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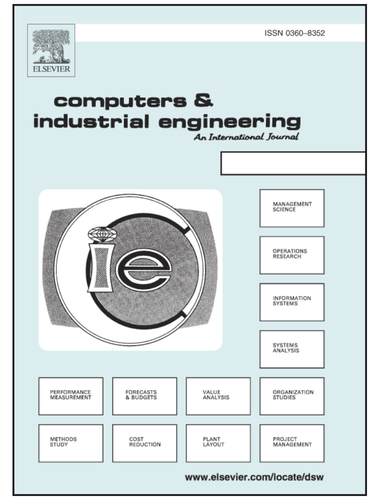

Next Generation Smart Sustainable Auditing Systems using Big Data Analytics: Understanding the interaction of critical barriers

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In the current scenario, sustainable auditing, for example roundtable of sustainable palm oil (RSPO), requires a huge amount of data to be manually collected and entered into paper forms by farmers. Such systems are inherently inefficient, time-consuming, and, prone to errors. Researchers have proposed Big Data Analytics (BDA) based framework for next-generation smart sustainable auditing systems. Though theoretically feasible, real-life implementation of such frameworks is extremely difficult. Thus, this paper aims to identify the critical barriers that hinder the application of BDA based smart sustainable auditing system. It also aims to explore the dynamic interrelations among the barriers. We applied Interpretive Structural Modelling (ISM) approach to develop the model that extrapolates BDA adoption barriers and their relationships. The proposed model illustrates how barriers are spread over various levels and how specific barriers impact other barriers through direct and/or transitive links. This study provides practitioners with a roadmap to prioritise the interventions to facilitate the adoption of BDA in the sustainable auditing systems. Insights of this study could be used by academics to enhance understanding of the barriers to BDA applications.

Keywords: Big data analytics; sustainable auditing systems; barriers; RSPO; interpretive structural modelling

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1 Introduction

Challenges to incorporate sustainable practices into the supply chains have grown notably over the past couple of decades (Gualandris, Klassen, Vachon, & Kalchschmidt, 2015). One of the challenges lies in the capability of firms to track and trace the sustainable practices of its suppliers all the way down the chain to the smallholder farmers. Driven by the global market demand for palm oil, the area of plantations is growing at a considerable rate in countries such as Malaysia, Indonesia, and, Thailand (Martin, Rieple, Chang, Boniface, & Ahmed, 2015; Mukherjee & Sovacool, 2014). The expansion of the palm tree plantations has resulted in significant deforestation and carbon emissions, which greatly affect biodiversity and water quality in these countries. Due to the harmful impact on the environment, non-governmental organizations (NGOs) have been pressuring the large buyers to procure sustainable palm oil. One of the potential and industry accepted solution is sustainable certifications of the suppliers. However, the effectiveness of these certifications rests on the auditing abilities of the certifying bodies such as Roundtable for Sustainable Palm Oil (RSPO) (Jia et al., 2016), which is constrained by the current manual process for data gathering and processing.

Technological innovations in the last decade have triggered an increase in technology adoption, advances in processing remote sensing data (e.g. RFID, ERP to the Internet of Things) contributing to vast data generation in supply chains. But organisations face a challenge in making sense and extracting value from the massive amount of data they acquire. Adoption of Big Data Analytics (BDA) is an opportunity and a valuable asset for management that can play an essential role (Arunachalam, Kumar, & Kawalek, 2017). This is a great opportunity for certifying bodies such as the RSPO to adopt BDA technology to analysis huge number of datasets. Some researcher such as Shukla and Tiwari (2017) have proposed a framework for the use of BDA to incorporate smallholder farmers in RSPO certification. But several barriers hinder the application of BDA for Smart Sustainable Auditing System. This paper aims to identify the critical barriers and to understand the dynamic interrelations among the identified barriers.

BDA has been defined in terms of the 5Vs: Volume, velocity, variety (merging of heterogeneous data), veracity (quality of data) and value (analytical usefulness). Previous literature on big data has investigated representation of BDA in various sectors such as the finance, healthcare and manufacturing sectors (Zhong, Newman, Huang, & Lan, 2016). Tiwari, Wee, & Daryanto, 2018 highlight the application and impact of BDA in supply chain management. Singh et al. (2017) proposed a framework using big-data analytics to identify supply chain issues in food industries. There exists few papers that attempted to identify the challenges for the adoption of BDA (Keeso, 2014, Hazen, Boone, Ezell, & Jones-Farmer, 2014; Brohi, Bamiah, & Brohi, 2016; Hazen, Skipper, Ezell, & Boone, 2016; Alharthi, Krotov, & Bowman, 2017; Arunachalam et al., 2017). Most of these papers are literature reviews that attempt to highlight the state-of-art of the domain. There is a lack of literature addressing real problem scenarios and identifying context based barriers that are more suitable to specific problems. This paper attempts to fill that gap by investigating the barriers that hinder the adoption of BDA for sustainable palm oil production.

We identified fifteen barriers based on systematic literature review and expert opinions both from the field of academia as well as the industry. The experts include procurement managers, an executive from RSPO, IT experts, academicians, etc. We aim to explore the barriers faced by firms in their attempt to adopt BDA technologies in the certification of sustainable palm oil. The main research question we had:

What are the barriers and their dynamics that constraint the application of Big Data Analytics in the sustainable palm oil industry?

a. Identify a comprehensive list of barriers to the adoption of BDA
b. Rank the barriers faced by the palm oil industry for the adoption of BDA
c. Establish the relationship among the identified barriers

To address the research question, we adopted interpretive structural modelling (ISM) approach. ISM is a well-established approach for understanding and identifying interrelationship between variables. We developed the ISM model based on the expert opinions. We also conducted MICMAC analysis to understand the driving and dependent power of each of the barriers and confirm the results of the ISM model. The results obtained are highly encouraging and useful for the industry practitioners as well as policy makers. The novel contribution of this research is developing an understanding of the barriers that can help the RSPO, Palm oil procuring organizations, and governments to develop incentives and policy interventions to overcome the barriers.

The paper is organized as follow: the next section presents a systematic literature review about BDA application. Section 3 presents the research methodology adopted for this study. The application of ISM approach is presented in Section 4. Section 5 presents the analysis and discussion and the paper in concluded in Section 6 with a discussion of scope for future research.

2 Literature Review

BDA can decipher data into information that can be used for predictive and preventative measures. Some of the benefits of BDA for firms, include the ability to personalize advertising, enhance decision making, and, improve product/service quality (Davenport, 2014). Addo-Tenkorang and Helo (2016) investigated the application of BDA in supply chain management. However BDA adoption has been proven to be very complex and difficult, managers need to consider several challenges when it comes to adopting BDA. Few researchers have recognised the barriers that can slow down and delay the adoption of BDA. A survey conducted by Russom (2011) investigated the top potential barriers for the implementation of BDA, inadequate staffing and skill, lack of business support, and problems with database software came at the top of the list. Other scholars identified lack of top management commitment and financial constraints as barriers for the adoption of new technologies whether it is information technology, clean technology or BDA (del Río González, 2005; Luken & Van Rompaey, 2008; Malomo & Sena, 2017).

BDA research is still in its early stages; the need to identify a comprehensive list of barriers is a step in the right direction. However, identifying the barriers to adoption BDA isn't enough. There is a need to rank these barriers and develop strategies to tackle them. Barriers to adopting BDA are general barriers to technology adoption, some of the barriers are more specific to BDA. For the purpose of the study, barriers of Information Technology as well as BDA were investigated. BDA is an information technology advancement, and thus barriers in information technology adoption apply to BDA. After conducting an exhaustive review of barriers to information technology and BDA adoption, over 50 barriers and challenges were identified. These were then group into 15 barriers according to the similarities, each of the barrier was investigated in the subsections below.

