ASSESSING ANALYTICS MATURITY LEVEL IN THE INDONESIAN TAX ADMINISTRATION: THE CASE OF COMPLIANCE RISK MANAGEMENT

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ABSTRACT

Using Grossman (2018)'s Analytic Process Maturity Model (APMM) Framework, we examine the maturity level of advanced analytics development related to taxpayer compliance management in the Indonesian Tax Administration, Directorate General of Taxes (DGT). The framework helps to indicate room for improvement within revenue bodies to allow the organisation to become more analytics-driven in dealing with the COVID-19 crisis and in the future. The results suggest that the organisation has reached a maturity level of 4.43 and capable of applying from enterprise-wide data analytics. To establish an analytics-driven organisation, remedial works are required to upgrade the current maturity level. Revenue authorities that have similarities in the economic background, compliance structure, and maturity level could acquire valuable lessons from Indonesia's experience that could be considered in the further development of advanced analytics within taxpayer compliance management.

ABSTRAK

Penelitian ini membahas kematangan data analitika menggunakan metode Analytic Process Maturity Model (APMM) pada pengelolaan manajemen kepatuhan wajib pajak di Otoritas Perpajakan Indonesia, Direktorat Jenderal Pajak (DJP). Kerangka penilaian ini membantu mengindikasikan area pada otoritas perpajakan yang memerlukan perbaikan untuk membangun pengambilan keputusan organisasi berbasis analitik dalam menangani krisis COVID-19 dan di masa depan. Hasil penilaian menunjukkan bahwa organisasi telah mencapai tingkat kematangan level 4.43 dan mampu menerapkan data analitika di seluruh sisi organisasi. Untuk mencapai organisasi yang berbasis analitik, beberapa perbaikan perlu dilakukan untuk meningkatkan kematangan analitik saat ini. Otoritas perpajakan yang memiliki kesamaan kondisi ekonomi, struktur kepatuhan wajib pajak dan tingkat kematangan analitik dapat memperoleh pembelajaran dari pengalaman Indonesia yang patut dipertimbangkan dalam pengembangan analitik tingkat lanjut pada manajemen kepatuhan wajib pajak.

1. INTRODUCTION

The coronavirus (COVID-19) disease has triggered the global crisis wave, which leads to the deepest worldwide recession since World War II (World Bank, 2020). A negative trend in global growth is predicted at 3.0%, and Indonesia is projected to shrink to 0.5 percent (IMF, 2020). Given these circumstances, the Government should carefully devise a strategy to alleviate the impact on the tax field, especially a strategy that enables a tax administration to maintain an acceptable level of taxpayer compliance and revenue.

To ensure both economic sustainability and fiscal sufficiency, the Government should revisit taxpayer compliance management. When the pandemic inhibits tax administration's assurance and engagement activities, making the best use of analytics is more important than ever, thus identifying one's analytics maturity level is necessary to take full advantage of data and compliance analytics.

While taxation played a significant role in protecting and supporting economic growth and securing revenue, managing taxpayers' compliance is always a challenging task: deterring non-compliance and establishing fairness and equitability. Jurisdictions tend to provide tax incentives during this pandemic. In a society where paying tax is not considered a norm, maintaining tax compliance is more difficult because taxpayers inclined to abuse the incentives.

Revenue authority should then distinguish the compliant from the incompliant and embed big data analytics into existing taxpayer compliance management might be the key. Compliance Risk Management (CRM) delivers a huge advantage compared to conventional approaches to put the right balance in enhancing voluntary compliance and deterring non-compliance during the crisis. COVID-19 opens the tax administration opportunity for to revisit taxpayer compliance management and assess its analytics maturity level in optimising big data analytics according to maturity stage.

This paper presents a review of the analytics maturity level of CRM in the Indonesian Tax Administration, Directorate General of Taxes (DGT), using the Analytic Process Maturity Model (APMM) Framework. This paper enriches data and findings to the data analytics maturity in the public institution, specifically in tax compliance management within the Revenue Body in an emerging country.

We believe that there is a limited number of researches that specifically assess the analytics maturity level of taxpayer compliance management within revenue authority in industrialised and emerging countries. As far as we know, this paper is one of the pioneer studies that investigate the analytics maturity level of Tax Administration's CRM in a developing country.

This paper begins by outlining the research background, followed by section two. In that section, we explore the theoretical background for why and how advanced analytics are used in taxpayers' compliance management and shows how

previous literature has looked at numerous analytics maturity assessment and analytics maturity models in the public sector.

