

Innovative Mobile Application for Measuring Big Data Maturity

Case of SMEs in Thailand

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Abstract—A Big Data maturity model (BDMM) is one of the key tools for Big Data assessment and monitoring, and a guideline for maximizing the usage and opportunity of Big Data in organizations. The development of a BDMM for SMEs is a new concept and is challenging in terms of development, application, and adoption. This article aims to create the novel online adaptive BDMM via responsive web application for SMEs. We develop the BDMM API and a responsive web application for easy access via mobile phone. We developed a model by analyzing the factors impacting the success of implementing Big Data Analytics (BDA) in SMEs based on literature reviews. The model was verified by conducting a survey of 180 SMEs in Thailand, interviewed against four extracted domains. Then, the scoring and classified levels for the model was developed through Latent Class Analysis (LCA) to depict four levels of each domain and four final maturity levels to create an adaptive model. As the experimental results with 33 users including executive officers, managers, IT, and data analytic officers. The user acceptance for our mobile application using TAM indicates that executive officer's group and non-executive group satisfied perceived usefulness, perceived ease of use, and intention to use factor. Use cases of the application include SMEs monitoring for their Big Data Analytics capability for improvement, and the Government Agency providing proper support on SMEs' level of competency.

Keywords—Big Data Maturity Model, Big Data SMEs, BDMM mobile application

1 Introduction

Data are an extremely valuable asset in every business from large-scale enterprises to small and medium-sized enterprises (SMEs) and are considered the new oil [1]. Analytics is applied to data for actionable decision making and competitive advantages. The term “Big Data” was initially defined in [2] to address the challenges of size, speed, and different formats of data that cannot be handled or processed by conventional methods. Since then, this term has been increasingly used in the fields of media, technology, and academics [3, 4]. Big Data analytics (BDA) comprises multiple technologies and usually requires high investments in various fields, such as IT, databases, data ingestion, machine learning, and data visualization.

SMEs are the lifeblood of Thailand and crucial for its economic growth. They are defined by the number of employees and assets or revenue. Thailand comprises about 3 million SMEs, which generate 43% of the country’s GDP, as of 2019. Many studies have been conducted to determine the factors affecting the successful implementation of BDA in SMEs [5-7]. Big Data maturity models (BDMMs) have been developed by multiple technology companies, researchers, and consulting firms. However, most of the existing BDMMs develop a set of assessment questions suitable for large-size companies, which invest in high technology, have many business units, and possess a large amount of staff to adopt the technology. Therefore, the existing BDMMs are ineffective for SME assessment, as the assessment could result in a low score and they cannot provide suggestions or recommendations for improvements in SMEs which is a guideline for using such a technology. Since BDA is a state-of-the-art technology, some BDMMs with static model cannot satisfy the fast-growing nature of the technology and the rapid changes in the SME’s industries. Therefore, an adaptive model would more appropriate in the scenario.

We developed an adaptive BDMM model for SMEs. First, we designed a questionnaire for determining the effects of existing BDMMs for SMEs based on factors against various challenges of BDA faced by SMEs in literatures, such as the adoption of BDA, data analytics (DA), and business analytics (BA) in SMEs. The questionnaire was provided both in the online and offline manner to business owners and management staff of SMEs, IT department staff, data analysts, and business users in various industries. Then, a latent class analysis (LCA) method has been applied to classify the SME’s levels according to the answers received to each domain and the final maturity level. Therefore, the model is adaptive depending on the questionnaire data gathered.

Since the model is adaptive, its usefulness would be greater if more assessment data from SMEs is accumulated. Therefore, we introduced an idea to develop an online model to gather data as much as possible. Consequently, in this article, we have developed the adaptive responsive web application for general SME users. We also have conducted a survey for the user’s technological acceptance for validating the user attitude through using application. Finally, we have discussed the usage scenarios of this mobile web application.

The remainder of this paper is structured into the following four sections. In Section 2, an overview of the existing background literature on BDMMs is provided. Section 3

presents the proposed methodology of the mobile web application development. Section 4 presents the discussions on the results obtained and research output of the mobile web application. Finally, in Section 5, discussions and conclusions are provided.

