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Big Data Analytics Capabilities and Eco-Innovation: A Study of Energy Companies

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Abstract: Increased greenhouse gas (GHG) emissions in the past decades have created concerns about the environment. To stymie global warming and the deterioration of the natural environment, global CO₂ emissions need to reach approximately 1.3 tons per capita by 2050. However, in Malaysia, CO₂ output per capita—driven by fossil fuel consumption and energy production—is expected to reach approximately 12.1 tons by the year 2020. GHG mitigation strategies are needed to address these challenges. Cleaner production, through eco-innovation, has the potential to arrest CO₂ emissions and buttress sustainable development. However, the cleaner production process has been hampered by lack of complete data to support decision making. Therefore, using the resource-based view, a preliminary study consisting of energy and utility firms is undertaken to understand the impact of big data analytics towards eco-innovation. Linear regression through SPSS Version 24 reveals that big data analytics could become a strong predictor of eco-innovation. This paper concludes that information and data are key inputs, and big data technology provides firms the opportunity to obtain information, which could influence its production process—and possibly help arrest increasing CO₂ emissions.

Keywords: eco-innovation; cleaner production; sustainable development; CO₂ emission; big data analytics; industry 4.0; resource-based view

1. Introduction

Increasing attention is being paid towards assessing the role greenhouse gas (GHG) emissions play in the current and future state of the environment. The emission of GHGs, such as carbon dioxide (CO₂), has been posited as potentially playing a role in increasing the greenhouse effect, subsequently affecting the planet's temperatures. This change in the planet's temperature, known as global warming, could have a catastrophic effect on the natural environment [1–3]. Concentration of GHG in the atmosphere has been steadily increasing—primarily driven by anthropogenic activities [4–6]. CO₂, one of the main GHG [1], needs to be contained to approximately 1.3 tons per capita by the year 2050 in order to avert environmental crises in the future [7]. In Malaysia however, levels of CO₂ emission per capita have been on the rise. They are expected to reach 12.1 tons per capita, raising notable concerns about the sustainability of the environment [8]. Therefore, finding solutions towards arresting rising GHG emissions and ensuring sustainable development ought to be a key priority amongst the various industries and stakeholders involved [9].

Consumption of fossil fuels is one of the primary drivers of CO₂ emissions [10,11]. Malaysia, which enjoys abundant reserves of oil and gas, has managed to generate adequate revenues and grow the economy from this resource [12]. As a result of economic growth, Malaysia's oil and gas consumption has also continued to grow, spurring further economic growth [13]. This has resulted in an increased reliance on oil and gas in Malaysia's energy mix, with the majority of energy derived

from fossil fuels [14]. However, this reliance on fossil fuels could be problematic on two fronts—firstly, the depletion of fossil fuels reserves [15] and secondly, inefficiency in the use of these fossil fuels for energy [16,17]. Therefore, there is a need to increase energy efficiency [17], as this may subsequently proliferate the efficient use of non-renewable energy resources. The greater efficiency will, in turn, help to tackle the growing GHG emissions.

Industry 4.0 promises to be a nexus for greater energy efficiency [18,19]. By making processes such as energy generation, transmission, and distribution smart, energy efficiency can be greatly improved [20]. Big data has been heralded as a key proponent in smart technology [21]. Hence, the ability to assimilate big data for increasing energy efficiency is crucial [22,23]. However, the full contextualization of big data has been problematic [24], and it has yet to be fully utilized towards increasing energy efficiency [25].

Interestingly, Industry 4.0 technologies such as big data analytics have displayed immense potential to drive improved energy efficiency and subsequently sustainable development [23,26] through fostering eco-innovations [27,28]. Eco-innovation has been proposed as being key to reducing negative environmental impacts and achieving sustainable development [27,29]. In fact, such is the increasing importance of eco-innovation—it has been demonstrating its potential ability in tackling rising environmental and ecological issues [30]. Hence, by improving environmental sustainability, eco-innovations are actively contributing towards sustainable development [31]. The adoption of eco-innovations has also been suggested as contributing to greater energy efficiency [32].

Whilst attention towards eco-innovation has been increasing, literature on the level of eco-innovation practices, and its impacts has yet to peak [33]. Investigations that explain the linkage between big data and analytics to eco-innovation, especially through quantitative models, are scant [34]. Despite the key role played by energy sector, investigations that specifically focus on energy sector firms' applications of big data towards eco-innovation are lacking [35].

This paper is motivated by the gap currently existing in the literature and thus, aims to explore the influence of big data analytics capability towards process eco-innovation. To explore this relationship through quantitative means a research model is proposed comprising of the capabilities of big data analytics. Hence, the objective of this paper is to investigate the influence of big data analytics capabilities on process eco-innovation of energy firms.

The rest of the paper is organized as follows: Section 2 consists of the materials and methods, including the review of literature. The results, discussion, and conclusion are found in Sections 3–5 respectively.

2. Materials and Methods

2.1. Development of Research

2.1.1. Big Data Analytics

'Big data' is a phrase often used to describe enormous amounts of data, collected for the purpose of processing [36]. This enormous amount of data is described in terms of its three key characteristics—i.e., volume, velocity, and variety [37].

