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Big Data Intelligence in Public and Financial Institutions: An Estimation of Ethical and Regulatory Issues

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Abstract

In this data-driven world, Big Data Intelligence has always been a critical technology in harnessing true values of data. Financial institutions can greatly benefit from its use, but the ethical risks associated to it and indistinct regulatory stance have made some financial institutions to hesitate on its implementation. The research has hypothesized that the adoption level of Big Data Intelligence in an organization, whether public or financial, is linked to the awareness on the concerns relating to its processes, measures taken to address related concerns and knowledge of various areas of focus for relevant regulations. To support the hypothesis, data was collected from various level of management and policymakers for both public as well as financial institutions of Brunei Darussalam through the distribution of survey questionnaires. The analysis has focused on using Cronbach Alpha, Pearson Correlation and Linear Regression techniques. The results showed that the hypothesis was partly correct as the analysis has supported that the knowledge on the concerns relating to processes in Big Data Intelligence and the understanding of key areas of regulators' relevance contribute towards the adoption level of Big Data Intelligence in an organization.

Keywords: Big Data, Data Analytics, Artificial Intelligence, Data Ethics, Organizational e-Policy

1 Introduction

Big data intelligence involves the analysis of multiple datasets so that it can be used by organisations in improving their services and to help them in making better decisions. Big data has always been an important driver of innovation that increases firms' competitive advantage in creating innovative data combination when shared across organisations. However, the sharing of big data across various organisations might lead to sharing of personal information about various dimensions of individuals' life which as a result is a compromise of individual rights about personal data. Therefore, various concerns have been raised about the

legitimate and ethical use of Big Data Intelligence in order to avoid unnecessary misuse of private information about individuals. The financial service industry is one of the industries that can greatly benefit from the use of Big Data Intelligence. The most crucial use by the financial institutions is the ability to reduce risks such as credit risks and liquidity risks. The public organizations, through the e-government initiatives are also generating huge amounts of data and thus have a huge potential to apply Big Data Intelligence. Financial institutions are committed in adopting innovation and technology, especially to harness consumer's data using Big Data Intelligence. The consumer protection of financial or public sector e-user can be compromised if there are not well guided regulations by the regulator.

There is limited research performed on the relationship between adoption level of Big Data Intelligence in an organisation with knowledge on ethical concerns relating to the technology and the mitigation strategies to address these concerns. This research has aimed to bridge this gap. The paper has been divided into five sections. The second section, preceding this section on introduction, reviews the literature and section three is about data description and methodology. Section four and five are on 'description of results and analysis' and 'concluding remarks' respectively.

2 Literature review

The study has performed literature review of several subject areas relevant to Big Data Intelligence in the context of Ethics, Governance, Data Collaboration, Legal Framework, Regulation and Policy. Regarding the literature on Ethics and Big Data, the Kantian aspect of ethics is concerned with what people should do based on the reflection of rules that everyone should follow and do things the right way (Herschel & Miori, 2017). When assessing the ethics of big data, actions should be assessed by weighing the positive or negative impact that the use of big data will cause. The social contract theory of ethics suggests that the moral obligations of a person depend on the agreement that people have made to form the society where they live (Richards & King, 2014). In relation to big data usage, people who use big data technology should be able to control how it affects them by collectively creating rational rules based on moral rights. People's action reflects their moral character.

Regarding the literature on Governance of Big Data Collaborations, according to van den Broek and van Veenstra (2018), four governance arrangements that are commonly investigated in the use of big data collaboration cases are market model, bazaar, hierarchical, and network. The database for the healthcare insurance company is used to investigate the case of a hierarchical arrangement. In this case, a large insurance company gathers information of healthcare patients into a centralised database for administrative and research purposes upon a thorough selection process (van den Broek & van Veenstra, 2018). It is not clear who owns the data and who is liable in cases of data misuse. Liability has to be determined on case by case basis. Meanwhile, for the network arrangement, an energy data platform is studies as a collaboration case where data is managed by grid operator with a research institute and telecommunication provider. The platform is also open to new participants and data sources. Participants of the network jointly own the energy data platform, but each individual member owned the data they publish on the platform. The literature on Big Data, Privacy and Con-

sumer Welfare states that making data accessible to various entities is one way of ensuring an organisation benefits from big data. An organisation is, however, still responsible for any misuse of data by third parties and other stakeholders (Kshetri, 2014). It is essential to have detailed information about every person that has access to the data. The regulatory guideline should take into consideration such factors and ensure that businesses only develop strategies that are understandable to the consumers.

