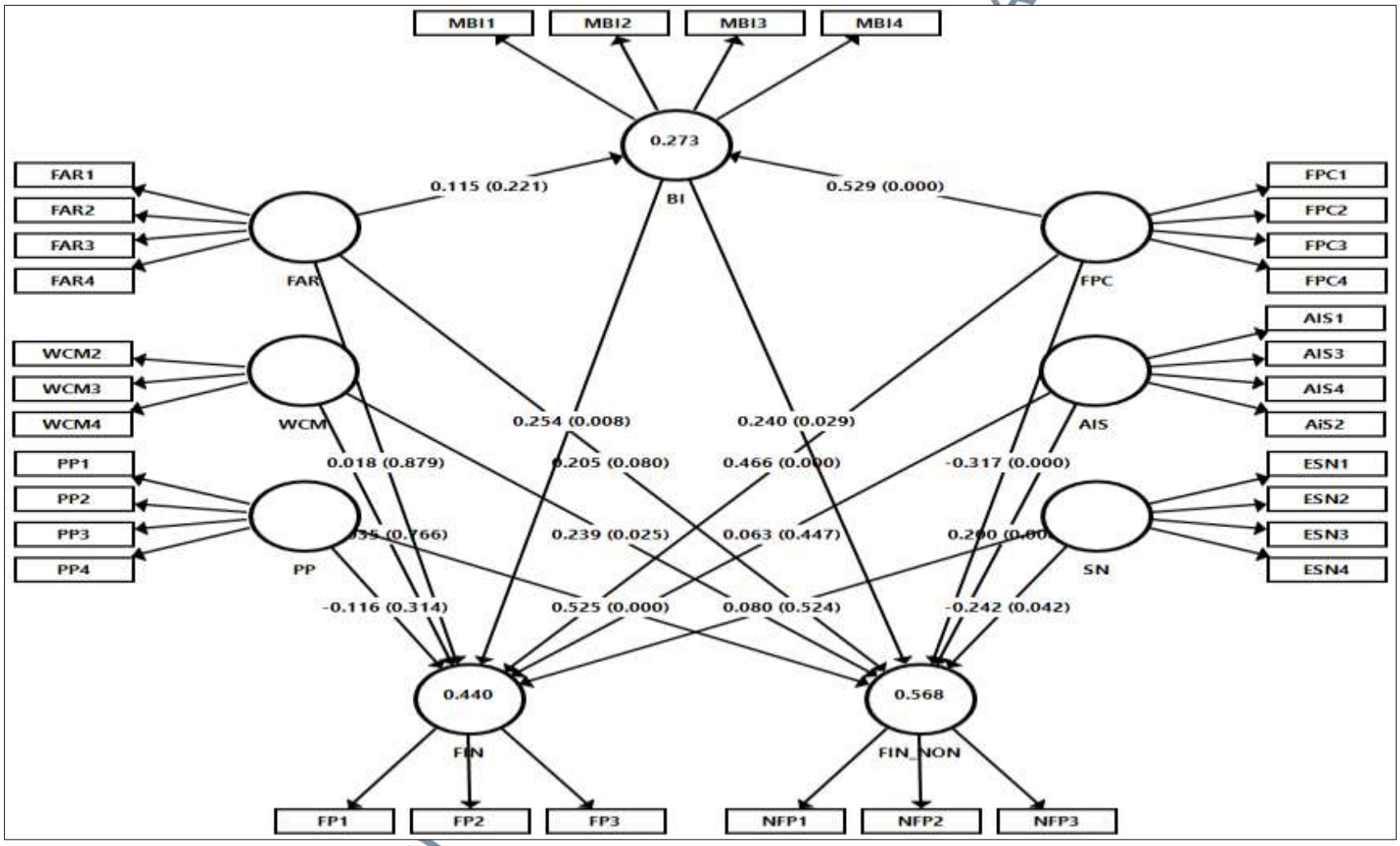
Latent Constructs	**1 AIS**	**2 MBI**	**3 FAR**	**4 FIN**	**5 FIN_NON**	**6 FPC**	**7 PP**	**8 SN**	**9 WCM**
1 AIS									
2 MBI	0.119								
3 FAR	0.385	0.112							
4 FIN	0.069	0.587	0.064						
5 FIN_NON	0.371	0.132	0.545	0.234					
6 FPC	0.108	0.585	0.213	0.677	0.411				
7 PP	0.277	0.204	0.266	0.217	0.600	0.220			
8 SN	0.392	0.097	0.459	0.055	0.445	0.099	0.749		
9 WCM	0.185	0.088	0.648	0.136	0.511	0.161	0.270	0.499	