Volume refers to the amount of data being generated [37]. Industry 4.0 technologies such as Internet of Things (IoT) and cyber-physical systems (CPS) have enabled firms to capture more parameters of data, hence increasing the required digital space to store this data. For example, sensors on aircraft jet engines, which use kerosene as a combustion fuel, generate hundreds of terabytes (TB) worth of data per flight operation. When this is put into perspective, a single flight alone can potentially generate far more data than what some firms have generated over their lifetime [38].

Velocity is concerned with the speed at which the data arrives. The technologies underpinning Industry 4.0 enable rapid and real-time transfer of generated data [39]. For example, an RFID chip placed in a multiphase pipeline enables the sensors measuring the displacement and corrosion rates to communicate the data in real-time [40]. Variety, meanwhile, is concerned with the different formats

or types of data. Data can basically be broken down into three main categories: structured, semi structured, or unstructured [41].

Structured data is data that is organized, has a defined format—i.e., numeric or alphanumeric—and can be stored in a database. The presence of separators makes data not have a defined format—thus making it fall into the semi-structured category [42]. Lastly, data that is maintained in the format that it was captured is classified as unstructured data. Examples of this data include natural language, audio, or images. This data is usually difficult to process via conventional software techniques and databases [42].

In order to leverage any value from this data in its different formats, firms need to have the relevant analytics technology to ingest, store, model, and secure this data [43,44]. Hence, firms seeking to improve their performance may realize performance gains through the utilization of analytics to process this data [45]. Structured data, which is storable in a database, can be processed by various analytics systems. However, it is also the least amount of data compared to the other two categories [45].

Semi-structured and unstructured data, which is more readily available to firms than structured data, require more advanced analytics, algorithms, and software to process and secure. As a result, firms are now developing more advanced analytics techniques such as machine learning, to analyze their semi-structured and unstructured data and improving their process efficiency [46]. Other firms are also developing capabilities in advanced analytics such as deep learning and natural language processing (NLP) to optimize their business processes activities such as product development, manufacture, and distribution [47]. Deep learning, which essentially bundles the dual functions of feature learning and model construction in one model, can potentially enhance business process efficiency through mapping and modelling complex input/output relationships in the production process [48].

2.1.2. Eco-Innovation

As was noted by the Brundtland Commission of 1987, mounting environmental challenges have necessitated the need for corrective action to ensure the longevity and foreseeable functioning of the biosphere, which houses both industry and people [49]. The transition towards sustainable development, which looks at ensuring economic growth without damaging the planet as well as prospects of tomorrow's generations [50], requires a shift from the "business as usual" attitude. All stakeholders—chiefly firms, governments, and industries—ought to be involved in addressing sustainable development challenges.

One method that provides stakeholders such as firms the pathway to address the mounting environmental challenges in an economically viable way is eco-innovation [51]. This is because eco-innovation goes an extra mile in that it is centered on the environment and economy. Such aims contribute towards sustainable development by reducing the ecological footprint of firms [52]. Eco-innovation has therefore demonstrated its ability to drive firms' transition towards sustainable development [53,54]. This is perhaps due to the nature of eco-innovation—defined as innovation that seeks to improve environmental sustainability [55]. By improving environmental sustainability, eco-innovations are contributing towards sustainable development.

Eco-innovation has also been conceived as any innovation which aims to reduce negative impact to environment. Eco-innovation can also be used to refer to products or processes which buttress sustainable development [56]. Eco-innovation is also closely linked to changes in product and production process technologies [57,58]. Therefore, in this study, eco-innovation refers to new or significantly improved products or processes that support sustainable development through environmental and economic means.

2.1.3. Overview on the State of Big Data Analytics and Eco-Innovation

Enhancing firms' knowledge transfer mechanisms and innovation networks can improve the flow of information [59]. Having more knowledge and information can enable firms to identify and exploit eco-innovation opportunities [59]. This is because information and knowledge are key resources and capabilities that can buttress breakthrough innovations [60,61]. Big data analytics,

through the increasing parameters and amount of data at its disposal, allows firms to generate information and knowledge that may be utilized towards churning out eco-innovations [62]. As sustainable development has become the benchmark to address the pressing global environmental issues, eco-innovation should be embedded in organizations' activities [63].

Big data analytics also enables real-time knowledge about market conditions. Hence, this knowledge can subsequently catalyze the ability of firms to incorporate servitization through the innovative combination of products and services (product-service systems) (see Stock, Obenaus, Kunz, and Kohl [34]). As firms practicing eco-innovation move towards the servitization of their business models [64], embracing big data analytics necessitates the usage of information by the various departments and divisions of the firm to increase productivity in a sustainable manner [65]. Other potential benefits of eco-innovative firms using servitization in tandem with big data analytics includes lower production costs and risks [66,67]. In addition, real-time optimization of production processes can be conducted, resulting in a better firm and production fit, as well as increased operational efficiency [68]. Hence, big data analytics has the potential to impact sustainable development through its utilization in eco-innovation.