Regarding the Principles in Artificial Intelligence and Data Analytics, Lepri, et al. (2018) has introduced five principles used in artificial intelligence and data analytics (AIDA). Fairness is one of the principles used in AIDA especially in the financial sector. It involves justifiability where individuals are not systematically disadvantaged through decisions that are driven by AIDA unless the decisions are justifiable based on personal attributes. Secondly, Accuracy and Bias principle involve regular review and validation of data and models used in making decisions driven by AIDA to ensure relevance and accuracy as well as minimising unintentional bias. Ethics is another principle that helps in making decisions driven by AIDA. The organisation's ethical standards, codes of conduct and values should be aligned with the use of AIDA. Decisions that are driven by AIDA are held to match the ethical standards of human-driven decisions. Next, the principle of Accountability includes internal and external accountability. Internal accountability involves the use of AIDA in decision making after approval by an internal authority so that the firm is deemed liable. The external accountability aspect involves the provision of data subjects with channels to inquire about, request reviews, and submit appeals for AIDA-driven-decisions that are affected by them. Transparency is a principle to increase public confidence by using AIDA to proactively disclose to the data subjects as part of general communication.

Legal framework is a key aspect in addressing ethical issues that are related to big data and privacy. According to Costanzo, D'Onofrio, and Friedl (2015), the European legal framework relating to data and privacy outlined that individuals' data must be processed lawfully, fairly, and only for specific and legitimate reasons. This directive was later extended to the electronic communication sector before a directive to the telecommunication service providers to retain data for purposes of investigation, detection, and prosecution relating to terrorism and serious crimes. Data protection was not guaranteed and thus raising concerns about the security of private information and ethics related issues. In 2008, the protection of individual data was established as it was perceived that individuals have right to have their data protected and to have right to a private and family life (Costanzo, D'Onofrio, & Friedl, 2015). In 2016, general data protection regulation requires non-Europeans companies that offered goods and services to provide transparency, easy access and efficient control to their customers for their respective data. According to Costanzo, D'Onofrio, and Friedl (2015), in 1996, the authority for personal data protection in Italy was established. The authority was established purposely to protect the rights, fundamental liberties, and enhance respect for personal dignity when processing individual data. The data protection rights resulted to control over individual's data and information. On the other hand, Secrecy rights introduced the right not to involve other parties from knowing about personal and family-related information. The framework categorised data into sensitive, judiciary, semi-sensitive and traffic data. The establishment of the

Centre for Elaboration of Data was purposefully to collect, elaborates, classify and store data and information in automated files for national security and crime fighting.

Big Data Regulation has its challenges as well. The regulation of big data usage is not efficient for various reasons. In Russia, the regulations are hindered by factors such as difficulty in obtaining informed consent from data subjects for all users of information. The personal datasets also include many safeguards that ensure the protection of the holder's identities. When such data combined with other datasets, a re-identification might occur. Another factor is the difficulty in applying withdrawal of consent in cases where individual data are already aggregated in a large volume of anonymized data (Zharova and Elin; 2017). According to Butterworth (2018), the opacity of processing and repurposing of data causes the challenge of big data processing that majorly relies on consent under the General Data Protection Regulation (GDPR). It becomes difficult to obtain consent as required by the GDPR if the purpose for which data is being collected and analysed is unclear during the data collection process. Big data analysis often involves the collection of data that is later analysed by correlating with information from other sources (Broeders et al., 2017). Regarding having the policy pertaining to Big Data and Data Management, it is recommended that all firms especially, in the financial sector to consider the emerging standards of accountability at every stage of the processes of development of data policy. The organisations should examine every process concerned with the gathering of information. The firms should clearly state the policies and guideline of internal employees concerning data management. The financial institutions should also put in place a breach notification process that incorporates procedures that would detect the breaches early enough. Any breach should be reported regardless of the presence of protective measure. A survey conducted by Edelman privacy risk index that involved 6400 corporate members indicated that 57% of the participants think their companies did not prioritise the protection of private data and thus raising concern on the development of data management regulation (Raymond, 2013).