Section 3 outlines the methodology and data for assessing the data analytics maturity, and section 4 reports the result of this assessment. This section also provides fruitful lessons learned that could be taken into consideration by other revenue administrations in emerging nations who have a similar economic background, compliance posture, and maturity level. Section 5 concludes the findings, limitations, implications, and possible forthcoming research.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

2.1 Tax Compliance

It is widely recognised that the tax authority's strategic objective is to enhance compliance through two approaches: facilitating tax services to those who willing to comply and performing a fight to combat tax fraud (Collosa, 2017). The OECD defines tax compliance as a degree of a taxpayer in complying with their country's tax rules.

At the current stage, the level of tax compliance in emerging countries is relatively low compared to advanced nations (Razak & Jwayire, 2013). Developing and emerging countries are dealing with a more challenging and vulnerable compliance deterioration since they have lower tax administrative capability (Sarker, 2003; The Commonwealth Secretariat, 2011), widespread tax evasion activities

(Gandhi, et al., 1987; GIZ, 2010; He &Xiao, 2019), high population density and large informal sectors (Ahmed, et al., 2012; OECD, 2020). The emergence of the risk of non-compliance is inevitable for each tax administration, and it should be kept at the minimum level (OECD, 2004).

2.2 Compliance Risk Management

OECD (2004) emphasises a taxpayers' obligation into four domains of compliance: (i) tax registration, (ii) on-time lodgement on particular taxation information, (iii) supplies correct and complete information, and (iv) prompt tax payment and such liability may fail to carry out by a taxpayer due to unintentional error, as an example, carelessness and intentended purposes such as aggressive tax evasion scheme.

To cope with tax non-compliance effectively and efficiently, the OECD suggests that a tax authority implements a taxpayer compliance risk management (CRM) practice, defined by the OECD (2014) as a systematic, well-structured, and iterative process in managing taxpayers' compliance risk. The management of taxpayers' compliance within tax authority is not merely about selecting the audit case but rather about an end-to-end approach to manage compliance holistically (ADB, 2020). Figure 1 below depicts the CRM procedure.
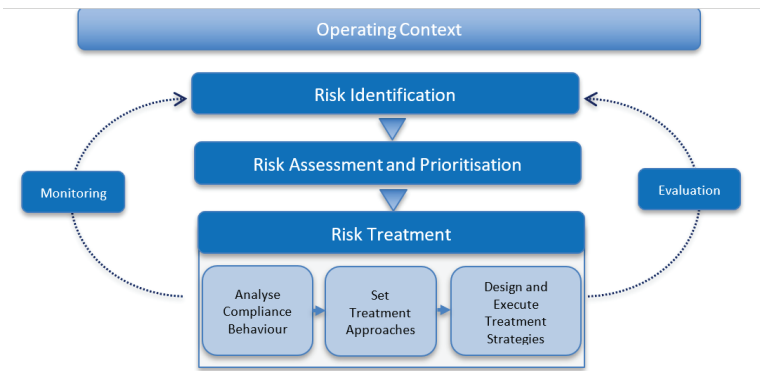
Concerning Figure 1, operating context is defined as a staple compliance context, driven by internal and external factors, such as, human resources and technology established in the institution (ADB, 2020). A challenge in the operating context cahnge may be coped with a research program and environmental

scanning, carried out by a dedicated CRM unit (ADB, 2020).

The process itself begins with identifying the underlying taxpayers' risks to minimise particular compliance risks comprehensively by starting with a big picture, minimising the possibility of oversight, and facilitating the subsequent in-depth analysis (OECD, 2004).

Figure 1 An Iterative Process of CRM within Tax Administration
Source: Own elaboration based on OECD (2004)

Once the risks have been identified, the following process is risk assessment and prioritisation, which determines the level of likelihood and consequences of compliance risks and risks that pose significant impacts to achieve a revenue body's objective. Moreover, this stage also determines the proper risk-based treatment based on the taxpayer's underlying compliance motives and postures. In addition, tax administration needs to acquire insights into the effect of various approaches on a wide range of taxpayers' compliance behaviour (OECD, 2010).

The last process is monitoring and evaluating inseparable activities to ensure the treatment output is set as feedback to the risk identification step. A clear and robust evaluation framework for the existing CRM procedures is necessary for a tax authority. It plays a significant role in establishing a continuous improvement of compliance strategy (OECD, 2004).