The rising prominence of eco-innovation is being buttressed by various enablers. Examples of such as enablers include renewable energy policies or niches like carbon offsetting trading [69]. In order to arrive at a leaner understanding of eco-innovation, most research has actively sought to discuss drivers of eco-innovation [70]. Besides identifying drivers, other eco-innovation research has also attempted to understand the impact of drivers [71].

However, several areas are still lacking in the literature. To begin with, research that assesses firms' level of eco-innovation practices, and the impact of these practices have on the firms, is still scant [72]—particularly from a strategic resource and capability perspective [73].

Secondly, Industry 4.0 has proliferated big data analytics [74]. This rapid increase in big data analytics has gifted firms the opportunity of turning information and knowledge into a competitive advantage at faster rates, even in real-time [75]. Even though big data analytics has the potential to drive eco-innovation, research confirming this notion is still in its infancy [76]. Investigations using quantitative methods are lacking, especially the ones that specifically measure the ecological impacts of big data analytics technology [34,77,78]. In fact, ecological dimensions have been omitted from previously developed models [79]. Hence, it is vital for more empirical research that maps big data analytics to eco-innovation.

Third, current big data and analytics research has yet to fully incorporate human capital dimensions. Hence, there is a need for research to consider the human capital aspect of big data and analytics implementation in eco-innovation, especially from different geographical contexts. This is important, given that this is an emerging field and political as well as industrial approaches may differ based on different cultures and acceptance of technology [68].

Fourth, research has mostly taken a broad approach to applications of big data and analytics. However, studies have been unable to consider the possible sectoral differences due to different polluting potentials—i.e., some industries may potentially be more susceptible to polluting than others due to their nature of business [80]. In fact, research has yet to specifically focus on the energy sector, despite its increasing application of eco-innovations [80]. Research ought to assess the impact of digitization capabilities on sustainable development efforts of the energy sector [80].

2.1.4. Resource-Based View

Firms need resources in order to function, as resources form the foundation for a firm to convert inputs into outputs—generating value in the process [81]. Resources can be turned into capabilities, which in turn, can possibly lead to a sustained competitive advantage [82]. Without resources, firms would not be able to produce value and the subsequent competitive advantage [83–85]. Therefore, the resource-based view places importance on the critical role that resources play in attaining and sustaining a competitive advantage.

The resources of a firm not only incorporate assets [86], but also includes information, knowledge, and firm processes [87,88]. Information and knowledge are important, due to their key role in the firm's information processing ability [89,90]. Information processing often influences the decision-making of the firm [91]. Decision-making itself is critical as numerous decisions which influence the firm's performance (such as the production, process, or service dimensions of the firm) need to be made [92]. Hence, gathering more information enables firms to arrive to better decisions [93].

Information is also critical as it can expand the firm's knowledge, further enhancing the firms' decision-making process. Information and knowledge in themselves are key resources. Information and knowledge are the key resources for decision making [94]. As a result, utilization of these resources results in competency and enhanced decision making—ultimately leading to a competitive advantage [95]. The key to information and knowledge is data [96]. This data can be analyzed and processed for value to be unlocked from it [97,98]. To tap into massive amounts of data (big data), firms need the systems and technologies [96].

Generally, information communication technologies have been rapidly developing and evolving, affording firms new methods for gathering information and knowledge. Examples of such technologies include cloud computing, IoT, and CPS [44]. These technologies, which consist of a mix of hardware and software, provide platforms for big data analytics through their intra-communication, inter-communication, and connectivity [44]. Having the above information technologies can enable establishment of big data services [99] and provide firms with the platform to develop analytics capability [100]. Hence, big data analytics systems can work in tandem with information communication technologies, in sifting data [101].

When observed from the resource-based view, the capability for big data analytics can propel firm performance [102,103]. Because data is sourced from various departments or divisions, cross functional co-ordination is improved, consequently helping to bridge information gaps in the firm and remove silos [100]. However, without the necessary skills to manage the analytics systems, firms would not be able to generate value from this information and knowledge [104]. Therefore, the human capital is one of the three vital pillars of big data analytics capability [104,105]. Human capital (through their skills and abilities to carry out analytics related tasks) enables firms to leverage the data [106].

By adopting the resource-based view, this paper conceptualizes that big data is a critical resource, which enables firms to develop capabilities. These capabilities in turn, enable firms to develop a competitive advantage. Big data analytics is thus summated by the three capabilities identified earlier in the literature, which are information technology [77], management [97], and personnel expertise [107].

2.1.5. Information Technology Capability

Whilst research has expounded on the technical implications of Industry 4.0, there is a lack of research that maps Industry 4.0 technological capabilities to economic and ecological benefits [108]. More research mapping Industry 4.0 capabilities is necessary, particularly as firms create environments for sensors for data collection from the evolving information communication technologies [109]. Consequently, this creates numerous big data points of origins. Adding onto the proliferation of big data collection are other Industry 4.0 technologies such as CPS, IoT and Cloud computing, presenting a challenge for firms in terms of convergence, fusion, and processing of this data from numerous sources [100].