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems;
ESN: social network; PP: ECF platform provider; FIN: financial performance; FIN_NON: non-financial performance; MBI: business intelligence (mediator)

5.8 STRUCTURAL MODEL ASSESSMENT (TESTING THE HYPOTHESES)

As proposed by Hair *et al.* (2017), to assess the structural model, a researcher needs to observe the beta (β), R squared (R^2), and the corresponding t-values through a bootstrapping technique with a subsample of 5,000. Also, they suggest reporting the effect sizes (f^2) and the predictive relevance (Q^2) as well since Sullivan and Fenin (2012) claim that the p-value determines whether the effect exists but does not disclose the size of the effect.

Evaluation metrics such as R^2 and Q^2 reported for PLS-SEM results provide in-sample predictions, but PLSpredict uses multiple randomly-selected holdout samples to calculate out-of-sample predictive power. Shmueli *et al.* (2016) propose the PLSpredict technique. PLSpredict applies a holdout sample approach to generate observation-level predictions on an item level (Shmueli *et al.*, 2019). Figures 5.2 shows the PLS bootstrapping (T statistics) results drawn from PLS version 3.0.



Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FIN: financial performance; FIN_NON: non-financial performance; MBI: business intelligence (mediator)

Figure 5.2: PLS Bootstrapping (T Statistics)

5.8.1 Estimate for Path Coefficient

Firstly, this study conducted the multicollinearity test by inspecting the variance inflation factor (VIF) as suggested by Hair *et al.* (2011; 2017). There will be no issue with multicollinearity if the VIF value is less than 5. Table 5.12 shows that all the VIF values are below 3.3 or 5 as recommended by Diamantopoulos and Siguaw (2006) and Hair *et al.* (2017), respectively. Therefore, there is no issue with multicollinearity in this study.

Table 5.12: VIF Value for Each Indicators

Indicator	MBI	FIN	FIN_NON
AIS		1.240	1.240
MBI		1.444	1.444
FAR	1.029	1.694	1.694
FIN			
FIN_NON			
FPC	1.029	1.432	1.432
PP		1.944	1.944
SN		2.423	2.423
WCM		1.656	1.656

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FP: financial performance; NFP: non-financial performance; MBI: business intelligence (mediator)

5.8.1.1 Assessment for path coefficient for Model 1

Based on the assessment of the path coefficient as shown in Table 5.13, the R^2 value is 0.440. The value of $R^2 = 0.440$ suggests that 44.0% of the variance in the firm performance can be strongly explained by the predictors of financial planning and control (β=0.466, T value=3.813, P value=0.000, BCI LL=0.201, BCI UL=0.678), thus H1c is statistically significant.

Table 5.13: Hypotheses and Results for Model 1

Hypothesis	Relationship	Std Beta	Std Error	T Value	P Values	BCI LL	BCI UL	Supported
H1a	AIS -> FIN	0.063	0.083	0.761	0.447	-0.079	0.240	No
H1b	FAR -> FIN	0.018	0.115	0.153	0.879	-0.219	0.224	No
H1c	FPC -> FIN	0.466	0.122	3.813	0.000	0.201	0.678	Yes
H1d	WCM -> FIN	-0.035	0.118	0.298	0.766	-0.268	0.179	No
H1e	SN -> FIN	0.080	0.126	0.638	0.524	-0.157	0.317	No
H1f	PP -> FIN	-0.116	0.116	1.007	0.314	-0.344	0.108	No
	R²	**0.440**						