2.3 Advanced Analytics in Taxpayers Compliance Management

A survey conducted by the Forum on Tax Administration (FTA) in 2015 suggests that numerous tax revenue bodies in developed economies have applied advanced analytics to a wide range of activities and ended by bringing high-value-added to enhance compliance level (OECD, 2016).

Advanced analytics is defined as applying statistical and machine-learning techniques to uncover insight from data, and ultimately to make better decisions about how to deploy resources to the

best possible effect (OECD, 2016). An array of sophisticated analytics is currently applied into a broad spectrum of tax administration system to reduce non-compliance, to give clear examples, the pre-filled tax return system, popups or nudges, debt management, and real-time risk reviews (IOTA, 2017; OECD, 2016; Veit, 2019).

Henceforward, a substantial number of revenue bodies that rely heavily on advanced analytics techniques, for example, predictive modelling as an initial detection of non-compliance and research competencies to deliver better service, supervision, and policy advise (ADB, 2020; IOTA, 2017; OECD, 2016; Veit, 2019). Cutting-edge data analytics within tax administration can be utilised in a broad range of tax compliance areas, such as suggesting the next-best alternatives, developing social network analysis to detect value-added tax (VAT) carousel fraud, and capturing a greater insight by blending predictive modelling and experimental design (OECD, 2016). Furthermore, the CRM dedicated unit within revenue bodies is responsible for enhancing data management and analytics capability to support acceleration, equitability, rational, and tax services (ADB, 2020).

2.4 The Demand for Analytics Maturity Model Assessment

A maturity model is a tool broadly utilised by an institution on a self-assessment basis wit to acquire an understanding of capacity and transformation that could be eventually taken to reach a higher maturity level (OECD, 2019). To date, various organisation's analytic maturity models (AMM) have been introduced, in which each model has a unique set of characteristics and a diverse assessment focus (Król & Zdonek, 2020).

The uniqueness of each maturity model can be applied in the context of the public and private sectors. To give a clear example, the Analytics Maturity Quotient Framework (AMQF), which Aryng introduces, offers data analytics maturity assessment in the private sector, which aims to distinguish a company's ability to generate insights from their customers feedback and the performance of the products provided (Jain, 2012).

Another illustration is the Data Analytics Maturity Model (DAMM), which Association Analytics introduces is tailored to measure the analytics maturity level of associations and non-profit organizations. In addition, Delta Plus Model (which initially comes from Delta Model), developed by Tom Davenport, Jeanne Harris, and Bob Morison (Davenport, 2018), is designed to measure the maturity level of corporate analytics (Król & Zdonek, 2020).

At present, public agencies accumulate a large quantity of dataset which spread across government institutions. However, big data is scattered and still in the early days of development in comparison with the private sector, which is ahead of the field (Kazantsev, 2015; Klievink, et al., 2006; Manikam & Selamat, 2017). In this regards, this paper employs a maturity assessment framework that Robert L. Grossman initiates, entitled The Analytics Processes Maturity Model (APMM), that enables tax administration

not only to recognize the features in the public sector mentioned above but also to incorporate analytic-related process. Including building and deploying an analytics model, administering and controlling current analytics infrastructure, securing current analytics assets, operating the existing analytics governance framework, and identifying opportunity based upon the organisation's analytics strategy (Grossman, 2018).

2.5 The Analytics Processes Maturity Model Framework

APMM allows an organisation to conduct an independent assessment towards maturity level in six main process areas as shown in Figure 2 below.

Figure 2 Data Analytics' Key Process
Source: Own elaboration based on Grossman (2018)

The first aspect goes to analytic modelling, which refers to adopting generally accepted statistical methodologies to build a data-driven model (Grossman, 2018). Second, Grossman (2009) defines analytics infrastructure as the applications, services, utilities, and systems that are used to either prepare data, estimate, validate, scoring, or related modelling activities which consist of three key process areas; 1) capability to administers the existing infrastructure, 2) ability in providing required data and infrastructure for building model, and 3) competence in delivering data and infrastructure needed to deploy a model. The third main area is the analytic operation, which explores the analytics process's diversity to produce the model's output for the decision-making process and the appropriate action (Grossman, 2018).

The next domain is the analytic strategy which refers to the organisation's decisions in utilising data to attain long-run objectives; specifically, in choosing opportunities and integrating operations, infrastructure, and models (Grossman, 2018). In establishing strategy,

institutions should consider: 1) data requirements, 2) data source and gathering, 3) applied analytics, 4) required technology infrastructure, 5) data-related competencies, and 6) data governance (Marr, 2020).