This complex challenge of big data, however, is also an opportunity. Big data is an asset for firms, as it is helpful towards problem solving. In addition, it assists in improving efficiencies in firm processes, activity co-ordination and production planning [110]. Hence, the usage of big data can enable firms to churn out more innovations, sustaining competitive advantage and/or cutting costs in its production processes [111]. Big data analytics information technology could potentially impact firm strategic processes such as innovation capability [77,78,105,112]. Therefore, we hypothesize the following:

Hypothesis 1 (H1). *Big data analytics information technology capability is positively related to process eco-innovation.*

2.1.6. Personnel Expertise Capability

The ability for a firm to leverage its analytics is dependent upon its human capital [113]. Even if firms have invested in state-of-the-art analytics technology to collect and manage the data, the skill sets of the analytics personnel available within the firm is a critical link to its analytics capability [105]. Research has also indicated that having appropriately skilled personnel can positively impact the firm [114]. For instance, it is theorized that skilled and experienced personnel can understand and draw conclusions from the large volumes of data that have been mined and aggregated [115]. Skilled personnel such as data scientists could support decision-making of firms through generating new understandings from data streams [116]. Hence, harnessing the human capital to leverage value from big data can be instrumental towards eco-innovation related activities such as product development or process refinement [117]. Human capital can also be vital in generating more value from big data through visualization and analysis at critical levels such as product/process design [118]. Despite these findings, research that investigates the contributory played by a firm's personnel in analytics is scant. Therefore, we propose the following hypothesis:

Hypothesis 2 (H2). *Big data analytics personnel expertise capability is positively related to process eco-innovation.*

2.1.7. Management Capability

In addition to information technology, having the ability to manage and utilize the big data can be a significant contributor to organizational performance, as firms that utilize big data analytics could experience an increase in their performance [119]. In fact, management capability could positively support performance through influencing the innovative ability of firms, together with its processes, products, and services [120–122]. Another reason for the upsurge in performance could be stemmed from the application of analytics to the organization's innovation process [111]. The applicability of big data analytics to the eco-innovation process of the organization could be useful in decision making [123], helping to determine the firm's eco-innovation strategy and configuration [124]. One practical example of this potential usage of big data in decision making and strategy is its application to eco-product lifecycle management [109] and new eco-product development processes [125]. Despite these facts, research has also noted the need to infuse a multi-faceted approach in mapping capabilities to sustainable value creation [79]. As a result of the above, we propose the following hypothesis:

Hypothesis 3 (H3). *Big data analytics management capability is positively related to process eco-innovation.*

The hypotheses proposed in this study, illustrating the relationship between big data analytics and eco-innovation, are exhibited by Figure 1 below:

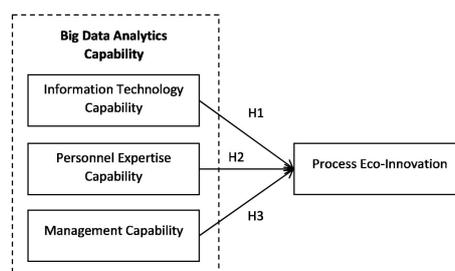


Figure 1. Research model of hypothesis utilized in this research [126,127].

Information technology, personnel expertise, and management are the independent variables whilst process eco-innovation is the dependent variable.

2.2. Methodology

2.2.1. Data Collection and Sample

In order to examine the influence of big data analytics capabilities towards process eco-innovation, this paper adopted a quantitative approach. This approach was undertaken as it enables this study to evaluate and map the three identified capabilities towards process eco-innovation in a deductive manner. Applying a quantitative research design is necessary as it enables the researchers to follow the rigorous procedures necessary to collect the data appropriately and achieve the objectives of the study.

This paper focuses on process eco-innovation of energy companies. The focal firms are, therefore, energy companies active within Malaysia. The sample is drawn from energy companies listed on Bursa Malaysia. This sample was chosen as public listed companies have access to a larger resource base, enabling them to readily adopt and practice process eco-innovation [128]. In fact, listed energy firms, have more resources to allocate towards research and development, a critical innovation function [129]. This enables them to be more eco-innovative, and thus a more appropriate representative.

Given the nature of questions in this study, the target respondents were operations managers of the sample of companies—drawn from the 41 energy and utility companies listed on the Bursa Malaysia Main Market as of the 1 June 2018. These listed energy and utility companies, which include the major oil and gas firms operating in Malaysia, collectively have a market capitalization of approximately RM190 billion on the Bursa Malaysia Main Market [130]. The companies were therefore ranked based upon their market capitalization, satisfying the requirements of a sampling frame [131].

Initial data collection for this study consisted of obtaining contact information of energy and utilities companies listed on Bursa Malaysia as of the 1 June 2018. After obtaining contact information, an invitation letter and memo to participate in the survey was distributed to the companies via electronic mail. Electronic mail provides an avenue for the researchers to communicate with the firms, as firms listed on Bursa Malaysia are required to have an electronic mail [130]. The data collection was then conducted via a questionnaire, consistent with the quantitative approach. The questionnaires were distributed in June 2018. Following distribution of questionnaires, the researchers followed up the survey via telephone call 7 days after sending them out. Follow up phone calls were also initiated at 14 and 21 days, respectively. In total, 41 questionnaires were distributed. Out of 41 questionnaires distributed, there were 32 completed questionnaires with complete responses for this preliminary study, representing a response rate of 78%. This number also satisfied the recommended minimum sample of an exploratory study [132,133].