3 Data Description and Methodology

Surveys are economical, convenient and efficient as compared to other data collection methods. However, Salan & Dillman (1994) reminds that survey can only provide estimates of true population and not the exact measurements. This research collects data using online survey questionnaire, Google Form because it will be faster to design the questionnaire and easier to compile all data because of its structured and already digital format. All questions will be closed ended questions to reduce inconsistency. Moreover, considering the high mobile penetration and internet usage in Brunei Darussalam, online survey questionnaire can reach out more audience and allow respondents to answer the questionnaire at their own preferred time. The objective of our survey is to verify if awareness of the ethical concerns relating to Big Data Intelligence processes, knowledge on the measures to address these concerns and expectation from regulatory guidelines have effects to the adoption level of Big Data Intelligence in an organisation. The target groups for this research were policymakers, which includes government agencies and statutory bodies; and the financial institutions, which includes banks, finance companies, Takaful operators, insurance companies, capital market companies, securities operators, money changing business and money remittance companies.

3.1 Research Questions, Variables and Instruments

This research believed that the adoption level of Big Data Intelligence in an organisation correlates with the organisation's awareness of the ethical concerns relating to the processes involved in Big Data Intelligence, and expectations on the regulatory guidelines. To support this thrust, two research questions have been investigated regarding an organization which is consider the implementing of Big Data Intelligence. These two pronged research questions have been illustrated in the following diagram.

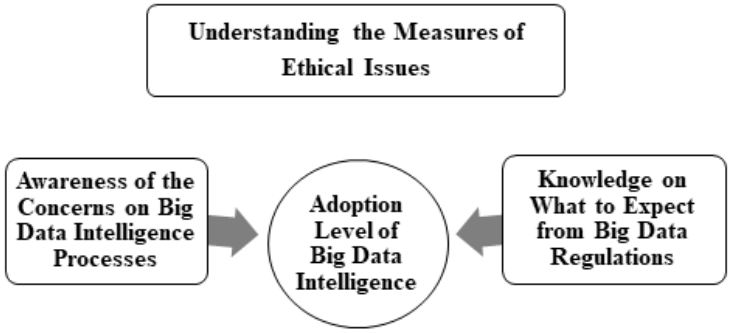

Figure 1: *Research Question Relationship Diagram*

There are three sections in the questionnaire with total of 18 questions which are being discussed in this article here. The sections one through three are abbreviated as BDI_ADPLVL, BDIPR_CON and REG_EXPCT representing the Current Adoption Level of Big Data Intelligence in an Organization, Awareness of the Organization about the Concerns on Data Processes and Knowledge of What to Expect from Regulation respectively. There are questions about organisation's current adoption level of BIG DATA i.e. whether not-considering it (BDI_NOT), already at Research and Testing stage (BDI_RSCH), already has a strategy for it(BDI_STRA), progress is ongoing (BDI_ONGO) or has already implemented it (BDI_IMPL), about the level of concerns of organisation/team i.e. about data collection (CON_COLLCT), classification (CON_CLASS), storage (CON_STORE), analysis (CON_ANLYS), sharing (CON_SHARE), publishing (CON_PUB), disposal (CON_DISP) and security (CON_SECURE) as well as about the extent of agreement in regards to the focus of regulations for big data intelligence in dimensions like Personal Data Protection (REG_DATPRO), Privacy Rights (REG_PRIV), Data Analytics (REG_DA), Big Data (REG_BD), Data Sharing (REG_SHARE), Artificial Intelligence (REG_AI), Machine Learning (REG_ML), Biasness of Algorithms (REG_BIAS), Code of Ethics (REG_COETHI), Data Governance (REG_DATGOV), Data Security (REG_DATSEC), Technology and Innovation (REG_TECH) and Cybersecurity (REG_CYBER).

3.2 Data Collection Methods and Response Rate

Primary data is collected through closed-ended questionnaires and analysed using quantitative methods. This is based on the hypothesis and research questions that were defined after the literature review. In order to increase the response rate, it is highly important to assure the respondents that individual responses will be treated with confidentiality. Personal information and identity of the respondents will be made anonymous and that some sort of aggregation of data will be performed before analysis results are made public. Privacy of the re-

spondents will be protected within possible limits at all costs. Therefore, a disclaimer has been added on the top of the questionnaire in order to inform respondents that the research is committed to protect the privacy of individual respondents.