The fifth domain, there is no commonly accepted definition of analytic governance presently (Grossman,2018). The terminology "IT governance" was applied to describe the set of mechanisms for ensuring the attainment of necessary IT capabilities (Brown & Grant, 2015). In particular, analytic governance often determines whether: 1) data is obtainable, (2) the model is biased/not, (3) the build model will be deployed, (4) the model delivers business value, and (5) the business value is acknowledged (Grossman, 2020).

Good analytics governance should: 1) ensure that long-term decisions about analytics are achieved and generate business value, 2) certify that data and analytic products are preserved and administered in accordance with compliance policies, 3) provide accountability, transparency, and traceability, 4) provide an organisation set-up to guarantee the availability of necessary resources (Grossman, 2018).

The final aspects, compliance, means ensuring an organization is compliant with the minimum security-related requirements. It focuses on the kind of data handled and stored and what regulatory requirements (frameworks) apply to its protection to manage risk and goes beyond information assets (Dobran, 2019).

Analytic security and compliance ensure analytical assets are secured with the relevant security and compliance (Grossman, 2018).

Each aspect of the APMM will be measured based on level 1 to 5. Each maturity levels indicates: 1) organizations that can build reports, 2) organizations that can build and deploy models, 3) organizations that have repeatable processes for building and deploying analytics, 4) organizations that have consistent enterprise-wide processes for analytics, and 5) enterprises whose analytics is strategy-driven (Król & Zdonek,2020). The higher the score, the more presumably to build and deploy an analytic model that is statistically valid, in a timely manner, can be deployed into an organization's products, services, or operations and meet the model's goals (Grossman, 2018).

3. RESEARCH METHODOLOGY

We apply the APMM framework in assessing the current maturity level of the existing data analytics within DGT's taxpayer compliance management. The APMM model is relevant to determine data analytics maturity in CRM compared to other approaches given that: 1) it delivers a more technical assessment context, in particular to an organisation that is currently building and deploying a specific analytics model, 2) the availability of the methodology which publicly accessible, 3) some maturity model does not apply in the context of the public body.

We first conduct a series of explorative interviews and panel

discussions with experts who have a deep understanding and are engaged in CRM policy-making from the strategic to the tactical level. The interview and discussion are carried out to three source persons who are directly involved in the progress of data analytics within CRM since the early stage: 1) a top-level manager (Echelon I) in the Ministry of Finance, 2) a middle-level manager is responsible for running and developing short and mid-term strategies for CRM's data analytics in the Directorate of Tax Data and Information, and 3) a data engineer in the CRM unit in the Directorate of Tax Data and Information that engaged on a day-to-day basis in building and deploying the analytics model. These interviews were conducted to verify the data analytics maturity level.

We collect information and assessment only from those three prominent people since: 1) the nature of data analytics in CRM, which a few people manage in DGT, 2) the three key players hold a comprehensive understanding of CRM's big data analytics since they were assigned in the lower management position before their current position. Thus, if other people in the organisation provide the data collection and analytics, maturity measurement might lead to bias due to false interpretation as lack of capabilities and capacities in CRM's data analytics.

Additionally, a type of psychometric response scale in which the three respondents specify their degree of agreement upon given statement on each key process specifically in five points: 1) Not at all, 2)

A Little, 3) Rather, 4) Much, 5) Entirely. For easy interpretation, we summarize findings by applying to mean as the statistical methodology to draw a general outline to what extent DGT's CRM stands on its analytics maturity. Third, we collect written data sources from internal memos and minutes of a meeting, strategic plans, published and unpublished regulations, and policies.

We utilise triangulation in setting the methodological framework of this research to gain a comprehensive understanding from the various perspective of the degree of the existing data analytics maturity in DGT's CRM. The goal is to verify and set up validity in a study by analysing a research question from a wide range of perspective (Guion, Diehl, & McDonald, 2011) by employing different methods of collecting data, namely interview, questionnaires, and documentation.

4. RESEARCH OUTCOME AND DISCUSSION

In this section, we will discuss the research outcome and deliver findings on the maturity level of analytics using the APMM approach in six primary areas: 1) building an analytic model, 2) deploying analytic model, 3) managing and operating analytic infrastructure, 4) protecting analytic assets through proper policies and procedures, 5) operating analytic governance structure, and 6) determining analytics strategies and opportunities.

