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Data Analytics Maturity of Customer Accounting in Thailand

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Abstract

In an era where data has become a strategic resource, companies focus on the development of data analytics capabilities to enhance their competitiveness. This study aims to explore the Data Analytics Maturity (DAM) of organizations in Thailand, covering four levels of analytics: Descriptive, Diagnostic, Predictive, and Prescriptive Analytics, by classifying data use or reporting for data analysis (Use-Level Classification) into three levels: extensive use, partial use, and limited use. Data was collected from 247 organizations and quantitatively analyzed using cross-tabulation and heatmaps to reflect data usage levels in each dimension. The results show that the majority of organizations most extensively use descriptive analytics (218 organizations), while many organizations still have limited use of Predictive and Prescriptive Analytics (50 and 54 organizations, respectively). The findings reveal the gap among Thai organizations in adopting advanced analytics and highlight the need to promote skills, invest in infrastructure, and provide policy support to sustainably drive data-driven business decision-making at the national level.

Keywords: Data analytics, Data analytics maturity, Customer accounting, Thai listed companies, Thailand

1. INTRODUCTION

In the era of the digital economy, information technology plays a crucial role in business operations and data has become the most powerful strategic resource for organizations. With both technology and data, data analytics has been employed as a strategic tool enhancing the efficiency of economic activities as well as business competitiveness, thereby enabling accurate decision-making. The development and application of data analytics has continuously and increasingly garnered interests in the global business sector. The analytics has been applied in analyzing customer demand data, forecasting sales, expenditures, and current and future profitability (Brock & Khan, 2017). These exampled analyses allow businesses to formulate customer strategies for enhancing their relationships with targeted clients (Ghasemaghaei & Calic, 2020), or to efficiently improve the quality and innovation of products or services (Côrte-Real et al., 2016). Therefore, data analytics capability becomes crucial for business. To acknowledge the state of data analytics encourages organizations to evaluate their use of data, their strength and weakness of data analytics, and consequently develop their own data analytics capabilities.

This research aimed to investigate the state of data analytics among Thai listed companies. It employed the concept of "Data Analytics Maturity" (DAM) model which categorizes the level of data analytics, ranging from the basic level, focusing on simple processing, to the highest level, where organizations can use data to forecast business trends and make real-time strategic decisions. The model (Gartner, 2019) included 1) Descriptive Analytics, 2) Diagnostic Analytics, 3) Predictive Analytics, and 4) Prescriptive Analytics. Thai companies were then investigated their level of usage according to these four categories and grouped into three levels: Extensive Use, Partial Use, and Limited Use. Firms with the extensive use of higher levels of data analytics maturity can derive greater added value from data, resulting in more operational efficiency and competitive advantages, and consequently, being better positioned to integrate insights into strategic decision-making, foster innovation, and achieve sustained competitive advantages in dynamic markets (Sharda et al., 2014; Gartner, 2019).

2. DATA ANALYTICS MATURITY MODEL

Data analytics generally refer to analyzing and processing data (Maroufkhani et al., 2020). It involves interpreting, analyzing, categorizing, grouping, and calculating data (Dow et al., 2021) using mathematical and statistical

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methods combined with various data analysis techniques and tools (Russom, 2011; Maroufkhani et al., 2020; Dow et al., 2021). Both basic and in-depth data can be analyzed, as well as past and current data, in order to forecast and predict future trends. Data analytics can also be used to analyze the relationships between various factors or variables (Gim et al., 2018; Dow et al., 2021). Therefore, data analytics are not only to extract previously unknown, useful, valid, and hidden patterns and data from large data sets, but also to detect important and meaningful relationships among the stored variables. This valuable insight allows firms to gain competitive advantage (Elgendy & Elragal, 2014).

As data analytics can generate various type of information for different purposes of usage, many researchers have conducted studies to recommend the levels of complexity in data analytics. For example, Gim et al. (2018) proposed classification of data analytics by considering the level of complexity. Descriptive analysis requires easy techniques and tools, so is the least complex. In contrast, prescriptive analysis emphasizes decision support; therefore, requires complicated techniques and tools to generate information for decision-making. Appelbaum et al. (2017) categorized business data analytics into three levels: descriptive, predictive, and prescriptive, to be employed by management accountants. These categories present different levels of complexity in data as well as methods employed.