2.1 Poor Business Case

A business case is the justification for undertaking a project. It is supposed to capture the reasons for adopting and approving a project. Scholars have agreed that the lack of a compelling business case is a barrier to BDA adoption (Russom, 2011; Sagiroglu & Sinanc, 2013). Practitioners find that actual use of BDA is limited thus without solid justification for investment it is hard to convince stakeholders to invest and adopt BDA (Lee, 2017). Keeso

(2014) argues that, though not all, but most of the businesses adopted BDA for economic gains and not environmental. Various researchers have found that the inability for businesses to see the value in investing in technologies such as BDA and applicability of these new technologies in their business as a major barrier. BDA's benefits are seen in the long term, BDA it self is not tangible. Investments are made for tangible products and financial gains. The fact is BDA doesn't directly increase sales or exports it is difficult to convince people in investing, especially when it has a high on-going cost and long payback period.

2.2 Financial Constraints

Financial constraints could range from inadequate budget distributions to high business and operation expenditures. Firms face difficulties in funding the capital and operation cost of BDA. The operation costs include the ongoing funds for analysing and storage of huge amounts of data. (Jharkharia & Shankar, 2005) found that lack of funds for IT enablement within supply chains is a major barrier for the adoption of information technologies in general. The rise of BDA technologies further enhanced the rate of data generations that required advanced skills and capacity for retrieving and storing it. Organizations found it difficult to allocate the required budget to for the additional advanced skills and capacity required. del Río González, (2005) found that the high implementation cost was a barrier for adoption of clean technology. Similarly, BDA has high implementation and overall costs related to training of employees, change in organization structure, equipment and IT infrastructure upgrades, as well as ongoing cost related to the storage and analysis of huge amount of data. Organizations tend to underinvest in ICT, and rather spend money on revue generating initiatives (Davenport, 2014).

2.3 Lack of Top Management Commitment

Top management commitment is very crucial to the achievement of the firm's goals and objectives. Scholars have identified that the lack of top management commitment is a constraint for the adoption of information technologies such as BDA. Zhang, Ren, Liu, and Si (2017) indicate that the lack of top management awareness and commitment to BDA is a major barrier. At present, BDA might not be of high priority for top management. Organizations that do not see BDA as an urgent need, at times may wait till the current equipment becomes obsolete before considering investment in BDA. It may also be a case that there are competing initiatives and top management might have to prioritise the investment decision (Malomo & Sena, 2017; Russom, 2011). The immature technology and the lack of skilled labour could justify the lack of management commitment. The lack of top management commitment to BDA adoption influences the amount of budget allocated to technology and the lack of infrastructure. Organizations will wait for the business risk to go down before committing to adopting new technologies such as BDA.

2.4 Organizational Resistance to Change

BDA adoptions will require radical changes to internal process in order to leverage capabilities and gain the most of BDA adoption. Individuals and organizations resist change as they often see change as a threat. They lack the overall understanding that BDA can improve business operations and consequently see little value in pursuing BDA. Instilling new management practices and data-driven culture across the organisation is very difficult. BDA will require extensive changes in the organization's vision, strategy and organizational culture (Davenport, 2014). Researchers have considered organizational resistance to change as a barrier as the organizations often lack the willingness to changes their current methods (Alharthi et al., 2017; Malomo & Sena, 2017). They are satisfied with the current working process and not willing to learn new ways of doing things (Zhang et al., 2017).

2.5 Legacy Systems in Place

The adoption of BDA requires a drastic change to the current process in the organisations; most firms will not be able to complete the changes fast enough (Malomo & Sena, 2017). Legacy systems in place can slow down the process of BDA adoption and thus is seen as a barrier. The legacy system in place as the significant changes to the current system will not happen overnight, adoption of BDA could potentially be put on hold. Firms will need to reconsider their vision and strategy in place to leverage their current capabilities and gain the most of BDA adoption (van der Voort, & Wahyudi, 2017).

2.6 Complexity of Data Management

The inherent complexity of BDA due to the data growth, diversification of data sources and formats, the unstructured nature of the data makes it extremely difficult to manage, store, and, retrieve the date (Alharthi et al., 2017). The complexity of data management deals with the process of identifying the relevant information and avoiding inaccurate information, as well the integrity, quality and volume of data available (Kache, Kache, Seuring, & Seuring, 2017). Data governance of how data stored, analysed and accessed besides determining its value and relevance is extremely complex (Luken & Van Rompaey, 2008). Firms need to consider the data replication capabilities, variety, collection, storage and analysis as a challenge thus are reluctant to adopt BDA (Russom, 2011). Due the complexity of the data and volume, organizations models like the ones based on simulation theory can't meet the demand of processing BDA. Current supply chain modelling methods are not prepared to handle BDA; new models will need to be developed to the vast amount of computation (Fan, Han, & Liu, 2014). Hazen et al. (2014) investigated the effectiveness of managerial decision making as the complexity of the data increases.

2.7 Poor Quality of Data

It has become evident the monitoring and control of data quality is key to successful implementation of BDA. Thus organisations aim to achieve high levels of data quality as well as data integrity. Data quality is a significant barrier due to challenges arising from capturing the data, collecting and sorting the data, to data analysis and data visualisation (Chen & Zhang, 2014; Kache et al., 2017). Entry errors, duplications and corruption of the data is being taken into consideration when investing in BDA as data of insufficient quality may be of no value (Hazen et al., 2016; Mazzei & Noble, 2017). The context of the data is crucial in respect of data quality. Janssen et al. (2017) argue that the contextual background of the data also needs to be considered as different results may be obtained for same data. Without the proper context, the data is of low value. The processing and manipulations of data can also be a challenge, how usable it is and the data quality concerning a specific context is essential.

2.8 Concerns for Data Security

Concerns for confidentiality of information and security against cyber-attacks is one of the most critical barriers to adopting BDA (Keeso, 2014; Sagiroglu & Sinanc, 2013). Unauthorised access to information may cost the company its reputation and legitimacy, thus data security is vital (Brohi et al., 2016). Cloud based storage has to be secured against unauthorised access to the data. Demirkan & Delen (2013) agree that security, service level, and, data governance are seen as barriers to the adoption of BDA.

2.9 Legal and Ethical Challenges

Concerns for the collection and unauthorised use of personal data have legal and ethical implications. Ethical concerns regarding using BDA for profiling consumers of a certain organization for a targeted marketing campaign could be very profitable but raise red flags on privacy. Brohi et al. (2016) among other scholars have acknowledged complexities of the collection, access, and, analysis of data, as well as the transparency of who is viewing and managing the data as challenges for BDA adoption. Concerns regarding issues such as ownership of the data, privacy concerns, geographic location of data storage, the jurisdiction of the data storages, among others have to be considered by the organization before BDA projects (Cullot & Nicolle, 2015; Malomo & Sena, 2017).

2.10 Lack of Knowledge Sharing

The reluctance of knowledge sharing is a barrier to BDA adoption, as firms need information to flow between suppliers to make the most of BDA. Firms may fear to share information, due to security and privacy concerns. Collaboration between firms is needed to reduce the barriers of BDA (Janssen et al., 2017). Shukla and Kiridena (2016) proposed distributed multi-agent system architecture for knowledge acquisition and visualisation. Jharkharia and Shankar (2005) highlight the need for supply chain partners to agree on the adoption and specification of information technologies, and they need to be aware of the availability and accessibility of these technologies among their suppliers. Supply chain partners may be reluctant not agree on the adoption and specifications of the barriers to availability and accessibility of the information or knowledge relevant. The ability to collaborate with BDA providers, analysts, and decision makers is a key condition to overcome fragmentation and create a BDA eco-system.