2 Literature Review

2.1 BDA-based challenges for SMEs

The earlier version of BDA initially considered the factors of volume, velocity, and variety, which were defined as the 3 Vs of BDA [8]. Later, Seddon and Currie [9] proposed the consideration of value, variability, visualization, and veracity in BDA, thus achieving the 7 Vs. The success of BDA involves not only the consideration of multiple technologies, such as IT infrastructure, application data sources, storage, data analysis, predictive analysis, and data visualization [5] but also the staff's ability, and learning culture [10]. Many researchers have evaluated the problems and challenges in adopting BDA in organizations [11]. Iqbal et al. [12] and Coleman et al. [5] addressed this challenge and put forward a path for implementing BDA in SMEs, which involved improving people skills, building analytic capability, determining use cases, and management support. The availability of multiple data sources in an organization is related to success in SMEs [13]. Agrawal [14] proposed the technology-organization-environment framework for adoption of BDA and found that complexity, organizational size, and environmental uncertainty were the influencing factors for BDA.

2.2 Impact of factors on BDMs in SMEs

We propose a BDM for SMEs based on existing models and literature to provide effective questions, domains, and results of assessment to SMEs. The assessment was based on four domains: organization and management attitude (OA), IT, analytic technology (AT), and people readiness (PP).

- a) **Organization and management attitude (OA):** OA are one of the most critical factors for BDAs in SMEs. In Thailand, we found that power, experience and culture accelerate innovativeness in family SMEs[15]. BDA challenge comprises the lack of business use cases or benefit of investment as parameters of its determination [5, 16], along with the willingness to change or experiment [17]. The predictive analyses of use cases for customer analytics have been performed to identify factors that impact the value-perceived attitude [18]. Noonpakdee et al. [19] reported that the financial performance of SMEs is also a key factor into utilizing BDA in Thailand.
- b) **Information Technology (IT):** The IT system is comprised of applications, such as Enterprise Resource Planning (ERP), customer relationship management (CRM) software, accounting software, databases, and Microsoft Excel, which are frequently used in organizations. The IT system is an essential part of any infrastructure for collecting, storing, and analyzing data. As a part of the 3 Vs, the variety of data is strongly related to software currently being used in a company, such as ERP and data analysis process

[20]. Multiple studies have reported on data sources for BDAs, for example, websites, ERP, human resources, and accounting [19]. Olszak and Mach-Król [1] studied sales management, CRM, marketing, and digital marketing to generate data. In addition, supply chain data in an industrial enterprise is used for decision making [5].

Data stores comprising spreadsheet applications, such as Excel, Excel online, and Google Sheets were surveyed in [21]. Database technology, data warehouse, and BD-Hadoop have also been used in BD research in SMEs [21], along with NoSQL and BD-Hadoop [22, 23]. Coleman et al. and El-Seoud et al [5, 23] suggested the use of cloud platform or software as a service. The data volume for SMEs is different than that for larger enterprises because SMEs have limited sources of data. Almeida and Bernardino [21] reported that 1 GB of data is the size limit for open-source software; however, this was contradicted by Iqbal et al. [12], who determined that many SMEs use several terabytes of data.

The velocity of transaction data, social media data, and Internet-of-Things was found to be a challenge [20]. Internal and financial data were considered by Ahlemeyer-Stubbe and Coleman [24], while Schmarzo [25] considered demographic, behavioral, and environmental data. In [26], customer satisfaction, feedback survey, and market data were studied in terms of BDA. Junqué de Fortuny [27] used a combination of multiple types of data from web pages, including visitor behavior, location, and feedback support for various types of businesses.

- c) **Analytic Technology (AT):** Analytic software conducts analyses through conventional Excel or spreadsheets, which are widely used by general users. These include analysis reports obtained from ERP or CRM [28] [20], as well as business intelligence and data visualization or Dashboard in BA [29] [16]. Cloud computing is a cost-effective approach for SMEs in terms of infrastructure, computing, and storage. It also helps to reduce the required number of IT staff for administration [30]. Almeida and Bernardino [31] studied the use of open-source software for data mining, predictive analysis, and prescriptive analysis for SMEs.
- d) **People (PP):** People are the most important resource in SMEs and for the success of DA. Education, including training and seminars, is a key activity for driving the learning of new technologies[32]. Experience-centered approach, including learning by doing has been proposed to fill the gap of education in practice [33]. The number of employees with multiple skills, such as business intelligence, data visualization, statistical analysis, advanced Excel, advanced analytics, or predictive modelling, was included as part of the experience in the DA technology. Online learning is also an effective way of learning for BDA [34].