Due to the diversity of research on data analytics categorization, the Data Analytics Maturity Model (DAMM) was proposed to provide an understanding of the state of data usage and analytics in organizations. Al-Sai, Abdullah & Husin (2019) suggested that a maturity model is a useful tool that can be applied to assess the "As-is" situation regarding specific key dimensions, where the maturity levels indicate an organization's current capabilities and the desirable state. Thus, the maturity models have two objectives: 1) to describe a given organizational context to assess the current level of maturity of an organization related to a particular technology or capability, and 2) to guide the organizations to improve their current level of maturity.

The DAMM has been structured by various researchers (Gartner, 2019; Sharda et al., 2014; Dahiya et al., 2021) to provide structured pathways for data analytics capability building. It is not only taxonomic but also strategic, guiding organizations from basic reporting towards predictive foresight and prescriptive decision support, and classifies the levels according to the data's complexity and analysis methods used (Bonaparte, 2020). Among the researchers of this area, the model of Gartner (2019) has been widely accepted and referred. The model classifies analytics into four levels: descriptive, diagnostic, predictive, and prescriptive analytics. Figure 1 presents the DAMM of Gartner (2019).

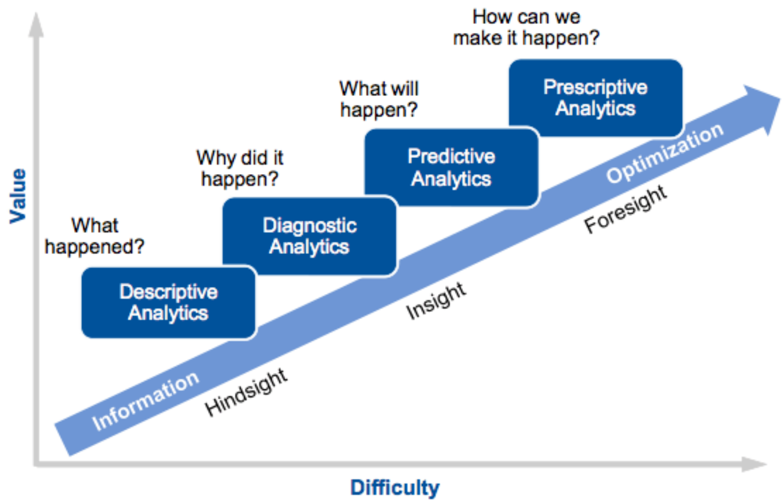

Fig. 1. The Data Analytics Maturity Model (Gartner, 2019)

- *Descriptive analytics* is a basic level of analysis that interprets past data to provide insights of business events. It typically answers the question, "What happened?" and thus helps to identify business problems and opportunities (Pinochet et al., 2021). This is the most fundamental type of data analysis (Contreras Pinochet et al., 2021). The analytics involves general presentation and analysis of data, which is mostly conducted using single-variable analysis (Ritbumroong, 2019), surveys of behavior, data summarization, or frequency analysis. Basically, from management accounting viewpoint, it is typically characterized by descriptive statistics, Key Performance Indicators (KPIs), dashboards, or other types of visualizations (Appelbaum et al., 2017; Dilla et al., 2010). Thus, basic data analysis tools or preliminary business reporting tools, such as excel and visualization, are typically used (Maoz et al., 2017).

The descriptive analytics include, for example, that the return on equity (ROE) ratio is analyzed by comparing the ratios in the past five years to determine the trend of this return metric (Appelbaum et al., 2017). Also, customer data is collected to analyze who make the largest purchases and their purchasing behavior by ranking the customers based on their actual orders and payments. Firms then can prioritize their customers. Furthermore, using descriptive analytics, firms can identify which types of customers and products contribute to overall company revenues by plotting graph using customers and products purchased data (Kokina et al., 2017). The analytics can also deliver customer satisfaction analysis and the classification of customers based on their purchasing behavior; consequently, firms can track their customer behavior at individual and group levels (Fatouretchi, 2019). This is useful for customer relationship management and marketing strategies (Suharto & Yuliansyah, 2023).