The questionnaires have been distributed through the use of Google Forms and circulated through email and Whatsapp. The email and questionnaire link were sent to all government ministries and departments, and all financial institutions through their official focal contact emails as provided in the government directories and financial institutions directories respectively. Their corporate communication representatives were contacted over the phone to follow up to the email. The research trusts that each representative of the organisation has distributed the questionnaire to their relevant units and team. Despite, the response rate has fallen short of expectations with total of only 58 completed responses. Once data has been collected, it has been extracted as Excel spreadsheet which then has been imported to SPSS for analysis purposes. All the questions have been tested based on five Likert scale options. Before applying analysis on the data, it must first be cleaned up.

4 Analysis Results and Research Findings

The data obtained from the questionnaires were compiled and cleaned for analysis. First descriptive analysis was applied on these data. Then, the data were analysed using inferential methods to assess validity, reliability and correlations. The analysis was performed using IBM SPSS software.

4.1 Descriptive Analysis

The descriptive analysis applied in this research has been based on Mean/Average. The BDI_ADPLVL were divided into five stages: BDI_NOT, BDI_RSCH, BDI_STRA, BDI_ONGO and BDI_IMPL. The research questions focused on organisations that consider implementing Big Data Intelligence so the main instruments for BDI_ADPLVL to be analysed were BDI_STRA, BDI_ONGO and BDI_IMPL. Instead of having three separate dependent variables, BDI_CONS was used as variable for organisation that consider implementing Big Data Intelligence. BDI_CONS is the Mean value of BDI_STRA, BDI_ONGO and BDI_IMPL.

Table 1
Cronbach's Alpha Test Result: Part 1

Variables	Instruments	Most Desirable Combination	Second Alpha	First Alpha
BDI_ADPLVL	BDI_CONS	-	-	-
BCIPR_CON	CON_COLLCT	CON_ANLYS	0.862	0.941
	CON_ANLYS	CON_PUB		
	CON_PUB	CON_SHARE		
	CON_SHARE	CON_DISP		
	CON_DISP			
	CON_STORE			
	CON_SECURE			
	CON_CLASS			

The Overall Cronbach's Alpha for the Questionnaire = 0.975

4.2 Cronbach's Alpha

The instruments for the variables BDI_ADPLVL, BCIPR_CON and REG_EXPCT were tested using Cronbach's Alpha on SPSS. The results of the reliability test are as shown in Table 1 and Table 2. The Overall Alpha was found to be 0.975, which is closer to value 1.0. This indicates that the entire instruments have good internal consistency but less unidimensional. The Alpha for the DATPR_CON and REG_EXPCT are 0.941 and 0.926 respectively. This suggests that the instruments combination for each variable also have good internal consistency but less unidimensional. Although the tests showed good reliability with the research objectives, some of the instruments may be redundant with each other. The desirable Alpha value should be closer to 0.8. Therefore, to obtain standardised Alpha for each variable, the number of instruments must be removed until desirable combination is found. For BCIPR_CON variable, CON_COLLECT, CON_STORE, CON_SECURE and CON_CLASS were removed to get standardised Alpha value of 0.862. Meanwhile, REC_ENCRY, REC_ACCESS, REC_ANON, REC_INTEG, REC_SANIT, REC_CLASS, REC_ASSET, REC_AUDIT and REC_DLP were removed to get standardised Alpha value of 0.898 for REL_REC. Next, the standardised Alpha for LIA_REC is 0.813 after LIA_PROCS, LIA_WITHDR, LIA_COMPLY, LIA_ACCESS and LIA_THIRD were removed from the combination. For REG_EXPCT, the Alpha value became 0.801 when REG_DA, REG_BD, REG_AI, REG_ML, REG_COETHI, REG_DATGOV and REG_DATSEC were removed.