2.3 Review of existing BDDMs

Many researchers and business consulting firm have introduced the BDDM to help organization to improve a capability in big data technology through assessment tools. Some researchers have conducted systematic reviews of existing BDDMs [35-37]. Braun [35] compared multiple maturity models (MMs) and provided the evaluation score for the top two highest performing MMs, i.e., TDWI [38] and International Data Corporation (IDC 2013). The top performer models are easy to use, extensive, well-

documented. The comparison of BDMMs with major characteristics are discussed and we extracted as shown in Table 1. Braun [35] also provided a negative report on lack of theoretical soundness, rigorous testing, and wide acceptance. Al-Sai and Abdullah [37] reported the limitation that most of models have been developed in industry, by either technology vendors or consulting partners that might expose them to biases. Most of the currently used BDMMs are old, and a few have been developed recently.

Table 1. Big Data Maturity Model Comparison.

| Primary Source | IDC (2013) | Halper & Krishnan (2013) | Infotech (2013) | Knowledgent (2014) | Betteridge (2014) | Our BDMM |
|-----------------------|---|--|---|---|--|--|
| Domain | 5 | 5 | 4 | 5 | 6 | 4 |
| Domain Question | Intent, Data, Technology, People, Process | Org., Infra., Data Mgmt., Analytic, Governance | Staff, Business, Data Management, Tech., Data | Business, Tech., Operating, Analytics, discipline | Strategy, Information, Culture, Architecture, Governance | Organization and Attitude, IT, Analytic Technology, People |
| Level | 5 | 6 | 4 | 5 | 5 | 4 |
| Target Company | Enterprise | Enterprise | Enterprise | Enterprise | Enterprise | SME |
| Assessment Instrument | Web based | Web based | Traditional Questionnaire | Web based | Text document | Responsive Web |
| Score scale | Static | Static | Static | Static | Static | Adaptive |
| Score level | Rule | Rule | Rule | Rule | Rule | Cluster |
| Recommendation | Yes | No | No | No | No | Yes |

This article introduces the novel online mobile adaptive BDMM for SMEs. As the BDA technology is fast growing, the model was developed in our previous works to be an adaptive model as described below.

2.4 Our BDMMs for SMEs

To develop our adaptive BDMMs for SMEs, we proceed the following three stages.

Questionnaire and validation: We analyzed challenging factors from the literature review of BDAs in SME and gathered the domain’s name and questions from BDMM, then we iteratively validated the questionnaires and grouped them into four domains by academic experts and BDA experts in Thailand who are familiar with SMEs. Then we conducted a final questionnaire-based survey for SMEs in Thailand by involving various groups of respondents, from business owners; executive managers or managing directors; operation leaders, such as business analysts, or data analysts; to IT managers. After we conducted a quantitative survey data to obtain model-development data for BDMMs. Four domains must be considered as factors for developing a BDMM for SME: OA (6 questions), IT (5 main questions, 26 sub-questions), AT (4 main questions, 17 sub-questions), and PP (4 questions).

Sampling and data collection: The survey was conducted incorporate with the Office of Small and Medium Enterprise Promotion (OSMEP), Thailand. We did sampling SMEs by 3 sectors which are services, manufacturing, and trading. Moreover, we sent

mail to the list we received from OSMEP and sent online survey by using www.surveymonkey.com to others SMEs by snowball sampling. The questionnaire consisted of five sections. The first section gathered demographic information of the organization and respondents. The respondents' information included age, education, and position in the organization. The second to the fifth sections gathered the factors and attitudes of BDA in SMEs that were used for developing our MM. The survey was conducted in the SMEs both online and offline from August 2019 to September 2019, with 180 respondents and 135 questionnaires completed. Majority of the respondents is 60.4% graduated in master degree and 29.63% in bachelor degree. Position of managing director or business owner Respondents are 52.59%, IT and Data Analyst are 33.34%. In industry point of view, the respondents were from Trading at 23.70%, Service at 61.48%, and Manufacturing business at 14.82%. Their companies' revenue is varied from less than 50 million baht to more than 500 million baht. The number of IT staff in the company ranges from none to more than 20 staffs.