- *Diagnostic analytics* is to find reasons – why did it happen? – and understand situations based on data. It helps to clarify rooted causes and realize why certain outcomes occur and how they come about (Gim et al., 2018). Diagnostic analytics often involves examining the relationships of two or more variables (Ritbumroong, 2019). Examples include analyzing the causes behind cost changes when comparing two years, investigating reasons for insufficient inventory in a business, examining the causes of changes in tax rates, or identifying the reasons for an increase in taxes paid by the company (Dow et al., 2021). It can also involve analyzing the differences in sales across different areas to consider whether geographic regions affect sales performance (Ritbumroong, 2019), and so forth.

- *Predictive analytics* refers to analysis for prediction or forecasting, so it is characterized by predictive and probability models, forecasts, statistical analysis and scoring models (Appelbaum et al., 2017). It aims to answer the question of what is likely to happen next and is often used to predict data behaviors in order to forecast results. To reach its aim, it uses historical data accumulated over time to analyze trends and/or what may happen, with a focus on building models to forecast future outcomes (Ritbumroong, 2019). Therefore, predictive modeling is generated to explain the relationships within the data (Contreras Pinochet et al., 2021).

  Statistical and mathematical techniques, such as random forecast regression (Fang, Jiang & Song, 2016), and logistics regression and decision tree (D'Haen, Van den Poel, & Thorleuchter, 2013) were utilized to support the analysis. The proposed application of this analytics, for example, is the research of Fang, Jiang, & Song (2016) which proposed the predictive customer profitability model for insurance companies in order to distinguish valuable and non-valuable customers, thereby create effective customer-specific strategies, as well as enhance the decision-making in marketing and provide a metric for the allocation of marketing sources to customers and market segments. Other examples include forecasting asset price movements, predicting warranty expenses, estimating future product demand, and projecting future expenditures (Dow et al., 2021).

- *Prescriptive analytics* refers to decision-driven analytics, involving identifying main issues to be addressed, finding alternatives for problem-solving, comparing the consequences of each alternative, and making final decision based on all data. As a result, ideally, firms obtain the most suitable, accurate, and precise solutions to the issues (Barton & Court, 2020), and develop strategies and action plans of business in order to achieve organizational objectives (Contreras Pinochet et al., 2021). From management accounting perspective, Appelbaum et al. (2017) explained that prescriptive analytics may be described as an optimization approach, recommending one or more solutions and showing the likely outcome of each. As such, in a prescriptive orientation, mathematical simulation models or operational optimization models are constructed to identify uncertainties and offer solutions to mitigate risks or adverse forecasts.

  Several researchers (Mišić & Perakis, 2019; Choi, Wallace, & Wang, 2018) had reviewed the application of data analytics in operation management. They presented the example of prescriptive analytics used in practices; for example, the use of approximation algorithm (Aouad et al., 2018) in revenue management, and was the use of machine learning algorithms (Appelbaum et al., 2017; Bilal et al., 2019), or. The algoritms was employed to train models for the purpose of taking an innovation perspective into consideration with other factors such as customer satisfaction and revenue of sales, and identifying the optimized strategy to improve the design of a new version of smart phones (Appelbaum et al., 2017).

  This prescriptive analytics are, for example, analyzing how to minimize product costs, maximize sales, or achieve the highest profit; determining the optimal route for product delivery; and analyzing to support investment decision-making (Dow et al., 2021).