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FIN: financial performance

5.8.1.2 Assessment for path coefficient for Model 2

Table 5.14 shows the results of the hypotheses in Model 2. The *R²* value is 0.568, suggesting that 56.80% of the variance in the non-firm performance can be strongly explained by the ECF platform provider (β=0.525, T value=5.291, P value=0.000, BCI LL=0.306, BCI UL=0.702). Followed by the working capital management (β=0.239, T value=2.252, P value=0.025, BCI LL=0.032, BCI UL=0.417), the accounting information system (β=0.200, T value=2.672, P value=0.008, BCI LL=0.0064, BCI UL=0.363), and the financial planning and control (β=-0.317, T value=3.836, P value=0.000, BCI LL=-0.492, BCI UL=-0.158). These indicate that hypotheses H2a, H2c, H2d, and H2f are statistically significant.

Table 5.14: Hypotheses and Results for Model 2

Hypothesis	Relationship	Std Beta	Std Error	T Value	P Values	BCI LL	BCI UL	Supported
H2a	AIS -> FIN_NON	0.200	0.075	2.672	0.008	0.064	0.363	Yes

Table 5.14 ***cont***

H2b	FAR -> FIN_NON	0.205	0.117	1.756	0.080	-0.037	0.412	No
H2c	FPC -> FIN_NON	-0.317	0.083	3.836	0.000	-0.492	-0.158	Yes
H2d	WCM -> FIN_NON	0.239	0.106	2.252	0.025	0.032	0.417	Yes
H2e	SN -> FIN_NON	-0.242	0.119	2.042	0.042	-0.463	0.000	No
H2f	PP -> FIN_NON	0.525	0.099	5.291	0.000	0.306	0.702	Yes
	R²	**0.568**						

Key: WCM: working capital managemt; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; NON_FIN: non-financial performance

5.8.2 Coefficient of Determination: R² Value

The R² value reveals the total variance of endogenous variables, which is explained by the exogenous variables. Thus, a larger R² value increases the predictive ability of the structural model. According to Urbach and Ahlemann (2010b), it is vital to make sure that the model's R² value is high enough to accomplish a minimum level of explanatory power. Table 5.15 explains the R² results for this study.

Table 5.15: Results of Coefficient of Determination R²

Exogenous Constructs	Endogenous Constructs	R²	Cohen (1988)	Chin (1998b)	Hair et al (2016)
AIS, FAR, FPC,WCM, SN, and PP	Financial performance	0.440	Substantial	Moderate	Moderate
AIS, FAR, FPC,WCM, SN, and PP P	Non-financial performance	0.568	Substantial	Substantial	Moderate

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FIN: financial performance; NON_FIN: non-financial performance; MBI: business intelligence (mediator)

5.8.3 The Effect Size (f^2) for all Models

Further, as proposed by Cohen (1988), the f^2 is 0.35 (substantial effects), 0.15 (moderate effects), and 0.02 (small effects). Table 5.16 shows that f^2 for financial planning and control (FPC) has a moderate effect size in both models producing R^2. However, f^2 in Model 1 (0.27) is larger than in Model 2 (0.16).

In Model 1, the f^2 for AIS, FAR, WCM, SN and PP have no effect size, indicating they have no effect in producing R^2. Contrarary, Model 2 shows that AIS, FAR, WCM and SN show a small effect in producing R^2. However, PP shows a moderate but near to large effect in producing R^2. Overall, in this current study, Model 2 depicts better effect power of the independent variables than Model 1.

Table 5.16: f^2 Results for Both Model 1 and Model 2

		Model 1		Model 2
Exogenous Construct	**Effect Power**	**Endogenous Construct Financial Performance**	**Effect Power**	**Endogenous Construct Non-Financial Performance**
AIS	No	0.01	Small	0.08
FAR	No	0.00	Small	0.06
FPC	Moderate	0.27	Moderate	0.16
WCM	No	0.00	Small	0.08
SN	No	0.01	Small	0.06
PP	No	0.01	Large	0.33

Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FIN: financial performance; FIN_NON: non-financial performance; MBI: business intelligence (mediator)

5.8.4 Predictive Relevance (Blindfolding) Q^2 for all Models

This study uses the blindfolding procedure to analyze the power of the research's proposed model in terms of predictive relevance. Hair *et al.* (2017) recommend that the blindfolding procedure use only endogenous constructs with a reflective measurement. If the value of Q^2 is greater than 0, then the predictive relevance