4.1 Building Analytic Model

In general, CRM has reached level 4 (advanced) out of 5 in building analytics

model criteria. The CRM's analytics model has already adopted the general statistical procedures. Moreover, the third-party data, internal data, and data from the internet platform are primary in building risk models. Both structured and unstructured big data sets are used to build models. A pre-processing phase is automated and managed by data management units, while a post-processing phase is administered within CRM's silo. Both processes are consistent with current standards and procedures and documented properly in the digital environment.

The risk model is robust and does not affect data change. Performance can be quantified with the statistical procedure, but there is still room for improvement in measuring the impact on business outcome precisely. Due to staff capability, a few models are not built on standard statistics techniques.

4.1.1 Deploying Analytics Models

Overall, CRM has reached level 4 of maturity in model deployment. Once the analytics model is drawn up, the model then ready to be deployed. Thus, an effective procedure in shifting the model from the modelling environment to the deployment environment is necessary (Grossman, 2018).

Some approaches which can be selected are: 1) using a similar application in building and deploying model, 2) applying the model in the development environment before loaded to deployment environment, 3) exporting analytics model to the development environment before imported in the deployment environment, 4) building model manually before it integrated into the deployment environment (Grossman, 2018).

Moving to the outcome, it was discovered that the model's performance is quantified and monitored periodically. Business impact is quantified with a conventional approach. Refinement is possible to carry out without disrupting other processes such as interface, business process, and model building code. Regular monitoring is carried out and appropriately documented.

Extensive quality assurance is performed before the deployment phase and adequately documented and accessible to internal teams. Access through models is adapted to necessities and in regards to policies and procedures. The mechanism of the compliance check is carried out periodically. However, the existing risk model is heavily affected by data issues such as missing and malformed data and errors.

4.1.2 Analytic Infrastructure

The maturity level in CRM's analytics infrastructure has reached a score of 4.4. An appropriate analytic infrastructure should: 1) sufficient to sustain the features of big data, analytics strategy and objectives, 2) provides data for analytics in a timely fashion, 3) allows an effective and reliable deployment, 4) promotes the management of analytics model over the entire lifespan, and 5) protecting data by integrating infrastructure with the appropriate security and compliance (Grossman, 2018).

From the measurement, it is discovered that a sophisticated big data

analytic infrastructure is available. Current infrastructure is designed to manage big data dimension with room for improvement to handle data velocity and variety. The existing infrastructure can provide raw data for building a risk model and slight improvement should be considered due to data readiness in a timely manner. Data is still needed to be processed further by the CRM unit for the analytics process. Further development should consider how analytics infrastructure could fully accommodate an organisation's analytics objectives and strategy.

Existing IT capacity allows advanced analytics structure in CRM to deploy risk quickly, efficiently, automated, and reliable. Model modification can be carried out in analytics infrastructure. Awareness of analytics management is still at a nascent stage and should be enhanced to create proper analytics management within analytics infrastructure. This can be done by building tools that allow tracking risk model's history.

Access through infrastructure for building a risk model is provided to authorised persons and secured concerning the organisation's data security and compliance. Appropriate security and compliance are integrated with existing analytics infrastructure.

4.1.3 Analytic Governance Structure

Overall, goals for this section have reached level 4.5 out of 5. To establish an appropriate analytic governance structure, the organisation should: 1) involving a liable team comprise relevant stakeholders and business owners for managing a model building, deployment, and analytics infrastructure, 2) involving executive committees to ensure the analytics strategy is developed and carried out, 3) engaging technical committees to measures evaluation and provide a recommendation of analytics processes and technology in a broader scale, 4) engaging the necessary stakeholders, decision-makers, and executives to develop proper analytics security and compliance policy, and 5) including analytics competence assessment and analytics maturity improvement (Grossman, 2018).

At the current stage, the CRM unit is the only dedicated unit in administering Big Data analytics in DGT. Analytics governance committees, including both technical and executive boards, are still at the development phase and have already become the primary concern at executive levels. A self-assessment towards governance structure is carried out regularly. Enhancement in quality assurance can be done by involving a third party to conduct an independent review.

There is a unit responsible for data and IT governance at the strategic level. The data science unit is a part of the CRM unit that administers analytics governance structure and is still at the emerging phase. Analytics culture within the organisation is currently at an early stage. There is a need for periodical analytics competence assessment. Analytics maturity awareness is starting within organisation. Improvement activities on analytics are carried out in an unstructured and incidental manner.