From the above explanation, characteristics of each data analytics level are summarized in Figure 2 regarding Contreras Pinochet et al. (2021)

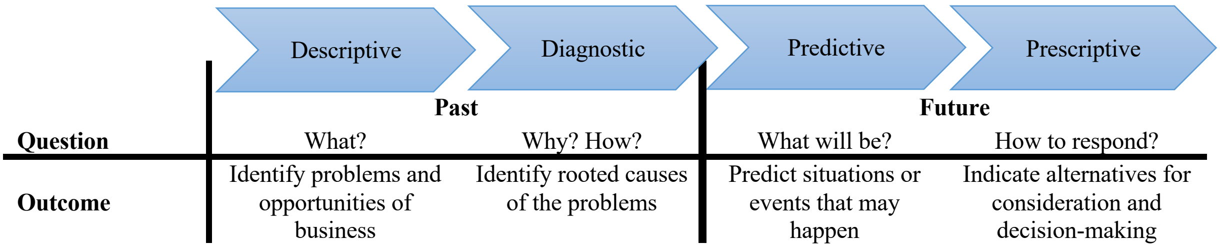

Fig. 2. Data Analytics Maturity (Contreras Pinochet et al., 2021)

3. RESEARCH METHODOLOGY

3.1 Sample

The sample was 703 companies listed on the Stock Exchange of Thailand (SET) (SET, 2024), and excluded those listed on the Market for Alternative Investment (MAI), as they are small and medium-sized enterprises (SMEs) (with paid-up capital after IPO starting from 50 million baht); as a result, they might have limited usage of technology and data analytics tools. The sample included eight sectors, i.e. agro and food, natural resources, technology, financial institutions, services, industrial products, consumer products, and property and construction.

The questionnaire was sent via e-mail to 703 companies and 251 responded, which was 35.7 percent of total sample. The questions were answered by a data analyst or other position being responsible for a company's data analysis. Only four responses were invalid; as a result, the sample consisted of 247 companies.

Table 1. The number of sampled companies in each sector

Sector	Number of companies	Percentage
Agro and Food	32	13
Natural Resources	13	5.3
Technology	15	6.1
Finance	10	4.0
Services	61	24.7
Industrial Products	38	15.4
Consumer Products	23	9.3
Property and Construction	55	22.3
Total	**247**	**100**

3.2 Data Collection and Analysis

The research instrument was developed and included 2 main parts:

Section 1: General Information part aimed to collect basic data about the respondents, including gender, job position, years of work experience, and type of business, totaling four items.

Section 2: Data Analytics part listed information and report according to customer accounting, and asked the sample whether their company had prepared such information and report for analysis and decision-making. This customer accounting was selected because customers are the main focus of corporations and we can ensure that every companies definitely had this type of analysis. The statement were, for example, at the descriptive level – 'The business prepares reports on the sales and expenses of individual customers, comparing data over 5 years', while at the diagnostic level – 'The business analyzes the reasons behind customer segments with high profitability'. The list of information and reports were constructed based on various researchers (Guilding & McManus, 2002; Lind & Strömsten, 2006; Lord et al., 2007; Al-Mawali et al., 2012; Sridhar & Corbey, 2015; Holm et al., 2016; Turner et al., 2017; Dow et al., 2021; Oyewo, 2021). A total of 30 items was listed: 7 items on descriptive analytics, 6 on diagnostic analytics, 10 on predictive analytics, and 7 on prescriptive analytics.

For each item, the score 1 was given when the sample prepared such information or reports and zero otherwise. Table 2 showed the full score of each level of data analytics and the range of score used to categorize the sampled companies into three different groups: limited use, partial use and extensive use of information and reports.

Table 2. Range of score employed to classify level of data analytics

DAMM	Descriptive	Diagnostic	Predictive	Prescriptive
Full score	7	6	10	7
Extensive Use	5-7	5-6	7-10	5-7
Partial Use	3-4	3-4	4-6	3-4
Limited Use	0-2	0-2	0-3	0-2

4. RESEARCH RESULTS AND DISCUSSION

A heatmap (Figure 3) showed the number of companies regarding data analytics level—namely descriptive, diagnostic, predictive, and prescriptive. For descriptive analytics, a substantial majority of 218 organizations demonstrated extensive use, while only 3 reported partial use and 26 indicated limited use. This widespread adoption of descriptive analytics among Thai companies is consistent with expectations, as it often serves as the foundational stage for data analytics, requiring less sophisticated technological infrastructure and expertise for initial implementation (Sharda et al., 2014). The presence of 29 companies reporting partial or limited use of descriptive analytics raises concerns that they may have deficiencies in basic customer data collection or an inability to effectively leverage existing big data for fundamental decision-making, potentially exposing them to high competitive risk.