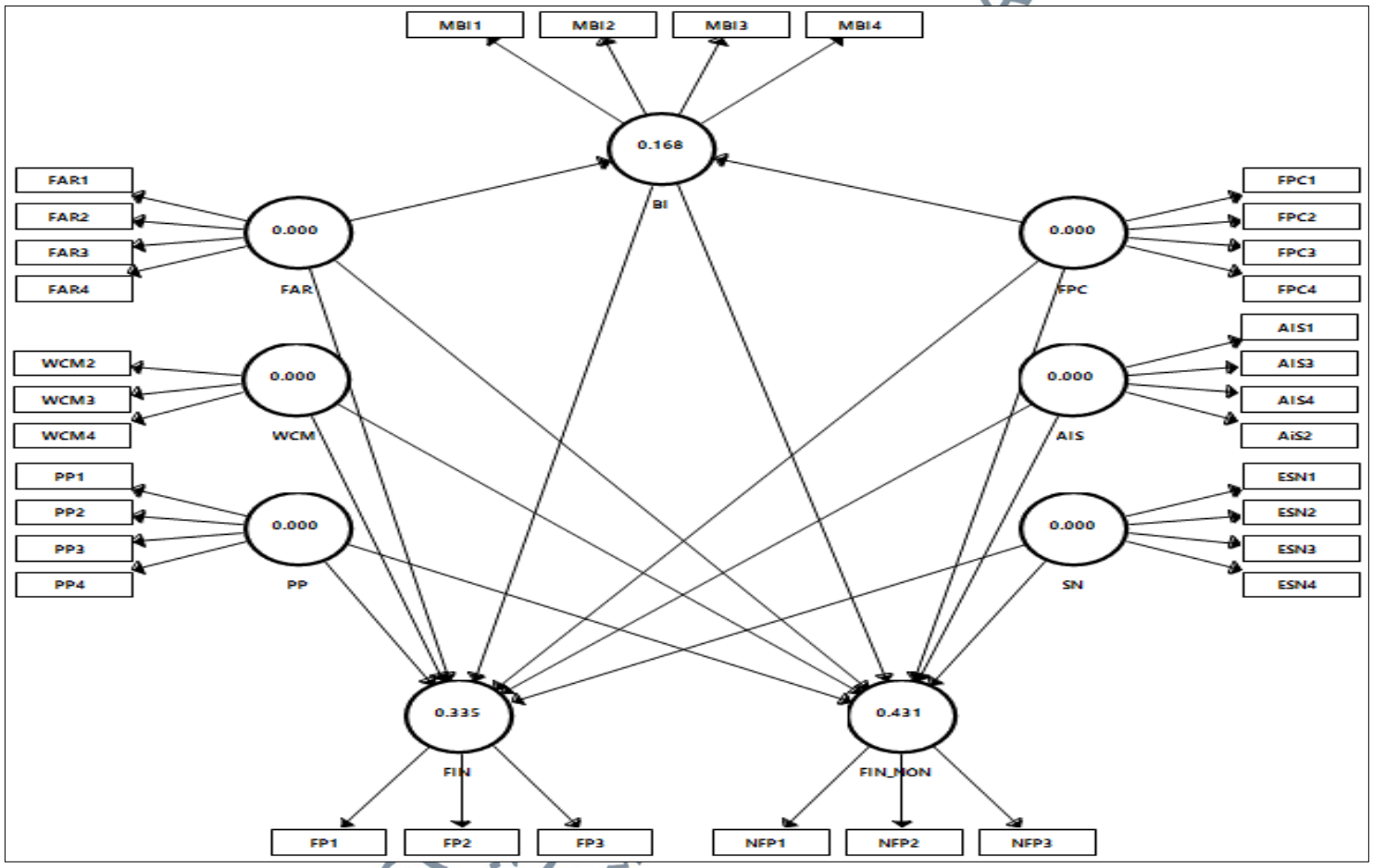
of the proposed model exists for a specific endogenous construct (Fornell *et al.*, 1994; Hair *et al.*, 2017).