The organisation has started to develop a long-term analytics goal, but it has not been set yet, leaving plenty of room for further remedial action. This could be done by building a broader analytics governance structure to ensure a clear responsibility through business value derived from the existing analytics structure. Moreover, the organisation should establish and set the responsible unit to 1) assessing analytics competence, 2) corroborating current maturity level, and 3) developing a long-term analytics strategy.

4.1.4 Analytic Strategy and Opportunities

Overall, the assessment score for analytics strategy and opportunities is 4.2 out of 5. The analytics strategy and opportunity aroused in the organisation should: 1) bring innovation and offer to provide a competitive advantage, 2) distinguish long-term analytics path, 3) enable the presence of comprehensive and structured analytics opportunity selection, 4) allow the analytics opportunity taken to be quantified and traced, and 5) treats data as an asset (Grossman, 2018). The existing condition denotes an early analytics awareness. Thus, analytics might not utilise deliberately and set less developed analytics governance. Big Data Analytics in CRM has been integrated into the organisation's strategic plan for 2015-2019, tax reform agenda as in Director General of Taxes Decision number KEP-389/PJ/2020 concerning DGT's Strategic Plan for 2020-2024, and aligned with key performance indicators.

Some limitations are found in the current maturity level, staff capability, and model option. There is a narrow process in selecting analytics opportunities and impact assessment in building an analytics model by optimising available resources and the organisation's context. Advancement can be done by building a robust management process in developing analytics opportunities. Analytics output can be tracked by key performance indicators with some limitations. Various levels of management value data as an organisation's asset. A data-driven culture exists, allows to exploit and explore data to draw insight. To bring higher business value in turning data into strategic assets entirely, analytics-driven culture should be adopted and instilled.

4.1.5 Analytic Security and Compliance

Overall, DGT has implemented best practice (level 5) to protect analytic assets. Analytics security and compliance within the organisation should able to guarantee that: 1) data is secured and protection methodologies are align with current policy, 2) enable organisation to perform collaboration with the third-party to align existing approach are relevant with the external policies, 3) an automated and ongoing monitoring to accommodate data grows, 4) analytics compliance is can cover security and compliance for internal and external parties, and 5) establish a system to monitor data utilisation by external parties is in accordance with the mutual agreement (Grossman, 2018).

Our findings demonstrated that there is a dedicated unit to manage data and analytics security within the

organisation which also works with an external advisor. Security and protection are automated and appropriate with the procedure and policy. Continuous monitoring is performed with a specific unit to ensure data operation is utilised according to the relevant access. When an agreement with a third party is made, a non-disclosure agreement (NDA) is carried out. An opportunity arises to refine data misappropriation detection and align existing policy and evaluation with taxpayer compliance analytics.

4.2 Further Discussion

Analytics maturity offers a considerable advantage to the tax authority in maximising the management of taxpayer compliance. Thus, the organisation should determine the current maturity level to bring analytics maturity to the next level. The taxpayer compliance management in DGT allows to builds a robust model, and deployment is carried out effectively and reliably. The analytic governance is at a development phase, which is in line with the organisation's analytics awareness. Moreover, DGT should instil an analytics-driven culture to exploit the analytics opportunity and advantage for a more extensive agenda. To complete the whole analytics area, security and compliance are set up based upon DGT policies.

The organisation should view this pandemic as a window of opportunity to build an analytics-driven organisation by upgrading the analytics maturity level to an ideal state.

Regardless of the current maturity level, the public institution has no choice besides treating big data as a strategic asset, setting an analytics governance structure, and widely dispersing analytics culture.

With the level of maturity of 4, the significant challenges faced by DGT are to carry out advanced analytics is institutionalised analytics culture and aligned with analytics strategy to turn into an analytics-driven organisation. The value of integrated collaborative effort with all management levels in constructing a vigorous analytics-driven institution is central to deliver more benefits entirely. Collaborating with other parties is equally important to unlock new insights and data exchange.

From now on, DGT should contemplate the development strategy of data analytics and CRM. The current Core Tax System (COTS) project enables DGT to speed up its analytics development by combining its capability to manage analytics and compliance internally and the international best practices embedded into COTS analytics solutions. Hence, this should be considered as a golden opportunity to enhance the current analytics maturity level and accelerate the establishment of a data and knowledge-driven organisation and a more sophisticated yet suitable compliance management.