2.2.2. Measures

Undertaking a review of the literature enabled this study to identify the analytics and eco-innovation indicators. The measurement scales for capabilities were hence identified from existing literature discussing big data analytics. The measurement scales for process eco-innovation were identified from existing literature discussing eco-innovation.

The three identified capabilities (information technology [77], management [97], and personnel expertise [108]) and their expected positive influence on strategic functions such as innovation consisted of 12 adapted variables each [126,127,134]. The measurement scale of process eco-innovation was derived from literature that identified six variables for its measurement [135].

Prior to distribution of the questionnaires, the adapted scales were face validated by experts from industry, policy, and academia to ensure that the adapted items were correctly worded within the context of their usage. Minor adjustments and refinements were then made to the wording of some of the items.

The adapted multiple-items constituting the capabilities as well as process eco-innovation were measured using a seven-point Likert scale—ranging from 1 (strongly disagree) to 7 (strongly agree). The seven-point scale was chosen because of its reliability [136]. An overview of the items can be found in Appendix A.

2.3. Data Analysis

To evaluate the three hypotheses proposed by this study in Section 2, multiple regression analysis was utilized [137]. Regression analysis has been instrumental in modern research, hence its continued use within management research [138].

Given that the aim of this study aims is to predict the influence of big data analytics on process eco-innovation, a multiple regression is an acceptable and beneficial approach. This approach is the most appropriate given the small sample size, as multiple regression analysis provides an adequate level of statistical power despite small sample sizes [139]. In addition, the model developed by this study is linear in nature, as highlighted in Figure 1. Hence, multiple regression analysis allows this study to distinguish the individual prediction ability of the identified capabilities [137], further developing theory. Statistical Package for Social Science Version 24 was the software package used by this study to undertake the multiple regression analysis.

2.4. Model Validation

To validate the developed model, this study followed the established procedures associated with multiple regression [140]. Normality tests were conducted first to assess the check whether the data was normal, then followed by a battery of checks that included linearity, homoscedasticity, as well as reliability [140]. Table 1 below provides the results of the procedures undertaken to validate the model.

Table 1. Summary of Normality and Reliability Scores.

	Skewness	Kurtosis	Cronbach's α
Information Technology	−0.353	0.048	0.929
Management	0.224	−0.173	0.919
Personnel Expertise	−0.146	0.680	0.962
Process Eco-innovation	−0.163	1.137	0.918

The skewness and kurtosis ranged between −1.2 to 1.2, indicating that data is normally distributed [141,142]. The relationship between the variables exhibited a linear distribution pattern indicating linearity and homoscedasticity. Internal consistency of the items constituting the variables was measured using Cronbach's alpha. Cronbach alpha values of 0.6 and above give an indication that the variables are acceptable and reliable [143,144]. All three variables had Cronbach alpha scores above 0.90, indicating high internal consistency [144]. Hence, all items constituting the variables were retained.

The correlation amongst the variables were also assessed, to detect if they may highly correlated. The correlation was assessed using the variance inflation factor (VIF) scores of the explanatory variables. VIF scores above 10 may indicate possible multicollinearity [145]. In addition, a correlation matrix above 0.9 suggests multicollinearity [140]. Both the VIF and correlation matrix of are below the established threshold, indicating that multicollinearity is not a concern in this study. Table 2 below indicates the VIF scores for this study's predictor variables.

Correlation assessment is also an important step taken prior to running the regression is to establish the correlation of the variables [139]. The results in Table 2 also indicate that all three independent variables are significantly correlated to the dependent variable.

Table 2. Summary of Correlation Coefficient and VIF Score.

	VIF Score	Process Eco-Innovation	Information Technology	Management	Personnel Expertise
Process Eco-Innovation		1			
Information Technology	2.623	0.605	1		
Management	2.234	0.428	0.666	1	
Personnel Expertise	3.056	0.538	0.771	0.723	1

3. Results

3.1. Correlation Analysis

Correlation assessment is also an important step taken prior to running the regression analysis, as it helps to validate the research hypotheses [139].

The results in Table 3 indicate that all three independent variables are significantly correlated to the dependent variable, validating the hypotheses in this study.

Table 3. Summary of Correlation Analysis.

	Process Eco-Innovation	Information Technology	Management	Personnel Expertise
Process Eco-Innovation	1			
Information Technology	0.001 ¹	1		
Management	0.021 ²	0.000 ¹	1	
Personnel Expertise	0.003 ¹	0.000 ¹	0.000 ¹	1

¹. Correlation is significant at the 0.01 level (two-tailed). ². Correlation is significant at the 0.05 level (two-tailed).

3.2. Hypothesis Testing

In order to test the hypothesis, the researchers performed a regression analysis. SPSS Version 24 was utilized to conduct the regression analysis. We entered the variables block by block, hence creating three models. Model 1 is information technology. Model 2 includes both information technology and management. Model 3 is inclusive of all three variables. The results from these models are presented in Table 4, thus explain the outcome of the hypothesis testing.