2.11 Lack Infrastructure Readiness

Poor IT infrastructure is a major barrier as it could deteriorate the adoptions for BDA (Alharthi et al., 2017). Lack of infrastructure readiness increases the difficulty of architecting a BDA due to the huge amount of data that needs to be stored and processed, and the need for greater network latency. BDA requires high specifications and great network latency due to a large amount of data. Zhang et al. (2017) emphasised in their study that current technology utilized is not designed to meet the growing requirement of BDA. Issues such as data processing bottlenecks could be unavoidable with current infrastructure. There is a need to address the challenges linked to the growing amount of data (Fan, Lau, & Zhao, 2015; Zhong et al., 2016). In addition to the challenges posed by a fast growing amount of data challenges, challenges such as security, service level, and data governance are all linked to infrastructure readiness (Demirkan & Delen, 2013).

2.12 Lack of Skilled Labour

Several studies have identified the need for skilled data scientist and data management experts (Keeso, 2014; Lee, 2017; Malomo & Sena, 2017; Sagiroglu & Sinanc, 2013). Analysing and manipulating heterogeneous (structured and unstructured text, video, images) is a very difficult task. According to Boulton (2015) firms with advanced analytical capabilities are unable to hire enough employees to deliver insight due to the shortage of data scientist and architects. Lack of experienced data scientist and high demand by firms is creating a huge shortage in skilled labour (Keeso, 2014). BDA is still relevantly new, and the skill set has not yet developed to the level of current business intelligence and data warehousing units. Analytical skills are crucial for originations that wish to embrace BDA.

2.13 Immature Technology

BDA technology is relatively new and needs to be developed further. Faster and more efficient data analysis is needed to make BDA more relevant. Firms are more reluctant in adopting BDA technologies due to its efficiencies (Davenport, 2014; Russom, 2011; Sagiroglu & Sinanc, 2013). Many issues in BDA needs to be resolved before adoption, as it effects the result and impact BDA could have. Organizations will be more willing to adopt BDA once the technology matures and the risk of system failure and other insufficiencies drop.

2.14 Scalability Challenges

The management and analysis of huge datasets due to the rapid growth in data is a major concern. The unmanageable data rate is a challenge to the current infrastructure and computers owned by firms (Russom, 2011; Sagiroglu & Sinanc, 2013). A need for more powerful computers and methods to analyse and filter meaningful information from a large-scale dataset is a major barrier, only a few organizations (e.g. Google Yahoo, Facebook) have access to the computer power need to analyse such datasets (Brohi et al., 2016). A key challenge that many data mining software has not been able to crack is how to extract knowledge from large and distributed data/text quickly and put it into the hands of managers to make better, more informed decisions (Demirkan & Delen, 2013; Labrinidis & Jagadish, 2012). Scalability and timelessness challenges are due to the requirement for timely analysis of considerable number of datasets. With the current rate of data generation, it may become outdated by the time it gets analysed by the current systems. The need for the timelessness of BDA is essential for providing decision maker with the right information, due to the volatile nature of market (Kaur & Singh, 2017)

2.15 Risk of System Failure

Fear of system breakdown is another concern for firms regarding BDA adoption. Uncertainty lack of clarity and the capabilities of BDA is a challenge that needs to be addressed (Luken &

Van Rompaey, 2008). Due to the fear of system failure and compromise of data security many firms delay adoption of BDA.

To summarise, there are many barriers that can hinder the adoption of BDA. These barriers are categorised into poor business case, financial constraints, lack of top management commitment, organizational resistance to change, legacy systems, complexity of data management, concerns for data security, legal and ethical challenges, lack of knowledge sharing, lack of infrastructure readiness and lack of skilled labor. Table 1 summarizes the literature review of barriers and challenges of adopting BDA.

<<Include Table 1 about here >>

3 Research Methodology

3.1 Research Approach

The study aims to gain insight on the interrelations of barriers to the adoption of BDA, the research design of the study is based on Interpretive Structural Modelling (ISM) which is a logical mathematically derived approach. ISM is used to not only recognise but analyse the relationships between variables, which define a complex issue or a problem (Sage, 1977; Warfield, 1974). ISM provides a visual representation of complex situations; it relies on the applied experience and knowledge of a group of experts to breakdown a complicated system into subsystems. It is an interactive learning process to structure variables in a model that identifies the contextual relationships among identified variables. ISM is a well-established methodology to analyse the relationship between variables to highlight potential influences and dependencies between the selected constructs into a visual model (Agarwal, Shankar, & Tiwari, 2007). It has increasingly been used by researchers for its ability to clarify interrelationships amid various variables that are associated with an issue or a problem.

Several scholars have implemented ISM approach effectively such as Kumar et al. (2016) identified barriers for green lean six sigma product development process using ISM approach. Mathiyazhagan, Govindan, NoorulHaq, and Geng (2013) used ISM approach to identify barriers to adopting green supply chain management. Mani et al. (2016) used ISM to recognize the interrelation between enablers of adopting social sustainability measures in the supply chain. Followed by another study that used ISM to recognize the challenges/barriers in embracing social sustainability measures (Mani et al., 2016). Talib, Rahman, and Qureshi (2011) used ISM to explore the interrelationship of barriers in total quality management implementation. ISM has been proven to be an effective tool for identifying variables and their interrelations and thus is the chosen method for this research.

ISM approach requires a small group of experts gathered by a questionnaire or focus group discussion to establish the contextual relationship between variables. In most of the literature, a small group of experts are consulted to develop an ISM model. Expert panels range in sizes, some had three experts others included 40 experts. Hughes, Dwivedi, Rana, and Simintiras (2016) had nine expert panels in his study of information system project failures. Agarwal et al. (2007) in their study on modelling agility of supply chain had 5 expert opinions to validate their construct. Figure 1 illustrates the step of applying ISM approach in identifying barriers and interrelation complexities to adopting BDA.

Step1: ISM technique begins by identifying the variables in a constituting system; in this study, barriers to BDA adoption are the identified variables. In all the previous studies a review of literature is used to identify a list of variables. Followed by a focus group discussion, expert opinions, etc. to validate the list of variables and add any overlooked variables.

Step 2: The expert panel validated the list of barriers

Contextual relationships between the variables are determined (Watson, 1978). Small groups of experts are used to validate the relationship between a pair of variables. Once contextual relationships are finalized, structural self-interaction matrix (SSIM) is developed demonstrating relationship between coupled variables. The matrix illustrates the pair-wise relationships between the variables of the systems.

Step 3: Reachability matrix is then built based on the SSIM. The reachability matrix is tested for transitivity, which essentially means that if a relation holds between a first variable and a second and between the second variable and a third, there is a relation between the first and third variable.

Step 4: Partitioning of reachability matrix into various levels.

Step 5: Based on the relationships given above in the reachability matrix draw a diagraph, while adding transitive links.

Step 6: Create ISM model.

Step 7: Check the model for conceptual inconsistencies

<<Include Figure 1 about here>>

3.2 Target industry for survey

The palm oil is one of the most important commodities in Indonesia and Malaysia. It is considered a key driver for the development of those two nationals. Over the past years, environmentalist have been concerned about burning of forests to make room for palm plantations. This resulted in NGO and consumer protest that pressurised large organizations such as Unilever, Procter and Gamble (P&G), Nestle, among others to adopted sustainable practices across their supply chains. Lead corporations are considered accountable for the environmental and social performance of their suppliers (Walker & Jones, 2012).

One of the industry accepted solution is procuring RSPO certified palm oil. Many large firms have pledged to procure 100 percent RSPO certified sustainable palm oil by 2020. However certifications are voluntary, and not enough farms have been certified. The growing demand for sustainable practice, and the nature of today's supply chains scale, scope of their impact, and various stakeholder expectation these certification schemes are no longer an accessory but an essential requirement for big firms to stay competitive. Over the past several decades, voluntary sustainability certification schemes such as Fairtrade, Marine stewardship council, Rainforest Alliance, Roundtable Palm Oil, Forest Stewardship Council, Cradle to Cradle, among many other available schemes, have emerged as a potential industry acceptable solution for sustainable production/ procurement

For firms to acquire sustainability certifications, their suppliers need to be sustainable as well, all the way down to the small farms. The certification process is very complex and requires a lot of data and efforts by multiple stakeholders. The process of preparing processes and the documentation required by the certification schemes also require knowledge and are very costly (White & Samuel, 2016). Researchers such as Shukla and Tiwari (2017) proposed that BDA adoption can solve the issue and relieve some of the pressures that farmers and certifying bodies face. Though theoretically, BDA adoption could be the key to solving the certification problem, yet several barriers hinder its real-life application. There is a need to be identified the barriers and to analyse their mutual relationships. Thus we applied ISM approach for analysing the barriers for adopting BDA within the sustainable palm oil industry.