There is no blanket solution for the analytics development option. Hence, appropriate cost-benefit analysis should be taken into account to deliver a crystal-clear view of the cost incurred from building or procuring an application that is tailored to the organisation's

specific needs. Furthermore, the organisation should consider and determine the risk that might bear, such as the risk of failure in new product development, potential loss measured by allocated human capital, time and maintenance cost. Finally, the organisation should draw up long-run analytics development and management for keeping analytics strategy on the right track.

5. CONCLUSION

This paper applies the APMM framework in measuring the current analytics maturity level in the management of taxpayer's compliance in the Indonesian revenue body. We carry out measurement in six main areas: 1) building analytics model, 2) deploying analytics model, 3) managing and operating analytics infrastructure, 4) analytic governance structure, 5) developing analytics strategies and opportunities, and 6) analytics security and compliance.

We carry out a set of panel discussions across management level that directly involved in the CRM's analytics development. In addition, data collection is also conducted by collecting written sources, both published and unpublished. Our study suggests that the analytics maturity level in CRM has reached level 4 (scored 4.43 out of 5). The score implies that CRM: 1) a consistent enterprise-wide analytics process, 2) allow to build and deploy a robust model in an efficient manner, 3) sustained with sufficient analytics infrastructure, 4) equipped

with developed analytics governance and awareness, 5) pioneering an analytics-driven culture, 6) protected by secured systems.

In the light of the COVID-19 pandemic, this finding implies The Indonesian Tax Authority is competent in shaping compliance resilience from the current data analytics readiness within the taxpayer compliance management. With a score of 4.43/5, DGT could utilise a wide range of advanced analytics to tackle the COVID-19 challenge towards tax compliance, as an example, predictive analytics to deter taxpayers who pose compliance brittleness and considering next-best alternatives as a pre-emptive action towards the risk of non-compliance.

Likewise, the score also indicates a necessity for each tax administration to start building an analytics-driven culture at any point of a maturity level to cope with the non-compliance risk at which exacerbated by the COVID-19 pandemic. Therefore, advanced analytics can be implemented optimally within the Indonesian Tax Authority in managing taxpayer's compliance during the pandemic.

6. RESEARCH IMPLICATIONS AND LIMITATIONS
6.1 Research Implications
Considering that, in general, the public institution's the current maturity level is lagging behind the private sector. Thus, it requires more studies. This paper significantly enriches data analytics literature in the government sector in developing countries by demonstrating that the APMM could be used to assess

the analytics maturity level in a public sector. In addition, this study identifies the importance of assessing the analytics maturity level. Thus, further study on the development strategy of data analytics in the public sector can be carried out more extensively.

For tax administrations, this study provides an example of how to perform an analytics maturity assessment and identifies key process areas that are needed to be improved, which are beneficial to design a long-run analytics strategy. Hence, this paper could become the cornerstone for developing a long-term analytics roadmap comprising both building analytics-driven organisation and harmonising a broader data governance policy ("Satu Data Indonesia").

Additionally, there is an opportunity for DGT to study a good practice of analytics governance from the public and private sector. The issue of how the organisation manages the analytics governance structure needs to be addressed in terms of how DGT at all levels brings more attention to the analytics governance structure. Data analytics mainstreaming to enhance compliance can be initiated from CRM implementation as an analytics utilisation in the business process's upstream level.

This study also raises a number of opportunities for future research, such as 1) assessing analytics maturity in a public organisation, particularly tax authority with different methodologies, 2) conducting a comparative assessment of maturity level among tax administrations, and 3) utilising more comprehensive methodologies, such as surveys and focus group discussions involving a wider scale of respondents.

6.2 Limitations of The Study

Given the novelty of the topic and context, some limitations should be noted. First, the assessment methodology only applies one maturity framework. Hence, analysing with other methods might demonstrate different assessment result.

Second, although we carried out observation and scrutinized CRM data analytics documentation, we could only interview three key persons. Due to the unique characteristics of data analytics development mentioned earlier in the methodology section, including persons who have not directly and significantly involved in the development will reduce the quality of information required to assess the analytics maturity of CRM. Adding more key persons for future research is viable due to establishing a CRM dedicated unit within DGT.

Third, the applied methodology is used to assess the entire analytics maturity level in an organisation. Hence, it may sound less precise in assessing data analytics in the taxpayer compliance management.