Model development through cluster analysis: Model development through machine learning is considered using latent class analytics (LCA) because of the LCA characteristic of clustering categorical variables. The comparison between multiple clustering methods and LCAs have been analyzed in [46]. Moreover, the LCA approach has been considerably used by researchers for conducting latent subgroup analyses in education, health, and behavioral research [47] [48]. Therefore, in this study, the authors used LCA to conduct clustering of multiple domains and classification of maturity levels.

We conducted a cluster analysis for building the BDMM through LCA by using the Proc LCA software [49] and R package v.1.4.1 [50]. The number of groups that were tested ranged from three to six, as BDMMs, in general, comprise four-six groups [34].

We also studied characteristic of each group by validating the comparison of the lowest number of The Akaike and Bayesian information criteria (AIC and BIC, respectively, [39, 40]). Based on the general assessment, a single number of groups was required for all domains. We selected to use $N = 4$ in balancing of multiple two lowest AIC/BIC values as shown in Table2.

Table 2. Comparison of the AIC and BIC analysis for $N = 3-6$ for each question domain.

| | N = 3 | | N = 4 | | N = 5 | | N = 6 | |
|----|--------------|--------------|--------------|--------------|--------------|------------|------------|------------|
| | <i>AIC</i> | <i>BIC</i> | <i>AIC</i> | <i>BIC</i> | <i>AIC</i> | <i>BIC</i> | <i>AIC</i> | <i>BIC</i> |
| OA | 2,001 | 2,225 | 1,989 | 2,288 | 1,989 | 2,364 | 1,999 | 2,450 |
| IT | 7,158 | 7,681 | 7,062 | 7,760 | 7,004 | 7,878 | 6,962 | 8,011 |
| AT | 4,011 | 4,380 | 3,918 | 4,411 | 3,859 | 4,476 | 3,919 | 4,660 |
| PP | 1,495 | 1,656 | 1,498 | 1,713 | 1,508 | 1,777 | 1,520 | 1,844 |

The highlighted numbers are the two lowest AIC and BIC values

We clustered the result of each domain, i.e., OA, IT, AT, and PP, into four groups, and run LCA again for clustering each domain to determine the number of final maturity level by AIC/BIC. Four maturity level were selected based on the same process. Moreover, we provide validation by analyzing the demographic separation of each maturity level. The model development uses a clustering technique to reduce the cost and

time required for the multiple steps and MM that is developed manually by experts. The data collected from 135 SMEs can be used to predict new organization assessment, and we can also provide the recommendation and model monitoring for model adjustment in the future.

The model was validated through descriptive analysis for the separation of demographic data, which are number of staffs, number of IT staffs, and revenue, interpret that the model can classify the domains into four different maturity levels as shown in figure 1.

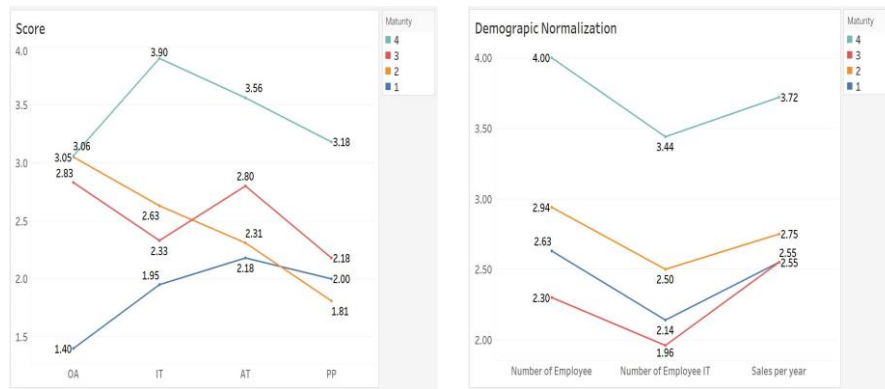


Fig. 1. Classification of maturity level versus domains and demographic

We classified each maturity level according to their characteristics as follows: 1) Low OA, IT and analytic; 2) High OA and IT, but low analytic and people; 3) High OA and Analytic but medium for IT and people; 4) High mature for all domains.