4 Development and Analysis of ISM

This section provides a detailed explanation for the implementation of ISM approach The result of each step are fully detailed and illustrate by the outputs of each step.

4.1 Identification of Barriers to BDA adoption

A systematic literature review was conducted to identify a list of barriers for BDA adoption, once the list was completed, over 50 variables were identified and grouped in one of 15 broader categories. Although a literature review is a sufficient way of identifying barriers for the ISM model, our panel of experts also validated the list of barriers. Seven-panel members were selected to review and analysis of barriers to BDA adoption. The chosen experts are practitioners and academics from varied industries, experiences, and positions. Survey responses included experts from the RSPO, P&G, big data scientist, and academics. These experts were asked if they have experience with BDA and Sustainability certification. The experts had from 8 to 15 years of experience with BDA, Certification, or both. The survey included a list of statements regarding the identified 15 barriers. The panel was requested to indicate the extent they agree with on a five-point Likert scale, 1 (strongly disagree) to 5 (strongly agree). Table 2 gives the descriptive statistics showing the mean score and standard deviation to the respective.

<<Include Table 2 about here >>

4.2 SSIM Model verification

The initial structural self-interaction matrix (SSIM) was built based on the list of identified barriers. The expert was requested to analyse the matrix of variables and verify the interrelationships between the identified BDA barriers based upon the ISM procedures and their expert opinion. The selected 15 barriers are: (1) poor business case, (2) financial constraints, (3) lack of top management commitment, (4) organizational resistance to change, (5) legacy systems, (6) complexity of data management, (7) poor quality of data, (8) concerns for data security, (9) legal and ethical challenges, (10) lack of knowledge sharing, (11) lack of infrastructure readiness, (12) lack of skilled labour, (13) immature technology, (14) scalability challenges, (15) risk of system failures.

The ISM approach in this study explores the relationship between the identified barriers in the context of how one barrier will help achieve or influence another barrier, and how a particular barrier may be affected itself by a separate barrier. The final SSIM is illustrated below in table 3 the relations between the barriers are described in Row *(i)* and column *(j)*. Specific relationships between barriers is represented using the following symbols: V, A, X and O.

V= Barrier *i* will help achieve barrier *j*;
A= Barrier *j* will help achieve barrier *i*;
X= Barriers *i & j* will help achieve each other;
O= Barriers *i & j* are unrelated.

For illustrative purposes, in the expert's opinion a poor business case (1) will help achieve lack of top management commitment (3). Therefore, a V is inserted in the matrix at the *i, j* cell reference (1:3). The Financial constraints do not affect the risk of system failure or vice versa, thus they are unrelated the symbol O is given. On the other end, lack of infrastructure readiness and immature technology will affect each other, this is indicated by giving the symbol X. The matrix is completed using the above notion until all the cells have been filled.

<<Include Table 3 about here>>

4.3 Reachability Matrix formation

The next step is the development of the initial and final reachability matrices. The SSIM needs to be converted to a binary matrix (into 1 and 0s) to develop the initial reachability matrix, the following rules are applied:

a. If *(i,j)* cell entry in the SSIM is a V, then for the reachability matrix *(i, j)* is 1 and the *(j, i)* is a 0.
b. If *(i,j)* cell entry in the SSIM is a A, then for the reachability matrix *(i, j)* is 0 and the *(j, i)* is a 1.
c. If *(i,j)* cell entry in the SSIM is a X, then for the reachability matrix *(i, j)* is 1 and the *(j, i)* is a 1.
d. If *(i,j)* cell entry in the SSIM is a O, then for the reachability matrix *(i, j)* is 0 and the *(j, i)* is a 0.
e. *If (i,j) has the same variable in both row and column (eg. i = poor business case, j= poor business case) 1 is entered in the cell.*

Table 4 illustrates the completed initial reachability matrix of barriers of adopting BDA in accordance with above rules.

To develop the final reachability matrix transitivity needs to be identified. Transitivity states that if Barrier 1 is connected to Barrier 2 (B1→ B2) and Barrier 2 is connected to Barrier 3 (B2 →B3), then there is a transitive relationship between Barrier 1 and Barrier 3.

A two-step process was implemented: the first step was identifying all the transitivity for each of the barriers. Starting form row 1 and working down the rows, each time transitivity occurs make was noted. The following step was cross-referencing each of the 0 with the list created in the previous step. All of the identified cells above should be represented or replaced by a 1*. Once you have gone through all the rows your final reachability matrix is created and all transitivity are identified. Table 5 demonstrates the final reachability matrix; transitivity is illustrated by 1* in the table.

<<Include Table 4 about here>>

<<Include Table 5 about here>>

4.4 Partitioning of reachability matrix into various levels.

Once the final reachability matrix was created, it was assessed based on the reachability and antecedent sets for each of the identified barriers in the matrix. A four-step approach is needed to partition of the reachability matrix into levels. In order to partition the matrix, reachability sets, antecedent sets and intersections are identified.

To populate the reachability set (row (i)) of each barrier, if a 1 is entered into the cell, a note is made of the equivalent column number. To populate antecedent set (row (i)) of each barrier, if a 1 is entered into the cell, a note is made of the equivalent row number. After each of the reachability and antecedent sets for each of the barriers is identified, the intersections of these two sets are identified to develop the final step of the top-level partition matrix, mutual elements between the two sets are noted.

Once the top-level partition matrix is completed then, top-level hierarchy is can be identified. The first level (iteration I), is identified by the most mutual number of matches between the reachability sets and Intersection set for each of the barriers. The identified barriers in Table 6 are organizational resistance to change, legacy systems, and lack of knowledge transfer, these three barriers are the make up the first level of the hierarchal model, where they do not help achieve any of the other barriers in our ISM model. To identify the next level, the same process is continued, with each time removing the previously identified level from the matrix. This process continues till each of the barriers is categorised into a level, as illustrated in Tables 7-11. A total of six levels were identified for, the last level containing three barriers complexity of Data Management, Lack of Skilled Labour, and Immature Technology will be positioned at the lowest level in the ISM model.

<<Include Table 6-11 about here>>

4.5 Developing the canonical form of Final Reachability Matrix

The development of the conical from of the matrix is the following step to creating the ISM model, it is illustrated in table 12. This is the final version of the final reachability matrix, the conical version of the matrix illustrates clearly the ordering of the barriers were connections line up. The barriers on the left side of the canonical are at the top-level of the ISM model, barriers on the right side will be at the lower end of the ISM model.

<<Include Table 12 about here>>

5 Discussion

5.1 MICMAC analysis

MICMAC analysis is applied to analyse the driving and dependent power of each barrier (Sharma & Gupta, 1995). Chandra and Kumar (2018) proposed a fuzzy MICMAC analysis to differentiate the factors based on the driving power and dependence. Gorane and Kant (2013) suggest that fuzzy MICMAC analysis can provide a better understanding of the driving power and dependence. Key drivers of BDA adoption are derived by applying the MICMAC analysis. Table 13 illustrates the driving and dependent power of each variable. Driving power is populated by adding all the ‘1' in each of the rows for each barrier; dependent power is populated by adding all the ‘1' in each of the barriers columns.