Acknowledgement

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APPENDICES

1. Assessment Form

Goals for Building Analytic Models	1 Not at all	2 A little	3 Rather	4 Much	5 Entirely
The risk models built from data ("empirically derived") and use generally accepted statistical procedures.					
The performance of models quantified with metrics and a process developed so that new models can be developed that outperform the current models with respect to these metrics.					
In case of applied rules are not empirically derived using generally accepted statistical procedures, business, compliance, or other reason for the rule known and managed, and the performance impact on the model of the rule are quantified (if possible).					
A small change to the data result in substantially similar models (robustness).					
The processes used to clean and transform data to create the features of models are separately managed, automated and documented, and follow the required pre- and post-processing phase.					
Goals for Deploying Analytic Models	1 Not at all	2 A little	3 Rather	4 Much	5 Entirely
The performance and business impact of the model in operations quantified and monitored regularly.					
It is possible to update the model without writing code that impacts operational products, services or systems.					
There is a process for validating and verifying models before deployed broadly.					
There is a mechanism for checking that models are being used as per compliance policies.					
the deployed models or operations disrupted by the existence of missing or malformed data, delayed feeds, etc.					
Goals for Managing and Operating Analytic Infrastructure	1 Not at all	2 A little	3 Rather	4 Much	5 Entirely
The analytic infrastructure for managing the data required for analytics adequate given the volume, velocity and variety of the data and the analytic objectives and strategy of the organization.					
The analytic infrastructure available to the modeling group provides data for building analytic in a timely fashion to those that build the models.					
The analytic infrastructure for deploying models allow analytic models to be deployed efficiently and reliably into operational systems, products and services.					
The analytic infrastructure supports the management of models over their entire life cycle.					
The analytic infrastructure integrates the security and compliance needed to protect the data as required.					

Goals for Operating an Analytic Governance Structure	1 Not at all	2 A little	3 Rather	4 Much	5 Entirely
The analytic governance structure includes the groups responsible for building models, deploying models and managing the analytic infrastructure and include the appropriate stakeholders and business owners from the organizations.					
The analytic governance structure includes executive committees that involve the appropriate business owners and stakeholders for making the decisions required so that the analytic strategy built can be developed and executed.					
The analytic governance structure includes technical committees for evaluating and making recommendations on analytic processes and technology that span more than one group or impact more than one stakeholder or business owner.					
The analytic governance structure includes the necessary stakeholders, decision makers, and executives so that the policies required for the security and compliance for analytic assets can be developed and implemented.					
The analytic governance structure includes a process for assessing the analytic competence of the organization and improving the analytic maturity of the organization.					

Goals for Developing an Analytic Strategy and for Selecting Analytic Opportunities	1 Not at all	2 A little	3 Rather	4 Much	5 Entirely
The analytics used by the organization to help differentiate itself from competitors and to provide a competitive advantage.					
The analytic strategy identifies long-range analytic directions for the organization.					
There is a process for selecting analytic opportunities that optimizes the value to the organization as a whole, given the limited resources for building and deploying models.					
The value brought by the analytic opportunities selected can be quantified and tracked.					
The analytic strategy manage data as institution assets.					

Goals for Providing Security and Compliance for Analytic Assets	1 Not at all	2 A little	3 Rather	4 Much	5 Entirely
The action to protects the confidentiality, integrity and availability data assets are integrated into the organization's security plans, policies, procedures and controls.					
Does the analytic group work with the institution's inside or outside counsel so that the collection of data assets, modeling practices, and the deployment of analytic models are compliant with all relevant local, state and national and international laws, regulations and policies.					
As the size of data grows, the institution makes greater use of automation and continuous monitoring to ensure that data is being properly protected and relevant policies, procedures and controls are being followed.					
The analytic security and compliance cover analytics within the institution and the compliance of data made available to third parties through cooperation agreement and other similar form.					
The institution has a system for monitoring how third parties use the data and whether it is consistent with the agreement.					

2. Overall Scoring for Analytics Maturity Assessment

Each score represents a different scope of view in measuring each key process area.

Key Process Area	High Level Management	Middle Level Management	Lower-Level Management	Weighted Score
Building Model	N/A	4,00	4,40	4,20
Deploying Model	N/A	4,60	4,20	4,40
Infrastructure	N/A	4,20	4,60	4,40
Governance	4,80	3,60	5,00	4,47
Strategy and Opportunities	4,80	3,20	4,60	4,20
Security and Compliance	N/A	4,80	5,00	4,90
Total Score	4,80	4,07	4,63	4,43

Table 1 Analytics Maturity Assessment on Each Management Level
Source: Researcher Analysis