This developed model is adaptive. When more SMEs assess themselves via this model, some technologies, such as Business Intelligence, data mining, and predictive analytic, may gain popularity over time. In contrast, some technologies, such as CRM and ERP, may become fundamental for SMEs. The scoring of such technologies may decrease gradually. However, if the scoring increases continuously, we can retrain the model to cluster new groups and levels. Moreover, when many firms self-assess, they could observe the average score of the same domain type in detail and desire to improve themselves to increase their competitiveness.

2.5 TAM

Technology acceptance for intention and behavior in information technology was introduced by [41] [42]. TAM was the first proposed and the most popular model by Fred Davis in 1985. Davis proposed that the intention to use directly influenced by the system’s capabilities and features. TAM was adjusted with the theory of reasoned action (TRA) [43] The TAM model consists of behavioral intention to use, which is measured users’ attitudes by the perceived ease of use and perceived usefulness. Relevant studies confirmed that TAM was used as the core framework for analysis the acceptance

of the mobile system. Many studies investigated users attitude on mobile technology through adoption of tools or consumer application such as mobile banking [44], google translation [45], e-learning in university system [46, 47] and mobile commerce adoption via mobile applications [48]. TAM model also used for organization assessment for the evaluate e-commerce assessment for SMEs [49] and university assessment [50] in Thailand. In summary, TAM is the most effective model and can be used as a tool to collect user’s comments for improving the system. Thus, for this research study, TAM was used as a core model to understand SMEs’ attitude in using an Big Data Maturity model of SMEs in Thailand.

3 Methodology

3.1 API and mobile web development

The proposed conceptual framework of the mobile web development consists of three phases, as shown in Figure 2: literature review of factors impacting the BDA for SMEs, model development, and model application and innovation acceptance. In our previous works, we already finished literature review and the model development. Therefore, in this section we explain about the application and innovation acceptance.

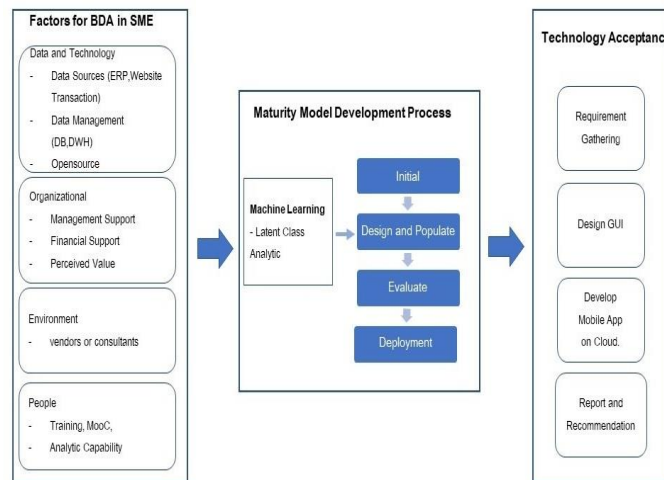


Fig. 2. Conceptual framework for the development of a BDMM for SMEs

We developed a BDMM-based web application by using .NET core framework with C#, an SQL Server as the DBMS, and a clustering model by using ProLCA with R package v.1.4.1. The model was developed using Alteryx desktop and ProLCA was embedded into the workflow. It was published to run on the Alteryx Server. Microsoft Azure was used at the front-end to connect the model clustering through API. The system architecture is shown in Figure 3.

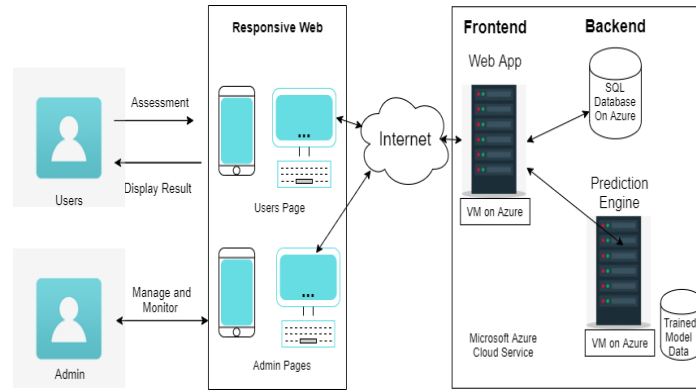


Fig. 3. System Architecture

3.2 Technology acceptance test

We conducted a technology acceptance test by using TAM for analyzing the result of our web application based on perceived usefulness, perceived ease of use, and the intention to use. The technology acceptance test was conducted from May 2020 to June 2020 to test the acceptance rate of the BDMM by collecting data from 33 respondents, including business owners, managing directors, managers, data analyst, IT, and business users. All of them have important roles in the decision making of using data analysis in the organization.