<<Include Table 13 about here>>

The influence of the dependency and power aspect of the relationships between each of the barriers is demonstrated in Figure 2. Each of the barriers will fall into one of the four quadrants, and each quadrant is classified as follow:

- Autonomous Barrier: barriers that fall in this quadrant have a low driving power and a low dependence power, they are relatively disconnected from the other barriers and therefore low impact.

- Linage Barrier: are barriers to high dependency power and a high driving power, these barriers are volatile any change on these barriers will have an effect on other barriers and on themselves.
- Dependent Barrier: these are barriers that have a high dependence power but low driving power, they are affected by other barriers but don't have effect other barriers
- Driving Barrier: these barriers are independent of other variables they have a high driving power and low dependency power, they are usually the key drivers.

<<Include Figure 2 about here>>

Figure 2 illustrates that a large portion of the barriers have a high driving power, with most of the barriers located in the top two quadrants, they fall mainly in the linkage quadrant. The clustering in this region illustrates that most of the barriers have a high driving and dependent power. Barriers in linkage quadrant are characterized as being volatile; this means actions on these barriers will have an effect on other variables and feedback on themselves. These highly inter-correlated barriers included (8) concerns for data security, and (15) risk of system failures (11) lack of infrastructure readiness, (3) lack of top management commitment, (2) financial constraints, (7) poor quality of data, (1) poor business case, and (14) scalability challenges. This quadrant appears to be split into two subsections of clusters, barriers 11,3, and 2 are at the top of the quadrant which indicates that they pose higher driving power.

The driving quadrant, includes a cluster three of the barriers (6) complexity of data management, (13) immature technology, (12) lack of skilled labour at the top of the quadrant and have very high driving power, while the (9) legal and ethical implications are at the bottom of the quadrant thus less influential. All four barriers are considered key barriers to BDA adoption and the highly influential on other barriers.

Three of the barriers fell in the dependent quadrant, (4) organizational resistance to change, (5) legacy systems, (10) lack of knowledge sharing, these barriers are dependent, changes on the other barriers will affect them. None of the barriers fell into the autonomous quadrant.

One of the major objectives of the study was to identify the barriers and their interrelations that significantly affect the application of BDA in the sustainable palm oil industry. This addresses in this section. The finding of the study illustrates the key barriers and the strength of links between the barriers in the context of their dependency and driving power. The results are reflected in Figure 3.

<<Include Figure 3 about here>>

5.2 ISM model

The final stage of the ISM approach is the creation of the ISM model. Figure 3 illustrated the visual representation of the interrelations and the barriers associated with BDA adoption. The diagram is structured according to the canonical for of the matrix. There are six levels in the diagram, the top level of the diagram includes three barriers (5) legacy systems, (10) lack of knowledge sharing and (4) organizational resistance to change. All of which characterised by high level of dependence power but with varying level of driving power. This means that these barriers highly rely on the barriers in lower level of the diagram, changes in the bottom lower level will affect them but they have little to no effect on the barriers below.

The next level of the diagram represents (3) lack of top management commitment, (14) scalability challenges, (1) poor business case, and (2) financial constraints also with very high dependent power but a higher driving power than the barriers (5,10,14). The next three levels down include (7) poor business case, (11) lack of infrastructure readiness, (15) risk of system failure, (9) legal and ethical challenges and (8) concerns for data security, these have very high driving power and varying levels of dependence power, these are the most volatile barriers that could greatly influence other barriers when comes to adopting BDA, linkage barriers. They have strong highly influential links to the level above and the levels below and are highly influenced by other connected barriers.

The final layer of the diagram represents the key barriers to BDA adoption. The following barriers have relatively low dependency and the highest driving power and greatly affect the barriers in the layers above, (6) complexity of data management, (13) immature technology, and (12) lack of skilled labour.

6 Conclusion

This study aims to identify the critical barriers and their dynamic interrelations that hinder the application of BDA based smart sustainable auditing system. BDA is a great tool for data analysis, with predictive and preventative features that could be of immense support if the barriers are overcome. A systematic literature review and expert opinions were considered to identify the barriers. We identified fifteen barriers of BDA application for smart sustainable auditing system. We applied ISM as a methodology to understand the barriers and their inter-relationships.

The outcomes of this study deepen the understanding of the interrelationships of the many factors surrounding the BDA adoption. It brought insight to the barriers of BDA adoption by the RSPO and other certifying bodies. BDA is a great opportunity to advance the auditing practices of sustainable palm oil but faces several challenges that have to overcome. A key has various barriers that need to be taken into consideration contribution is the identification of key barriers and illustrating the links between the barriers and how these links are represented in the context of their driving and dependence power. The study highlights the most critical barriers that need to be resolved which included advancing immature technology, resolving the complexity of data management, lack of skilled labour, and legal and ethical challenges. These results are highly insightful and practically useful for procurement executives and policymakers. BDA as a technology has shown immense potential for application across a number of industries including agriculture. It can facilitate better visualisation, collaboration, and, decision-making. But the technology is still in its nascent stage and needs to overcome some of the disadvantages. The managers need to understand the potential of the technology as well as the challenges they might face while implementation. This paper makes a significant contribution by identifying the key barriers that managers might face. This helps the manager understand the overall challenges that they need to consider while evaluating the potential of BDA application. This paper also identifies the mutual relationships and hierarchy of the barriers that will help the managers understand the relative importance and dependence of the barriers on the overall system. This will also help them develop intervention plans to overcome the identified barriers

6.1. Limitations and Future scope for research

These results shall be treated as an initial step towards the understanding of the BDA adoption barriers. The strength of the current ISM model is that it is generated based on the expert opinion without any prior knowledge but it is not statistically validated. In future researcher may explore the dynamic changes in barrier priorities using statistical modelling approaches such as Partial Least Square modelling or structural equation modelling approach. Researchers can also apply the Total Interpretive Structural Modelling with Fuzzy MICMAC analysis using this study as a foundation. Researchers may also explore the potential interventions and its impact on the barriers.

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Literature Review on Barriers for Technology & BDA adoption

List of Barriers related to BDA adoption is created

Obtaining Expert review of barriers & contextual relationships

Process the reachability matrix into different levels

Develop contextual relationship between barriers (SSIM)

If reachability and intersection at final level, develop canonical form of reachability matrix