Table 5.17 indicates that the predictive relevance Q^2 of financial performance has a value of 0.335 and non-financial performance has a value of 0.431, which are considerably above zero, showing an adequate predictive relevance for the proposed model and Figure 5.3 represents for blindfolding results' Q^2 diagram.

Table 5.17: Predictive Relevance (Blindfolding) Q^2

Model	Q^2 (=1-SSE/SSO)	Predictive Relevance
Model 1 = FIN	0.335	Exist
Model 2 = FIN_NON	0.431	Exist

Note: FIN= Financial Performance; FIN_NON= Non-Financial Performance



Key: WCM: working capital management; FPC: financial planning and control; FAR: financial analysis and reporting; AIS: accounting information systems; ESN: social network; PP: ECF platform provider; FIN: financial performance; FIN_NON: non-financial performance; MBI: business intelligence (mediator)

Figure 5.3: Blindfolding Results Q^2

5.8.5 PLS Predict (Q^2predict) Assessment

Table 5.18 shows majority of endogenous variables of the PLS model were above zero and lower than the LM model values. Shmueli *et al.* (2019) suggested that the Q^2predict for this study can be concluded to have a **strong predictive power**. As the general principle says, once all PLS-SEM analysis indicators have lower RMSE or MAE values than the linear model (LM) benchmark, the model has high predictive power. As analyzed, majority of the indicators in PLS are demonstrating a lower RMSE and MAE value as compared to LM. Therefore, the assumption is that this model has high predictive power and it can be used in predicting new cases (out of the samples).

Table 5.18: Predict Assessment

	PLS		LM (predictive model)		PLS less LM (Q^2 predict)	
Item	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**
FP2	0.740	0.566	0.867	0.674	-0.127	-0.108
FP3	0.667	0.511	0.712	0.539	-0.045	-0.028
FP1	0.710	0.567	0.808	0.649	-0.098	-0.082
NFP1	0.556	0.441	0.539	0.428	0.017	0.013
NFP2	0.611	0.492	0.615	0.495	-0.004	-0.003
NFP3	0.574	0.432	0.647	0.499	-0.073	-0.067

Key: FP= financial performance; NFP: non-financial performance

5.8.6 Assessment on Mediating Effects – Model 1 and Model 2

This research has developed the hypothesis that business intelligence positively influences the relationship between financial analysis and reporting and financial planning and control practices on the firms' performances (H1g, H2g, H1h and H2h) to test business intelligence as a mediator. To test the significance level of each mediating effect for those hypotheses, the bootstrapping method with 5000 bootstrap re-sampling and bias-corrected confidence intervals was utilized (Hair *et al.*, 2016; Hsu *et al.*, 2020).

Bootstrap samples are derived by repeatedly estimating the coefficients with a minimum of 5,000 bootstrap samples, each of which comprises N cases randomly sampled with replacement from the original sample N=92.

Recent PLS-SEM literature proposes the introduction of mediation types to examine the mediation effect (see Hair *et al.*, 2017; Nitzl *et al.*, 2016). Nitzl, Roldan and Cepeda (2016) further explain that it is important to ensure the mediating effects exist when the indirect effect (a x b) and the p-value are significant.

Table 5.19 shows that the p-value for business intelligence is 0.012 and 0.029 for both performance models. Thus, it is significant to test the hypotheses.

Table 5.19: P-value for Mediator

Relationship between mediator and performance	P Values	BCI LL	BCI UL	Significant
MBI -> FIN	0.012	0.041	0.438	Yes
MBI -> FIN_NON	0.029	0.019	0.446	Yes

Key: FIN: financial performance; FIN_NON: non-financial performance; MBI: business intelligence (mediator)

The next step is to check the degree of mediation. Table 5.20 shows that no degree of mediation exists in H1g and H2g as the indirect effects' p-values for both models are insignificant. For H1h and H2h, their indirect effects' p-values and direct effects were significant, showing the partial degree of mediation exist.