Questionnaire reliability: The questionnaire consists of 2 parts: demographic and opinions on using the system. The survey opinion was categorized into 6 dimensions with 26 variables, which uses a 5-point Likert Scale. The questionnaire was validated for reliability by using Cronbach’s alpha coefficient, which result show reliable for all dimensions with value higher than 0.7. The reliability analysis is shown in Table 3.

Table 3. Cronbach’s Alpha Coefficient for reliability analysis

| Dimension | Number of variables | Internal Consistency |
|-----------------------|---------------------|----------------------|
| System Efficiency | 5 | 0.746 |
| Usage | 5 | 0.811 |
| Data Security | 5 | 0.931 |
| Perceived Usefulness | 5 | 0.847 |
| Perceived Ease of Use | 3 | 0.831 |
| Intention to Use | 3 | 0.714 |

Data analysis: The survey data were analyzed with descriptive statistics tools for means and standard deviation using Statistical Package for Social Sciences Program (SPSS), Version 26.

4 Results

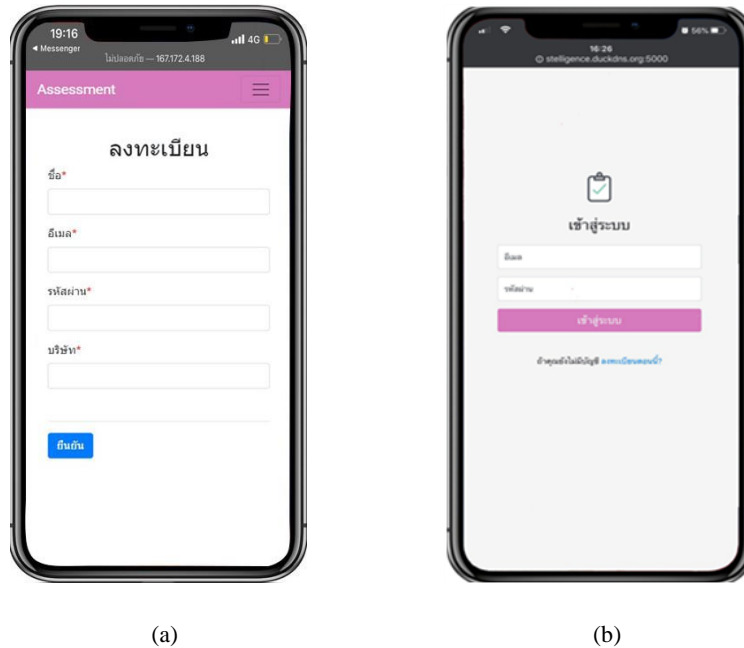


Fig. 4. BDMM; Registration page(a) and Login page(b)

4.1 Mobile web application for our BDMM

We developed our BDMM as a mobile web application to create an easy-to-use, real-time, adaptive assessment tool to monitor the continuous improvement of organizations and gain the highest value of BDA for SMEs.

The BDMMs for the mobile web application of SMEs were developed by considering the ease of use, no installation requirement, and the ability to access from any device. This allows SMEs to access and check their BDA status of each domain and each question that must be answered for achieving improvement (Figures 4 and 5). The administrator page was developed considering its usage in the web application for both mobile and desktop. The mobile version of the application is shown in Figure 6. The application contains features as follow:

- Login and registration pages: If user access for the first time, the user must register and provide information such as name, email, and organization for identification as shown in figure 4(a). If user already registered, user can login as shown in figure 4(b).

- Assessment pages: After login, the user takes an assessment based on the domains from OA, IT, AT, and PP as shown in figure 5(a). After the user finishes providing data, the prediction engine will show the reports after a few seconds and reach the report pages.
- Report pages: The report shows maturity level, results of each domain (OA, IT, AT, and PP) score and demographic information. The user is able to see the average score of its peers with the same level and average score of the next higher level for each domain in detail as show in figure 5(b). Moreover, application provide the visualization in radar chart for easier understanding and provides improvement level in each domain in graph format as shown in figure 5(c).
- Administrative pages: For manage users, the administrative function of managing user’s authorization between administrator and users as shown in figure 6(a). For model monitoring, it provides the descriptive analysis of users, distribution of maturity levels over domains and demographics as shown in figure 6(b).