Develop Initial reachability matrix

Develop diagram

Identify any Transitivity

Replace variable nodes with relationship statements

Develop Final reachability matrix

Conceptual inconsistencies

Yes

No

Create ISM model representing the relationship statement

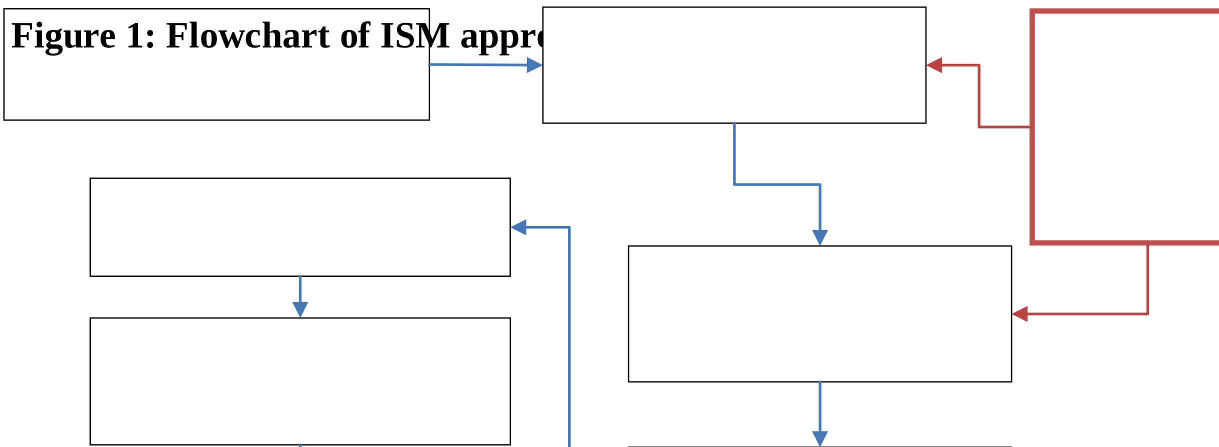

Figure 1: Flowchart of ISM appr

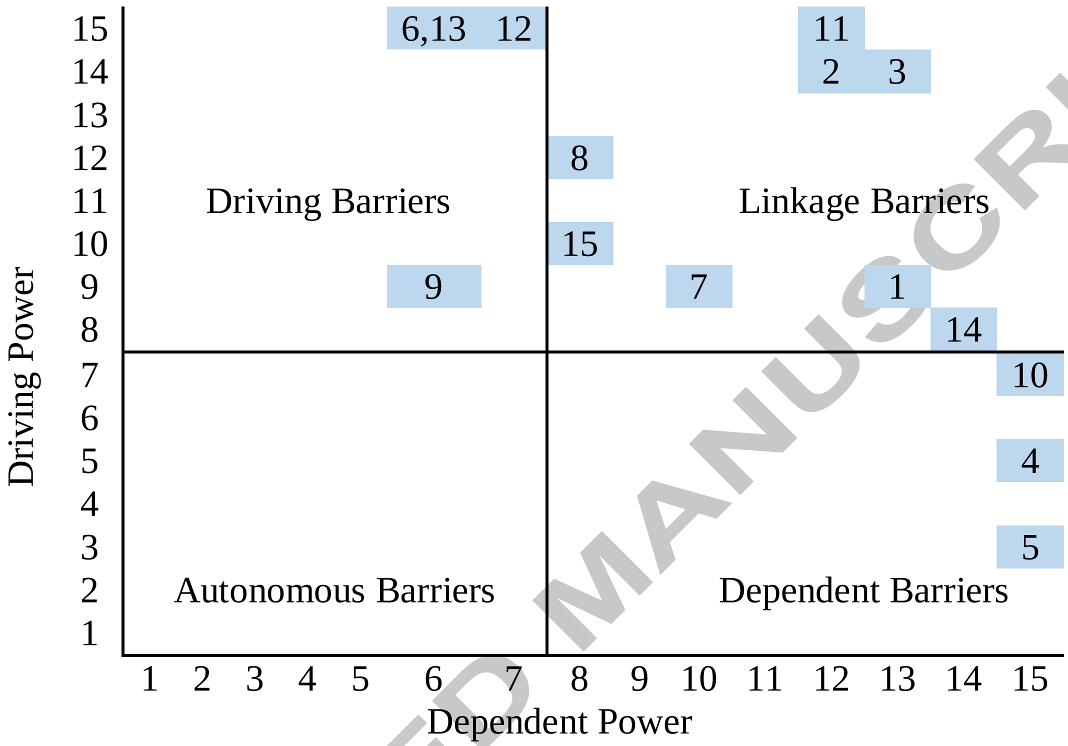

Figure 2: MICMAC Diagram

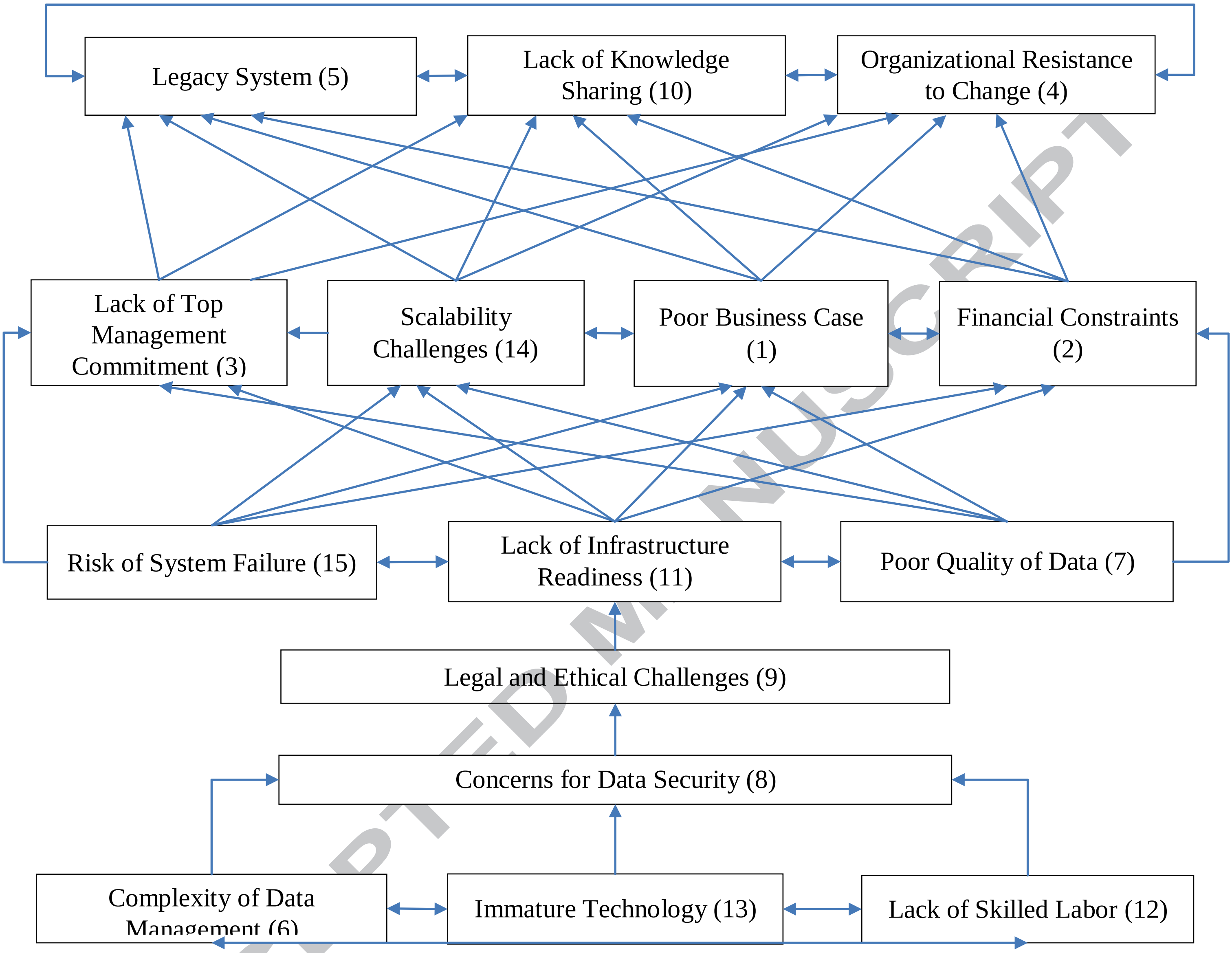

Figure 3: ISM model of BDA adoption barriers

Table 1: Summary of literature on barriers and challenges of adopting technology

Barrier	Description	(Jharkharia & Shankar, 2005)	(del Río González, 2005)	(Luken and Rompaey, 2008)	(Russom, 2011)	(Sagiroglu and et al., 2013)	(Davenport, 2013)	(Villars, Olofson, & Eastwood, 2011)	(Keeso, 2014)	(Malomo et al., 2016)	(Alharthi et al., 2017)	(Zhang, 2017)	(Lee, 2017)	(Mazzei et al., 2017)	(Janssen et al., 2017)	(Brohi et al., 2016)	(Chen & Zang, 2014)	(Kache & Stefan, 2017)	(Hashem et al., 2015)	(Schoenherr & Speier-Pero, 2015)
1. Poor Business Case	Most firms have concerns justifying large investments required to implement big data technologies. Concerns for long payback period, concerns of applicability, no economic values such as increase in sales or exports.		X		X	X			X		X		X					X		X
2. Financial Constraints	Lack of funds to finance the initial and running cost (e.g. data storage, training of employees…). Firms usually underinvest in ICT as not enough budget is allocated to upgrading technologies.	X	X	X		X			X	X								X		X
3. Lack of Top Management Commitment	Lack of top management commitment due lack of awareness of BDA, other priorities, don't see the benefits of BDA to their line of business.	X	X	X	X					X										X
4. Organizational resistance to change	The organizational behaviour is resistant to change and is comfortable with current methodologies used. Organization culture is resistant to technology.	X	X						X	X	X	X		X				X		X
5. Legacy System	Current systems not obsolete yet, relay on current systems as they are reliable. Drastic change is need to utilise new systems, can happen quickly.	X	X							X					X					X
6. Complexity of Data Management	Heterogeneous and massive amounts of data is generated, most firms will not be able to invest in storing and updating the current architecture of their data centres				X		X		X	X	X			X		X	X	X	X	X
7. Poor Quality of Data	The more unstructured the data is and the wide array of source, quality of data tends to decline (data noise). User entry errors, replication, and the possibility of corrupted data are reasons for poor data quality							X						X	X	X	X		X	X
8. Concerns for Data Security	Data security issue can cost firms their reputation and legitimacy. Confidentiality of information and security against cyber attacks	X				X	X		X	X						X	X	X	X	X

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9. Legal and Ethical Challenges	Collection of personal data raises red flags for individuals, firms, and government. Governance and data ownership and data exploitation raises ethical, legal and privacy concerns. Use of data to profile consumers can be unethical. Transparency, trust and privacy concerns for use of third party cloud service providers		X							X	X		X		X	X		X	X	X
10. Lack of Knowledge Sharing	Reluctance to share information with suppliers and collaboration with other stakeholders.	X		X								X			X			X		
11. Lack of Infrastructure Readiness	Business lack the infrastructure to implement BDA, greater network latency, higher CPU to process data, upgraded in order to adopt BDA technologies and resolve bottlenecks.	X			X	X					X	X						X		
12. Lack of Skilled Labour	Shortage of experienced and skilled data scientists and staff. Firms are sometimes unwilling to invest in technologies as they don't have the in-house capabilities to use these systems. There is high shortage in qualified data scientist.			X		X			X	X	X	X		X				X		X
13. Immature technology	Existing BDA technology is relevantly new and is still developing. Current technology has many flaws and is unlikely to improve in the short run. Current analytics are too slow and inadequate. Timeliness of an important attribute that need to be resolved. The incapability to make use of the data as the analysis takes too long and becomes outdated.	X	X		X	X	X									X	X			X