Table 4. Summary of Regression Models.

	Model 1	Model 2	Model 3
R ²	0.366	0.379	0.379
ΔR ²	0.366	0.013	0.000
ΔF	15.608 ¹	0.531 ²	0.015 ²

¹. $p \leq 0.001$ ². $p \leq 0.01$.

Hypothesis 1 proposes that information technology capability has a positive effect on the process eco-innovation of energy firms. The empirical results from Model 1 highlight a significant and positive relationship between information technology and process eco-innovation as $R^2 = 0.366$, $\beta = 0.605$, and $p < 0.05$. The proposed Hypothesis H1 is thus, accepted.

Hypothesis 2 posits that the expertise of personnel positively affects process eco-innovation of energy firms. The results from Model 2 seem to indicate a positive but statistically insignificant relation ($\beta = 0.177$, $p > 0.05$) between personnel expertise and process eco-innovation. From Model 1 to Model 2 the R^2 increased by 0.013. The F-test, used to scrutinize if there was a significant change in the square of the multiple correlation coefficients, also was statistically insignificant. Hence, the Hypothesis H2 is rejected.

Hypothesis 3 suggested that management capability had a positive influence towards the process eco-innovation of energy firms. There was no increase in the variance from Model 2 to Model 3 ($\Delta R^2 = 0.000$), suggesting a statistically insignificant and negative relationship ($\beta = -0.029$, $p > 0.05$). The F-test also indicated a statistically insignificant relationship. The suggested Hypothesis H3 is thus rejected.

4. Discussion

4.1. Capabilities and Process-Eco-Innovation

This study sought to mainly investigate how process eco-innovation in energy firms is influenced by big data analytics capabilities. Conceptual and empirical studies posit that Industry 4.0 technologies such as big data and analytics have a formidable role to play in addressing sustainable development challenges [28,34,146]. This study contributes towards understanding Industry 4.0 from a unique perspective. Another contribution is the applicability of a distinct Industry 4.0 perspective in addressing a specific area of sustainable development—the environment. In addition, this study focuses on energy firms. Energy is a critical area for sustainable development as numerous industries are linked to it [147]. This study's results seem to suggest that big data analytics capabilities could possibly influence process eco-innovation of energy firms—which concurs with our theoretical assumptions. However, not every capability significantly influenced process eco-innovation.

Information technology proved to be an important capability in predicting process eco-innovation. As has been highlighted in Section 2.1.2, information technology plays a critical role in big data analytics, as it provides firms the vehicle to mine data from various points. Information technology also enables firms to mine higher quality data and information. High quality data enables energy firms to have a better understanding of their operating environment, enabling them to make better predictions and more efficient operational decisions. Other research corroborated this finding, as information technology is essential in mining higher quality data [148]. Operational decisions can have large implications towards the sustainable development of the firm. Hence, it is critical that energy firms collect as high-quality data as possible. This notion is in accordance with previous studies that highlighted the importance of information technology to collect data for operational decision making of energy firms [146,149]. Without the latest information technology, energy firms would have to rely on secondary or redundant sources to obtain data for their decision-making. This would severely hamper their strategic decision making, as operational, financial, and strategic decisions need the latest, up-to-date information from various points. Previous research also concurs with this viewpoint [150] particularly for energy firms [151].

Personnel expertise was not a significant predictor to process eco-innovation. In the case of Malaysia, this provides an interesting result. Although firms are investing in state-of-the-art information technology to obtain more data, Industry 4.0 and its sub-sets such as big data analytics are still in their infancy. In fact, in the context of Malaysia, numerous firms have yet to develop all the relevant capabilities to leverage the big data. Other research has indicated that Malaysian companies have an interest in Industry 4.0, but they are not fully ready [152]. The lack of preparedness for Malaysian firms can be attributed to personnel expertise. Hence, whilst the information technology is present, there is yet to be a sufficient pool of data qualified and experienced personnel, similar to what other research has found [153–155]. Malaysia also, may be facing such a situation, as also found by other research [156]. In addition to a potential shortage of personnel, some of the personnel in Malaysian companies are skeptical of Industry 4.0 technologies which includes big data, suggesting possible resistance [157,158].

Unsurprisingly, management capability did not yield any significance towards predicting process eco-innovation. Without the necessary human capital, managing the big data would remain a challenge for firms. Management of big data is hinged upon the human resource that is at the disposal of the firm. Other research has confirmed similar findings, given that without the right skills it is not possible

to manage well [159]. In fact, in the case of energy firms in Malaysia, the results seem to suggest that management capability negatively influenced process eco-innovation. The reason for this could be due to personnel. Without appropriately qualified and experienced personnel, wrong inferences and understandings may be deduced from the collected big data. Hence, wrong strategic, operational or financial decisions could be made—at the detriment of the firm. Other research confirms this argument [160–162].