Table 2
Cronbach's Alpha Test Result: Part 2

Variables	Instruments	Most Desirable Combination	Second Alpha	First Alpha
REG_EXPCT	REG_DATPRO	REG_DATPRO	0.801	0.926
	REG_PRIV	REG_PRIV		
	REG_DA	REG_SHARE		
	REG_BD	REG_BIAS		
	REG_SHARE	REG_TECH		
	REG_AI	REG_CYBER		
	REG_ML			
	REG_BIAS			
	REG_COETHI			
	REG_DATGOV			
	REG_DATSEC			
	REG_TECH			
	REG_CYBER			

4.3 Pearson Correlation

The second inferential analysis performed in this research was (Karl) Pearson Correlation analysis. The result of the correlation analysis for all instruments are shown in tables 3 and 4.

Table 3

Pearson Correlation Analysis Result for Variable BDI_CONS: Part 1

Variables	Variable 2	r Correlation Coefficient	p Significance (2-tailed)
BDI_CONS	CON_COLLCT	0.402	0.003 *
	CON_STORE	0.404	0.003 *
	CON_CLASS	0.280	0.047 **
	CON_SECUR	0.321	0.022 **
	CON_ANLYS	0.453	0.001 *
	CON_PUB	0.554	0.000 *
	CON_SHARE	0.353	0.011 **
	CON_DISP	0.494	0.000 *

Note: (Applicable to Tables 4, 5, 6, and 7)

* means Correlation is significant at less than 0.01

** means Correlation is significant at less than 0.05

*** means Correlation is significant at less than 0.1

There were moderate, positive correlation between BCI_CONS with CON_COLLECT (r = 0.402, p-sig < 0.01), CON_STORE (r = 0.404, p-sig < 0.01), CON_ANLYS (r = 0.453, p-sig < 0.01), CON_PUB (r = 0.554, p-sig < 0.01) and CON_DISP (r = 0.494, p-sig < 0.01). Weak positive correlations were observed between BDI_CONS with CON_CLASS (r =0.280, p-sig < 0.05), CON_SECUR (r = 0.321, p-sig < 0.05) and CON_SHARE (r = 0.353, p-sig < 0.05) as have been shown in table 3.

Table 4

Pearson Correlation Analysis Result for Variable BDI_CONS: Part 2

Variables	r Correlation Coefficient	p Significance (2-tailed)
REG_DATPRO	0.279	0.047 **
REG_PRIV	0.311	0.026 **
REG_DA	0.438	0.001 *
REG_BD	0.410	0.003 *
REG_SHARE	0.328	0.019 **
REG_AI	0.374	0.007 *
REG_ML	0.326	0.019 **
REG_BIAS	0.439	0.001 *
REG_COETHI	0.250	0.077 ***
REG_DATGOV	0.394	0.004 *
REG_DATSEC	0.241	0.089 ***
REG_TECH	0.204	0.150
REG_CYBER	0.096	0.502

Lastly, there were moderate positive correlation between BDI_CONS with REG_BIAS (r = 0.439, p-sig < 0.01), REG_DA (r = 0.438, p-sig < 0.01) and REG_BD (r = 0.410, p-sig < 0.01). There were weak positive correlation between BDI_CONS with REG_DATGOV (r =

0.394, p-sig < 0.01), REG_AI (r = 0.374, p-sig < 0.01), REG_SHARE (r = 0.328, p-sig < 0.05), REG_ML (r = 0.326, p-sig < 0.05), REG_PRIV (r = 0.311, p-sig < 0.05), REG_DATPRO (r = 0.279, p-sig < 0.05), REG_COETHI (r = 0.250, p-sig < 0.1) and REG_DATSEC (r = 0.241, p-sig < 0.1) as have been shown in table 4.

4.4 Linear Regression

The next analysis performed in this research was the Linear Regression analysis. The result of the regression analysis between BCI_CONS as the target or dependent variable with all instruments of each variables as predictor or independent variables are shown in tables 5 & 6.