14. Scalability Challenges	Unmanageable data growth rate, the rapid growth of data and the ability to process this data remains a concern regarding BDA technologies.				X	X										X	X		X	X
15. Risk of system failure	Fear of system breakdown, uncertainty of performance impact and lack of clarity of the systems capabilities.	X		X					X											

Table 2: Barriers to adopting BDA in certification of sustainable palm oil				
#	**Barriers to adopting BDA**	**Mean score**	**Standard Deviation**	**Rank**
1	Poor Business Case	3.9	0.89974	8
2	Financial Constraints	4.1	0.69007	3
3	Lack of Top Management Commitment	4.0	1.00000	6
4	Organizational resistance to change	4.0	1.41421	7
5	Legacy System	3.9	1.06904	9
6	Complexity of Data Management	3.6	1.27242	13
7	Poor Quality of Data	3.6	1.27242	14
8	Concerns for Data Security	4.1	0.69007	4
9	Legal and Ethical Challenges	3.9	1.06904	10
10	Lack of Knowledge Sharing	4.1	1.46385	5
11	Lack of Infrastructure Readiness	4.4	0.53452	1
12	Lack of Skilled Labour	4.3	1.25357	2
13	Immature Technology	3.9	1.67616	12
14	Scalability Challenges	3.9	1.46385	11
15	Risk of System Failure	2.9	1.46385	15

Table 3: Final Structural self-interaction matrix

#	Barriers (i)	Barriers (j) 15	14	13	12	11	10	9	8	7	6	5	4	3	2
1.	Poor Business Case	A	X	A	A	A	O	A	A	A	A	V	V	V	X
2.	Financial Constraints	O	V	O	V	V	O	O	O	O	O	V	O	X	
3.	Lack of Top Management Commitment	A	A	A	A	X	V	A	A	A	A	V	V		
4.	Organizational resistance to change	A	A	A	A	A	V	A	A	A	A	X			
5.	Legacy System	A	A	A	A	A	A	A	A	A	A				
6.	Complexity of Data Management	O	V	A	X	X	O	V	V	V					
7.	Poor Quality of Data	O	O	A	A	A	A	O	O						
8.	Concerns for Data Security	X	V	A	O	A	V	V							
9.	Legal and Ethical Challenges	O	O	O	O	O	V								
10.	Lack of Knowledge Sharing	O	V	O	O	O									
11.	Lack of Infrastructure Readiness	V	V	X	A										
12.	Lack of Skilled Labour	O	V	O											
13.	Immature Technology	V	V												
14.	Scalability Challenges	A													
15.	Risk of System Failure														

Table 4: Initial reachability matrix

	Barriers (j)														
Barriers (i)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Poor Business Case	1	1	1	1	1	0	0	0	0	0	0	0	0	1	0
Financial Constraints	1	1	1	0	1	0	0	0	0	0	1	1	0	1	0
Lack of Top Management Commitment	0	1	1	1	1	0	0	0	0	1	1	0	0	0	0
Organizational resistance to change	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0
Legacy System	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0
Complexity of Data Management	1	0	1	1	1	1	1	1	1	0	1	1	0	1	0
Poor Quality of Data	1	0	1	1	1	0	1	0	0	0	0	0	0	0	0
Concerns for Data Security	1	0	1	1	1	0	0	1	1	1	0	0	0	1	1
Legal and Ethical Challenges	1	0	1	1	1	0	0	0	1	1	0	0	0	0	0
Lack of Knowledge Sharing	0	0	0	0	1	0	1	0	0	1	0	0	0	1	0
Lack of Infrastructure Readiness	1	0	1	1	1	1	1	1	0	0	1	0	1	1	1
Lack of Skilled Labour	1	0	1	1	1	1	1	0	0	0	1	1	0	1	0
Immature Technology	1	0	1	1	1	1	1	1	0	0	1	0	1	1	1
Scalability Challenges	1	0	1	1	1	0	0	0	0	0	0	0	0	1	0
Risk of System Failure	1	0	1	1	1	0	0	1	0	0	0	0	0	1	1

Table 5: Final reachability matrix

	Barriers (j)														
Barriers (i)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Poor Business Case	1	1	1	1	1	0	0	0	0	1	1	1	0	1	0
Financial Constraints	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
Lack of Top Management Commitment	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
Organizational resistance to change	0	0	0	1	1	0	1	0	0	1	0	0	0	1	0
Legacy System	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0
Complexity of Data Management	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Poor Quality of Data	1	1	1	1	1	0	1	0	0	1	1	0	0	1	0
Concerns for Data Security	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1
Legal and Ethical Challenges	1	1	1	1	1	0	1	0	1	1	1	0	0	1	0
Lack of Knowledge Sharing	1	0	1	1	1	0	1	0	0	1	0	0	0	1	0
Lack of Infrastructure Readiness	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Lack of Skilled Labour	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Immature Technology	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Scalability Challenges	1	1	1	1	1	0	0	0	0	1	1	0	0	1	0
Risk of System Failure	1	1	1	1	1	0	0	1	0	1	1	0	0	1	1