Further explain, if the degree or types of mediation, the direct effect (c') and indirect effect (a x b) move towards the same direction (positive or negative). Thus, it concludes that complementary partial mediation exists. However, competitive partial mediation occurs when they have different directions (Nitzl *et al.*, 2016). In Model 1, both the direct and indirect effects have the same direction (positive), thus portraying

the complementary partial mediation. In contrast, Model 2 is a competitive partial mediation. Both have a different direction because the direct effect has a negative sign and the indirect effect has a positive sign. Table 5.20 and Table 5.21 present the direct effect, indirect effect, total effect, and the degree of mediation of the hypothesized paths for Model 1 and Model 2.

Table 5.20: Degree of Mediation – Model 1

Hypothesis	Mediator - Criterion	Direct Effect (c')	Indirect Effect (axb)	Total Effect c=(c'+(axb))	Degree of Mediation
H1g	FAR -> MBI -> FP	0.018	0.029	0.047	No
H1h	FPC -> MBI -> FP	0.466*	0.134*	0.600*	Partial

Note: * p<.05; N=92; FAR=financial analysis and reporting; FPC= financial planning and control; MBI= Business Intelligence; FP= Financial Performance

Table 5.21: Degree of Mediation – Model 2

Hypothesis	Mediator-Criterion	Direct Effect (c')	Indirect Effect (axb)	Total Effect c=(c'+(axb))	Degree of Mediation
H2g	FAR -> MBI -> NFP	0.205	0.028	0.233	No
H2h	FPC -> MBI -> NFP	-0.317*	0.127*	-0.190	Partial

Note: * p<.05; N=92; FAR=financial analysis and reporting; FPC= financial planning and control; MBI= Business Intelligence; NFP= non-financial Performance

Tables 5.22 and 5.23 show the indirect effect, T value, P-value, lower bootstrap, and upper bootstrap of the mediation effects on both financial analysis and reporting and financial planning and control. As indicated by Preacher and Hayes (2008), when the indirect effect of the mediations' 95% lower (BCI LL) and upper (BCI UL) do not overlap a 0 in between, this indicates mediation. Therefore, the hypotheses H1h and H2h are confirmed. Hence, business intelligence has an influence on financial planning and control to boost better performance for the firms. In contrast, business intelligence

for this study does not affect the financial analysis and reporting practices (H2g and H2h) in boosting its performance.

Table 5.22: Hypotheses and Results for Mediating Effect (Model 1)

Hypothesis	Relationship Effect	Indirect Effect	T Value	P Value	BCI LL	BCI UL	Supported
H1g	FAR -> MBI -> FIN	0.029	1.041	0.298	-0.013	0.097	No
H1h	FPC -> MBI -> FIN	0.134	2.272	0.023	0.028	0.259	Yes

Note: N=92; FAR=financial analysis and reporting; FPC= financial planning and control; MBI= Business Intelligence; FIN= Financial Performance

Table 5.23: Hypotheses and Results for Mediating Effect (Model 2)

Hypothesis	Relationship Effect	Indirect Effect	T Value	P Value	BCI LL	BCI UL	Supported
H2g	FAR -> MBI -> FIN_NON	0.028	1.090	0.276	-0.010	0.093	No
H2h	FPC -> MBI -> FIN_NON	0.127	1.944	0.050	0.011	0.268	Yes

Note: N=92; FAR=financial analysis and reporting; FPC= financial planning and control; MBI= Business Intelligence; NFP= non-financial Performance

5.9 CHAPTER SUMMARY

This chapter began by presenting the response rate, common method bias, data screening, and suspicious response patterns. It then concentrated on the descriptive statistics of constructs and normality test. After that, the researcher assessed the measurement models and the assessment of the structural models. The assessment of the measurement model included indicator and constructs' reliability and construct analysis. Meanwhile, the assessment of the structural model involved the estimation of the path coefficients, the effect size (f^2), the predictive relevance (Q^2), the PLS predict (Q^2predict) and finally, the assessment on mediating effects.

The following chapter will discuss the results reported in this chapter and presents the present study's contributions to the existing body of knowledge. The researcher evaluated the key empirical findings to examine their implications for academics and practitioners. The study also presented the limitations of the current study, and finally, this study outlines consideration for future research.