Regarding diagnostic analytics, the majority of firms (197) reported extensive use. However, 50 companies (5 partial use, 45 limited use) indicated posibilities to have limited proficiency in diagnostic analytics implying a potential inability to accurately identify the root causes of underperformance, which can hinder effective decision-making and strategic planning. As Shah (2022) highlights, diagnostic information is crucial for addressing "what went wrong" or conducting "why-analysis," which subsequently informs the accuracy and utility of predictive analytics. Thus, this limitation in diagnostic capability may compromise the reliability of data for advanced analytics, thereby weakening the analytical capability of some Thai listed companies. Nevertheless, the extensive use of 197 companies signals a positive shift towards data-driven practices within Thai firms.

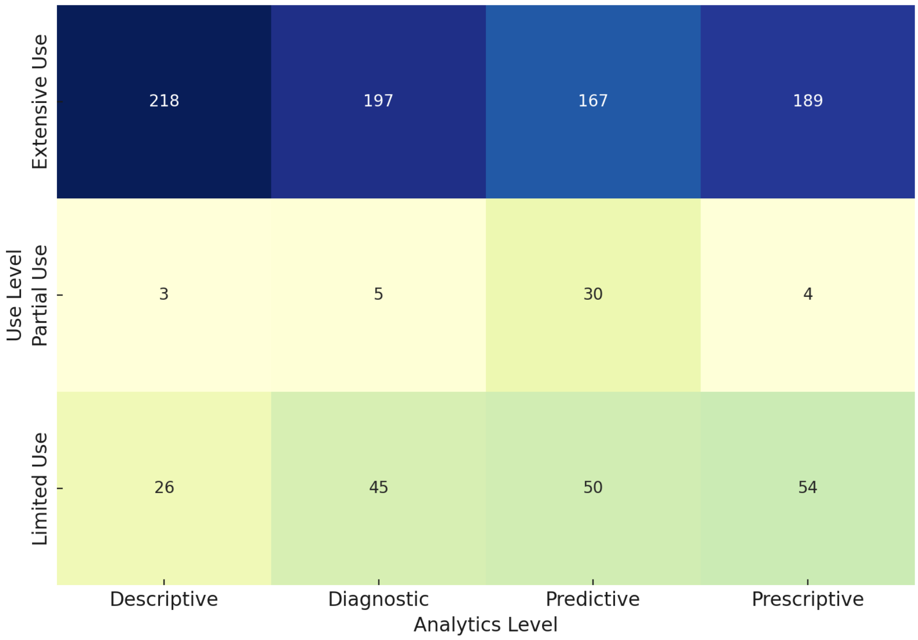

Fig. 3. Heatmap shows the level of data analytics and the number of companies

At predictive analytics level, 167 firms utilized forcasted customer information and reports extensively in their future decision-making, followed by 30 reported partial use and 50 indicated limited use. The cumulative total of 80 firms with partial or limited use is proportionally higher than observed at the descriptive and diagnostic levels. This suggests that many Thai firms are not yet fully capitalizing on the insights embedded within their existing data to anticipate future trends. A similar pattern emerged for prescriptive analytics. While 189 organizations reported extensive use, a considerable 59 firms (54 limited use, 4 partial use) demonstrated limited application of this advanced analytical capability. These findings highlight a need for these 59 Thai firms to enhance their data analytics capability to leverage data for optimal decision-making recommendations.

The higher number of companies with partial and limited use of predictive and prescriptive analytics, compared to descriptive and diagnostic, was unsurprising, as both advanced analytical approaches demand complex data infrastructure, extensive executive support, and highly skilled personnel for effective implementation. LaValle et al. (2011) pointed out that predictive analytics was a critical tool for strategic competition, but it needed executive support and a robust data management structure, requirements that extend equally to prescriptive analytics. Therefore, it is challenging for Thai firms to transition to this level of analytics.