Table 6: Level Partition –Iteration I

Barriers (i)	Reachability set	Antecedent set	Intersection	Level
Poor Business Case	1,2,3,4,5,10,11,12,14	1,2,3,6,7,8,9,10,11,12,13,14,15	1,2,3,10,11,12,14	
Financial Constraints	1,2,3,4,5,6,7,8,10,11,12,13,14,15	1,2,3,6,7,8,9,11,12,13,14,15	1,2,3,6,7,8,11,12,13,14,15	
Lack of Top Management Commitment	1,2,3,4,5,6,7,8,10,11,12,13,14,15	1,2,3,6,7,8,9,10,11,12,13,14,15	1,2,3,6,7,8,10,11,12,13,14,15	
Organizational resistance to change	4,5,7,10,14	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	4,5,7,10,14	I
Legacy System	4,5,10	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	4,5,10	I
Complexity of Data Management	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	2,3,6,11,12,13	2,3,6,11,12,13	
Poor Quality of Data	1,2,3,4,5,7,10,11,14	2,3,4,6,7,8,10,11,12,13	2,3,4,7,10,11	
Concerns for Data Security	1,2,3,4,5,7,8,9,10,11,14,15	2,3,6,8,11,12,13,15	2,3,8,11,15	
Legal and Ethical Challenges	1,2,3,4,5,7,9,10,11,14	6,8,9,11,12,13	9,11	
Lack of Knowledge Sharing	1,3,4,5,7,10,14	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,3,4,5,7,10,14	I
Lack of Infrastructure Readiness	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,6,7,8,9,11,12,13,14,15	1,2,3,6,7,8,9,11,12,13,14,15	
Lack of Skilled Labour	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	1,2,3,6,11,12,13	1,2,3,6,11,12,13	
Immature Technology	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15	2,3,6,11,12,13	2,3,6,11,12,13	
Scalability Challenges	1,2,3,4,5,10,11,14	1,2,3,4,6,7,8,9,10,11,12,13,14,15	1,2,3,4,10,11,14	
Risk of System Failure	1,2,3,4,5,8,10,11,14,15	2,3,6,8,11,12,13,15	2,3,8,11,15	

Table 7: Level Partition –Iteration II

Barriers (i)	Reachability set	Antecedent set	Intersection	Level
Poor Business Case	1,2,3,11,12,14	1,2,3,6,7,8,9,11,12,13,14,15	1,2,3,11,12,14	II
Financial Constraints	1,2,3,6,7,8,11,12,13,14,15	1,2,3,6,7,8,9,11,12,13,14,15	1,2,3,6,7,8,11,12,13,14,15	II
Lack of Top Management Commitment	1,2,3,6,7,8,11,12,13,14,15	1,2,3,6,7,8,9,11,12,13,14,15	1,2,3,6,7,8,11,12,13,14,15	II
Complexity of Data Management	1,2,3,6,7,8,9,11,12,13,14,15	2,3,6,11,12,13	2,3,6,11,12,13	
Poor Quality of Data	1,2,3,7,11,14	2,3,6,7,8,11,12,13	2,3,7,11	
Concerns for Data Security	1,2,3,7,8,911,14,15	2,3,6,8,11,12,13,15	2,3,8,11,15	
Legal and Ethical Challenges	1,2,3,7,9,11,14	6,8,9,11,12,13	9,11	
Lack of Infrastructure Readiness	1,2,3,6,7,8,911,12,13,14,15	1,2,3,6,7,8,9,11,12,13,14,15	1,2,3,6,7,8,9,11,12,13,15	
Lack of Skilled Labour	1,2,3,6,7,8,9,11,12,13,14,15	1,2,3,6,11,12,13	1,2,3,6,11,12,13	
Immature Technology	1,2,3,6,7,8,9,11,12,13,14,15	2,3,6,11,12,13	2,3,6,11,12,13	
Scalability Challenges	1,2,3,11,14	1,2,3,6,7,8,9,11,12,13,14,15	1,2,3,11,14	II
Risk of System Failure	1,2,3,8,11,14,15	2,3,6,8,11,12,13,15	2,3,8,11,15	

Table 8: Level Partition –Iteration III

Barriers (i)	Reachability set	Antecedent set	Intersection	Level
Complexity of Data Management	6,7,8,9,11,12,13,15	6,11,12,13	6,11,12,13	
Poor Quality of Data	7,11	6,7,8,11,12,13	7,11	III
Concerns for Data Security	7,8,911,15	6,8,11,12,13,15	8,11,15	
Legal and Ethical Challenges	7,9,11	6,8,9,11,12,13	9,11	
Lack of Infrastructure Readiness	6,7,8,911,12,13,15	6,7,8,9,11,12,13,15	6,7,8,9,11,12,13,15	III
Lack of Skilled Labour	6,7,8,9,11,12,13,15	6,11,12,13	6,11,12,13	
Immature Technology	6,7,8,9,11,12,13,15	6,11,12,13	6,11,12,13	
Risk of System Failure	8,11,15	6,8,11,12,13,15	8,11,15	III

Table 9: Level Partition –Iteration IV

Barriers (i)	Reachability set	Antecedent set	Intersection	Level
Complexity of Data Management	6,8,9,12,13	6,12,13	6,12,13	
Concerns for Data Security	8,9	6,8,12,13	8	
Legal and Ethical Challenges	9	6,8,9,12,13	9	IV
Lack of Skilled Labour	6,8,9,12,13	6,12,13	6,12,13	
Immature Technology	6,8,9,12,13	6,12,13	6,12,13	

Table 10: Level Partition –Iteration V

Barriers (i)	Reachability set	Antecedent set	Intersection	Level
Complexity of Data Management	6,8,12,13	6,12,13	6,12,13	
Concerns for Data Security	8	6,8,12,13	8	V
Lack of Skilled Labour	6,8,12,13	6,12,13	6,12,13	
Immature Technology	6,8,12,13	6,12,13	6,12,13	

Table 11: Level Partition –Iteration VI

Barriers (i)	Reachability set	Antecedent set	Intersection	Level
Complexity of Data Management	6,12,13	6,12,13	6,12,13	VI
Lack of Skilled Labour	6,12,13	6,12,13	6,12,13	VI
Immature Technology	6,12,13	6,12,13	6,12,13	VI

Table 12: Canonical form of the Final Reachability Matrix

Barriers	**4**	**5**	**10**	**1**	**2**	**3**	**14**	**11**	**7**	**15**	**9**	**8**	**6**	**12**	**13**	**Level**
4	1	1	1	0	0	0	1	0	1	0	0	0	0	0	0	**I**
5	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	**I**
10	1	1	1	1	0	1	1	0	1	0	0	0	0	0	0	**I**
1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	**II**
2	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	**II**
3	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	**II**
14	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	**II**
11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**III**
7	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	**III**
15	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	**III**
9	1	1	1	1	1	1	1	1	0	0	1	0	0	0	0	**IV**
8	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	**V**
6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**VI**
12	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**VI**
13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**VI**

Table 13: The driving power and dependence powers

Barriers	**4**	**5**	**10**	**1**	**2**	**3**	**14**	**11**	**7**	**15**	**9**	**8**	**6**	**12**	**13**	**Driving Power**
4	1	1	1	0	0	0	1	0	1	0	0	0	0	0	0	**5**
5	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	**3**
10	1	1	1	1	0	1	1	0	1	0	0	0	0	0	0	**7**
1	1	1	1	1	1	1	1	1	0	0	0	0	0	1	0	**9**
2	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	**14**
3	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	**14**
14	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	**8**
11	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**15**
7	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	**9**
15	1	1	1	1	1	1	1	1	0	1	0	1	0	0	0	**10**
9	1	1	1	1	1	1	1	1	0	0	1	0	0	0	0	**9**
8	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	**12**
6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**15**
12	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**15**
13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**15**
Dependent Power	**15**	**15**	**15**	**13**	**12**	**13**	**14**	**12**	**10**	**8**	**6**	**8**	**6**	**7**	**6**	

Highlights

1. Addresses the critical issue of sustainable auditing systems
2. Identifies a comprehensive list of barriers to the adoption of BDA
3. Rank the barriers faced by the palm oil industry for the adoption of BDA
4. Establish the relationship among the identified barriers
5. Proposes solutions for possible interventions