4.2. Implications for Theory

Firms need to develop a sufficient complement of capabilities in order to establish innovativeness [163]. Innovativeness, is increasingly becoming indispensable, given the hyper-competitive nature of the modern business environment [164]. Adding on to the hyper-competitive business landscape are mounting environmental challenges facing the planet. Firms, especially those of the energy sector need to shift towards sustainable development by focusing on environmental innovations. As an extension of the resource-based view (RBV), eco-innovativeness can be a new frontier for energy firms' competitive advantage. Energy firms can develop Industry 4.0 capabilities such as big data analytics. The more valuable, rare, costly to imitate, and non-substitutable the big data analytics capabilities of the firm is, the more competitive it can be. Other research also supports this viewpoint, as firms are adopting proprietary analytics systems to have a competitive edge and outperform rivals [165]. Hence, energy firms can also derive eco-innovativeness from big data analytics capabilities. Eco-innovativeness will enhance energy firms' economic gains whilst concurrently minimizing harm to the environment.

As new challenges and technologies emerge, new capabilities and the drivers of these capabilities change, competitive advantage takes on a new dimension. However, the RBV is still relevant today, particularly in applying resources and capabilities towards tackling the wave of environmental challenges facing the planet. Tackling environmental challenges in an economically sustainable way has thus revolutionized what constitutes a competitive advantage. Evidence of this notion can be seen by the rise in energy companies that conceptualize innovative ways to tackle environmental challenges. In fact, other research supports this, as more energy companies are shifting away from the traditional approach and beginning to base their competitiveness on tackling environmental challenges [166].

4.3. Implications for Managers

In addition to theoretical implications, this study highlights some interesting managerial implications. Firstly, given the importance of analytics capabilities for developing eco-innovativeness, managers need to allocate more financial resources to develop and maintain high capability levels. As has been pointed out by this study, personnel expertise did not contribute to process eco-innovation. As a result of not having the personnel, management capabilities are impacted. Although these capabilities are distinct, they never-the-less hinge on each other. For without the information technology, energy firms cannot mine data. If firms indeed do have the necessary information technology to mine data, without the required human capital, they will not be able to generate any value from it. Therefore, energy firms should not only focus their R&D investments towards technology acquisition only, but they must also intensify their training and development expenditure, particularly towards developing Industry 4.0 human capital. Data scientists and other Industry 4.0 ready personnel can be the resource that drives big data analytics capabilities of energy firms. Other research seems to support this perspective, particularly in the Malaysian context [156,158].

Secondly, although commercial analytics technology, applications and systems are readily available, intensifying R&D expenditure towards human capital can enable energy firms to develop their own proprietary analytics. Developing solutions in-house, although costly, can give energy firms an even greater competitive edge compared to rivals. In addition, trade secrets, formulas, and other sensitive data can potentially be compromised in the hands of third parties. Hence, housing data and doing the analytics in-house enhances data security, integrity, and can give energy firms an edge. Earlier research

has also supported this argument [167,168]. However, this can only be realized with the appropriate human capital which is Industry 4.0 ready.

4.4. Limitations and Future Research

This study was not without limitations. Firstly, although gathering momentum, research on Industry 4.0 and its subset—big data analytics is still in its infancy. Hence, the big data analytics capabilities identified are within the current knowledge available. As more knowledge on the subject is added, other capabilities may be identified. Secondly, this study employed quantitative methods. Future research could employ a different approach. An approach with a qualitative element such as mixed methods approach. Taking this approach could possibly unearth other capabilities, which can then be quantitatively tested for significance.

Secondly, this study focused on the influence of one aspect of Industry 4.0 towards process eco-innovation of energy companies. Future research could thus explore how other Industry 4.0 dimensions such as additive manufacturing, cloud computing, cyber-physical systems, and Internet of Things may impact process eco-innovation. Another dimension worth further exploring is automation, particularly its applications within advanced analytics (unsupervised machine and deep learning, etc.).

Third, only one dimension of eco-innovation was considered in this study. Future research could also explore the effect big data analytics capabilities have on other eco-innovation dimensions such as product, service, marketing, and organization.

Fourth, only public listed energy firms were considered in this study. Future research could also focus on non-listed energy firms. The results may then be used in a comparative study to produce meaningful cross-sectional findings, especially since innovativeness is also key to the survival of small-to-medium enterprises (SME's).

Also, the results of this study were captured in one moment in time. Longitudinal studies could analyze the influence of time on big data analytics capabilities on process eco-innovation.

Lastly, the sample size is relatively small. The researchers faced challenges increasing the response rate. Because of the size of the sample, caution must be exercised with generalizing the results. Further investigations with a larger sample size would help to reaffirm the findings of this study.