Table 5

Linear Regression Analysis Results for dependent variable of BDI_CONS: Part 1

Independent Variables	B Coefficient	R Square	F-stat Significance	t-value	P Significance
CON_COLLCT	-0.052	0.455	0.001*	-0.189	0.851
CON_STORE	0.122			0.416	0.680
CON_CLASS	-0.525			-2.451	0.019*
CON_SECUR	0.069			0.318	0.752
CON_ANLYS	0.251			1.341	0.187
CON_PUB	0.471			2.250	0.030*
CON_SHARE	-0.034			-0.166	0.869
CON_DISP	0.301			1.989	0.053**

Notes: (Notes are applicable to all the Table no. 5 and 6)

* means Regression is significant at less than 0.05

** means Regression is significant at less than 0.1

The overall regression between BDI_CONS with CON_COLLECT, CON_STORE, CON_CLASS, CON_SECUR, CON_ANLYS, CON_PUB, CON_SHARE and CON_DISP are moderately varied (R Square = 0.455) and are statistically significant (F-sig < 0.05). There are significant differences between BDI_CONS with CON_CLASS (t = -2.452, p-sig < 0.05) and CON_PUB (t = 2.250, p-sig <0.05) towards the hypothesis. In addition, CON_DISP has slight significance (t = 1.989, p-sig < 0.1) to the hypothesis.

Meanwhile, for BDI_CONS with REG_DATPRO, REG_PRIV, REG_DA, REG_BD, REG_SHARE, REG_AI, REG_ML, REG_BIAS, REG_COETHI, REG_DATGOV, REG_DATSEC, REG_TECH and REG_CYBER, the regression showed overall significance and moderate variability (R Square = 0.430, F-sig < 0.05). BDI_CONS have good significances with REG_BIAS (t = 2.752, p-sig < 0.05) and slight significance with RE_AI (t = 1.959, p-sig < 0.1).

5 Discussion and conclusion

To start discussing on the result, the research hypothesis would be represented as the equation below:

$$y = \alpha + \beta x_1 + \beta x_2 \quad (1)$$

where: y represents Adoption Level of Big Data Intelligence
x_1 represents Awareness on the Concerns of Big Data Intelligence Processes
x_2 represents Knowledge on What to Expect from Regulation

Table 6
Linear Regression Analysis Results for dependent variable of BDI_CONS: Part 2

Independent Variables	B Coefficient	R Square	F-stat Significance	t-value	P Significance
REG_DATPRO	-0.382			-0.844	0.404
REG_PRIV	0.323			1.136	0.263
REG_DA	0.200			0.874	0.388
REG_BD	0.322			1.353	0.184
REG_SHARE	0.163			0.735	0.467
REG_AI	0.569			1.959	0.058**
REG_ML	-0.823			-2.606	0.013
REG_BIAS	0.534			2.752	0.009*
REG_COETHI	-0.278	0.430	0.035*	-1.362	0.181
REG_DATGOV	0.328			1.171	0.249
REG_DATSEC	-0.084			-0.185	0.854
REG_TECH	-0.095			-0.490	0.627
REG_CYBER	-0.310			-1.007	0.321

5.1 Awareness on the Concerns of Big Data Intelligence Processes

Based on the Cronbach Alpha Test, initially the combination of all instruments for BDIPR_CON has good internal consistency, so it suggested for good reliability with the research objectives. The result from the overall Linear Regression Analysis between BDI_CONS with all instruments of BDIPR_CON showed that the entire instruments have moderate variation and are significant to the hypothesis.

However, their high Alpha value suggested that the combinations were less unilateral and there was redundancy in the instruments. Therefore, after removing some instruments, the desirable combinations are CON_ANLYS, CON_PUB, CON_SHARE and CON_DISP. From the Pearson Correlation result, CON_PUB and CON_DISP have moderate positive correlation with BCI_CONS, while CON_SHARE has weak positive correlation with BCI_CONS but CON_ANLYS was found to be not significant. Meanwhile, CON_PUB has significant difference towards the hypothesis and CON_DISP has slight significance to the hypothesis, based on the Linear Regression.The findings suggested that Awareness on the Concerns of Big Data Intelligence Processes does have impact to the Adoption Level of Big Data Intelligence, supporting the first research question. However, the most significance and most reliable contributors to the Awareness on the Concerns of Big Data Intelligence Processes are Concerns on Data Publication (CON_PUB) and Concerns on Data Disposal (CON_DISP).