The results also lead to concern on the firms' competitive capability in this data-driven business world, as data analytics, especially at the predictive and prescriptive level, is a crucial component of decision-making processes. It can give an incisive insight into various organisational phenomena and their causal relationships, thereby enhances proactive and forward-looking capability of the firms (Wamba et al., 2017; Shah, 2022). Wamba et al. (2017) further posited that the big data analytics is a major tool to differentiate between high-performing and low-performing organizations. Consequently, the limited utilization of advanced analytics by a segment of Thai firms may result in lost opportunities to effectively manage customer relationships and optimize operational efficiencies. This disadvantage is particularly pronounced for companies that possess substantial big data assets but fail to analyze them at predictive and prescriptive levels. Wamba et al. (2017) (referred in Shah, 2022) reviewed the examples of successful companies using big data analytics at the advanced level to cut cost and attract potential customers. Amazon created algorithms employed to offer personalized product recommendations to their customers, while Target Corporation collected and analysed their customers' purchasing behaviours through its loyalty card program and predict their future buying trends.

In summary, the research indicates that most Thai firms have achieved proficiency in foundational data analytics (descriptive and diagnostic). While there is an observable trend of growth in the adoption of higher-level analytics (predictive and prescriptive), a proportion of organizations still demonstrate only limited engagement with these advanced capabilities. This poses a potential concern regarding the competitive positioning of Thai firms. The partial and limited adoption of advanced analytics can be attributed to various factors, including technological infrastructure deficiencies, insufficient personnel training, and a lack of organizational culture that actively fosters data-driven competitiveness.

5. CONCLUSION, LIMITATIONS AND RECOMMENDATIONS

This study provided empirical evidence on the levels of data analytics usage among Thai firms. While a substantial majority of firms exhibited strong proficiency and extensive adoption of foundational descriptive and diagnostic analytics, a considerable proportion demonstrated notable limitations in the application of advanced predictive and prescriptive analytics. These findings highlight that numerous Thai firms are not yet fully capitalizing on its potential for forward-looking strategic advantage. The observed gaps in advanced analytics adoption are likely attributable to various factors, including sophisticated infrastructure requirements, the need for executive support, and, critically, a scarcity of highly skilled personnel capable of implementing and interpreting these complex analytical techniques. Consequently, a segment of Thai organizations possibly remains at a competitive disadvantage, potentially missing opportunities to optimize operations, enhance customer relationships, and respond proactively to market dynamics in an increasingly data-driven global economy. Advancing beyond foundational analytics presents a significant challenge requiring targeted investment in technology, talent, and an organizational culture that champions data-driven decision-making.

Although this research provided in-depth information regarding the maturity level of data analytics usage and the various analytics levels within organizations, there were still some limitations that should be considered. First, there was sample limitation, meaning that the sample size consisted of only 247 companies, which might not sufficiently cover the diversity of industries, business sizes, and geographical areas; consequently, might affect the generalizability of the findings, since businesses from different industries might have distinct approaches to data analysis. Second, single time point study was conducted. Data was collected at a single point in time, which failed to reflect long-term changes in data analytics maturity. As data analytics complexity often relies on rapidly evolving technologies, the long-term results could differ significantly. Third, the study had not dealt with causal analysis. This research was primarily descriptive and comparative. There has not yet been any statistical or in-depth causal analysis conducted.

With the limitations, future studies may expand the sample size and use more diverse samples in terms of industry, organizational size, and region to increase the comprehensiveness of the results. There should be continuous tracking of DAM development within organizations, or studies examining the relationship between DAM levels and organizational outcomes such as profitability. A combination of quantitative and qualitative data collection, such as in-depth interviews, should be considered to better understand data analytics practices. Since the use of questionnaires limited the range of possible responses, some companies might use additional forms of analytics not covered in the survey. Interviews would provide richer information.

Regarding practical implications, organizations could employ the DAM model to assess their current status and systematically plan for the next stage of analytics capability development. Also, policymakers and government agencies can use the research results to formulate supportive policies, such as tax incentives for investments in analytics technologies or grants for SMEs looking to develop analytics capabilities.
At the policy level, regulators and government agencies should consider targeted incentives such as analytics training programs, R&D tax credits, or sector-specific grants to accelerate DAM adoption across industries. These measures can strengthen Thailand's data-driven economy and narrow the analytics capability gap with global competitors.

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