5. Conclusions

Despite its small sample size, this study makes meaningful theoretical and managerial contributions. Eco-innovation is an emerging area of research. Interest in this research area is increasing as firms strive to become more sustainable in their economic functions. Furthermore, eco-innovation could usher in sustainable development. Energy firms can realize economic performance gains whilst reducing harm to the environment by adopting eco-innovations. For example, energy generating firms can adopt eco-innovations such as combined cycle power plants to increase efficiency. Increased efficiency leads to better economic and environmental performance. Energy distributing firms can also adopt eco-innovations, such as smart grids, to improve their energy efficiency, leading to better performance. Oil and gas firms can adopt also process eco innovations such as carbon capture and utilization (CCU) to reduce CO₂ emissions and costs. CO₂ from energy generation using fossils fuels can be captured and utilized. Other examples of process eco-innovations can be utilization of captured CO₂ in enhanced oil recovery (EOR). Since Industry 4.0 technologies can facilitate eco-innovativeness, this study aimed to analyze the potential influence the capabilities of big data analytics towards process eco-innovation. Information technology, personnel expertise, and management capabilities are all capable of driving process eco-innovation. However, in the case of Malaysian energy firms, information technology capability was the strongest predictor. Hence, energy firms are able to mine more data due to this capability. This means that energy firms in Malaysia are readily able to provide higher quality data for process eco-innovations such as CCU. Oil and gas producers can immensely benefit from big data analytics with their operations such as EOR. However, despite having the information technology, Malaysian energy firms seem to lack the human capital to capitalize on this data. Information and

knowledge are key aspects in firm's strategic decision making. Hence, energy firms in Malaysia could possibly invest more on their big data analytics teams and personnel to ensure that they extract value from the data sourced from their information technology.

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Appendix A

Table A1. Summary of Indicator Scores.

Variable	Factor	Mean	SD
Information Technology Capability [126] $\alpha = 0.950$	Analytics systems: better than competitors	5.03	1.49
	Data sharing intraorganizational: branch office connection to main office	5.58	1.29
	Network connectivity: utilization of open systems.	5.10	1.01
	Intraorganizational communication: removal of communication barriers in sharing analytics results	4.93	1.27
	Data integrity: security and firewalls	5.03	1.42
	Ease of distribution of software (apps) for multiple analytics platforms	4.89	1.44
	Transparency and ease of access: interface of applications and platforms	5.03	1.37
	Intraorganizational communication: ease of sharing of analytics driven information	5.03	1.34
	External end-users of big data: provision of points of entry	4.96	1.20
	External end-users of big data: allow creation of external analytics apps through object-oriented modules	5.51	1.27
	Analytics software: utilization of reusable modules.	4.96	1.17
	Analytics software: usage of object-oriented technologies.	5.20	0.94
	Analytics software: adaptability of applications	5.75	1.12
	Management Capability [126] $\alpha = 0.964$	Usage of big data analytics: strategic innovation	5.48
Usage of big data analytics: planning		5.34	1.14
Usage of big data analytics: systematic organizational processes		5.06	1.30
Usage of big data analytics: adaptability to dynamic conditions		5.13	1.32
Usage of big data analytics: organizational investment decisions		5.00	0.92
Usage of big data analytics: organizational human resource impact		5.31	1.28
Usage of big data analytics: end-user decision making		5.48	1.05
Usage of big data analytics: end user training requirements		4.89	1.17
Intraorganizational usage: line and analysts' interaction frequency		5.10	1.01
Intraorganizational usage: cross-functional meetings frequency		5.24	1.09
Intraorganizational usage: line and analysts co-ordination		5.17	1.10
Intraorganizational usage: information sharing and ease of access between line and analysts		5.31	1.00
External communication: outperform competitors		5.17	1.10
Competitiveness: we are more cost effective than competitors		5.20	1.28
Competitiveness: we boast more advanced analytical methods than competitors	5.06	1.06	
Competitiveness: we are better at information gathering than competition	5.31	0.92	

Table A1. Cont.

Variable	Factor	Mean	SD
Personnel Expertise [126,127] $\alpha = 0.974$	Big data experience: analytics personnel capability	4.96	1.32
	Programming skills: analytics personnel capability	5.31	1.16
	Management of project lifecycle: analytics personnel capability	5.41	0.98
	Network management and maintenance: analytics personnel capability	5.13	1.15
	Decision support systems: analytics personnel capability	5.13	1.15
	Technological development trends: analytics personnel ability to understand trends	5.06	1.13
	Technological development trends: Analytics personnel learning ability of new technologies	5.24	1.15
	Organizational assimilation: analytics personnel knowledge levels of critical factors for the success of organization	4.96	1.37
	Organizational assimilation: analytics personnel knowledgeable about the role of big data analytics	5.37	1.11
	Organizational assimilation: Analytics personnel's understand of organizational policies and plans	5.51	1.24
	Technical solutions: analytics personnel capability	5.41	1.11
	Business functions: analytics personnel knowledge	5.24	1.18
	Business environment: analytics personnel knowledge	5.13	1.12
	Project planning, leading, organizing, and controlling: analytics personnel capability	5.24	1.21
	Execution of work: analytics personnel capability	5.17	1.19
	Teaching others: capability of analytics personnel	5.24	1.12
Customer relationship: ability of analytics personnel to maintain productive relationships with users and clients	5.37	1.01	
Process Eco-Innovation [135] $\alpha = 0.956$	Lowering consumption of energy during production	4.48	1.29
	Reuse of material	4.68	1.10
	Adoption of cleaner technology	4.58	1.11
	Reduction in emissions and waste generation	4.93	1.09
	Reduction in raw material usage	4.62	1.14
	Energy saving technology adoption	4.72	1.16

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