5.2 Knowledge on What to Expect from Regulation

The result from Cronbach Alpha Test on all instruments of the variable Knowledge on What to Expect from Regulation (REG_EXPCT) indicated that the instruments have good internal consistency and are reliable to the research objectives. The result from Linear Regression Analysis between BDI_CONS with all REG_EXPCT instruments showed that the they have moderate variation and are significant to the hypothesis. However, the high Alpha value suggested that the combinations were less unilateral and there was redundancy in the instruments. Therefore, five instruments were removed leaving REG_DATPRO, REG_PRIV, REG_SHARE, REG_BIAS, REG_TECH and REG_CYBER as the desirable combinations. There were moderate, positive correlations observed between BDI_CONS with REG_BIAS, REG_DA and REG_BD; and weak, positive correlations between BDI_CONS with REG_DATGOV, REG_AI, REG_SHARE, REG_ML, REG_PRIV, REG_DATPRO, REG_COETHI and REG_DATSEC.

6 Limitations and Conclusion

This section will provide the limitations of this study and then will provide a conclusion of the results from this research.

6.1 Limitations of the study

Despite that the target group and estimated responses have been forecasted during planning for the data collection, lists of organisations have been collected from official sources and contacted through their official contact to ensure formality of the questionnaire, the response rate, however, has shorted far of our forecasted response rate with total of only 58 completed responses, 14 from financial institutions and rest from government ministries have been received back which clearly indicates that the response rate has not met our expectations. Besides, the analysis may have used the other statistical or estimation techniques than the simple correlation and regression analysis used here.

6.2 Conclusion

Based on the discussion above, the variables Awareness on the Concerns of Big Data Intelligence Processes (x_1) and Knowledge on What to Expect from Regulation (x_2) are proven to have positive relationship with the Adoption Level of Big Data Intelligence (y). When the

Beta Coefficient value of both or either x_1 or x_3 increases, the value of y will also increase. Therefore, hypothesis of the research is partially correct, in which adoption level of Big Data Intelligence in an organisation does have relation with the organisation's awareness of the ethical concerns relating to processes involved in Big Data Intelligence and knowledge on regulatory expectations. However, there were not have enough evidence to suggest connection between knowledge on the measures to address these concerns and the adoption level.

This conclusion suggests that organisations including financial institutions should be aware of the concerns and ethical issues relating to Big Data Intelligence not just on the surface but also the processes involved. Relevant corporate policies and strategies should be set up or enhanced before the implementation, such as to strengthen the data management processes that are currently weak. Finally, regulations should be regarded as important enabler for innovation including Big Data Intelligence by the industry.

References

Broeders, D., Schrijvers, E., van der Sloot, B., van Brakel, R., de Hoog, J., & Ballin, E. H. (2017). Big Data and security policies: Towards a framework for regulating the phases of analytics and use of Big Data. *Computer law & security review*, *33*(3), 309-323.

Butterworth, M. (2018). The ICO and artificial intelligence: The role of fairness in the GDPR framework. *Computer Law & Security Review*, *34*(2), 257-268.

Costanzo, P., D'Onofrio, F., & Friedl, J. (2015). Big data and the Italian legal framework: Opportunities for police forces. In *Application of big data for national security* (pp. 238-249). Butterworth-Heinemann.

Herschel, R., & Miori, V. M. (2017). Ethics & big data. *Technology in Society*, *49*, 31-36.

IBM Corp. (2017). IBM SPSS Statistics for Windows, Version 25. Armonk, NY: IBM Corp.

Kshetri, N. (2014). Big data′ s impact on privacy, security and consumer welfare. *Telecommunications Policy*, *38*(11), 1134-1145.

Lepri, B., Oliver, N., Letouzé, E., Pentland, A., & Vinck, P. (2018). Fair, transparent, and accountable algorithmic decision-making processes. *Philosophy & Technology*, *31*(4), 611-627.

Raymond, A. H. (2013). Data management regulation: Your company needs an up-to-date data/information management policy. *Business Horizons*, *56*(4), 513-520.

Richards, N. M., & King, J. H. (2014). Big data ethics. *Wake Forest L. Rev.*, *49*, 393.

van den Broek, T., & van Veenstra, A. F. (2018). Governance of big data collaborations: How to balance regulatory compliance and disruptive innovation. *Technological Forecasting and Social Change*, *129*, 330-338.

Zharova, A. K., & Elin, V. M. (2017). The use of Big Data: A Russian perspective of personal data security. *Computer Law & Security Review*, *33*(4), 482-501.