Fig. 5. BDMM; Examples of Fill-in questions page and Report pages for SMEs

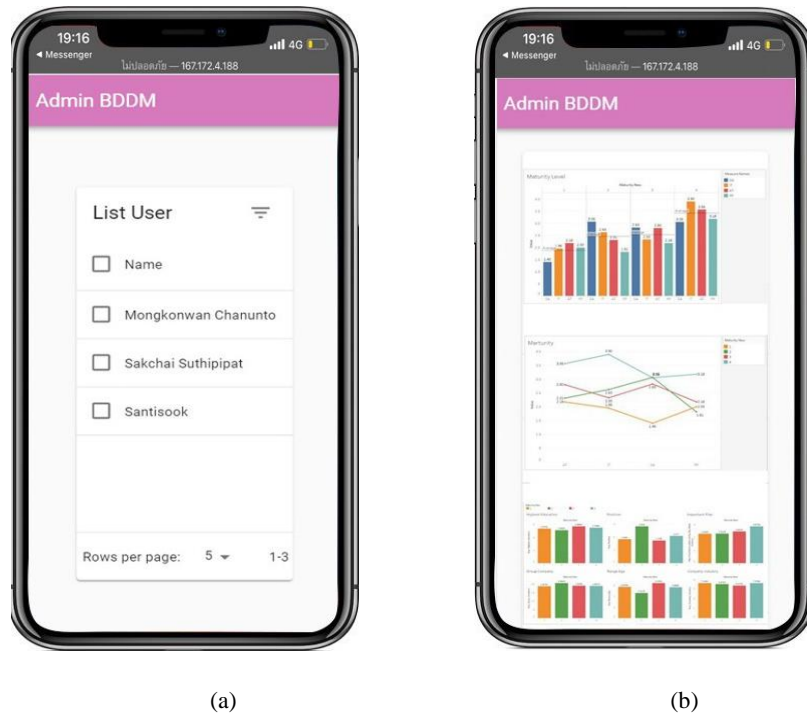


Fig. 6. BDMM; Example of Admin pages for user management and model monitoring

4.2 Technology acceptance of BDMM mobile web

The technology acceptance model was applied to test the acceptance rate of the BDMM by collecting data from 33 respondents, which are business owners, managing directors, managers, data analyst, IT and business users who have involved the decision making of using data analyst in the organization from May 2020 to June 2020 as shown in Table 4.

Table 4. Demographic data of respondents and their organization

| Variable | Description | n | % |
|---------------------------|---------------------------------|----|------|
| Age (years old) | < 25 | 0 | 0 |
| | 26–35 | 8 | 24.2 |
| | 36–45 | 19 | 57.6 |
| | ≥ 45 | 6 | 18.2 |
| Education (highest level) | Less than bachelor degree | 0 | 0 |
| | Bachelor degree | 2 | 6.1 |
| | Master degree | 19 | 57.6 |
| | Doctor degree | 12 | 36.3 |
| Position | Top Executive or Business Owner | 15 | 45.5 |
| | Manager or team lead Level | 10 | 30.3 |
| | IT or Data Analyst | 3 | 9.1 |
| | Business users or Employees | 5 | 16.1 |
| Type of business | Retail | 2 | 6.1 |
| | Service | 20 | 60.6 |
| | Manufacturing | 11 | 33.3 |

There were 20 service businesses (60.6%), 11 were manufacturing businesses (33.3%), and 2 was a retail (6.1%). Data providers from each organization reported a total of 15 business owners/top executives (45.5%), 10 managers or equivalent team leads (30.3%), 3 from IT heads or Data Analysis department (9.1%), and 5 business users or employees (16.1%). The results are displayed via six indicators in Table 5.

Table 5. Questionnaire Result for Technology Acceptance Test.

| Indicator | Details | Overall Mean | Overall SD | Mean of Executive Officers | Mean of Managers and Staffs |
|-------------------|---|--------------|------------|----------------------------|-----------------------------|
| System Efficiency | Convenient and efficient | 4.30 | 0.77 | 4.60 | 4.06 |
| | Accurate systematic order | 4.52 | 0.51 | 4.67 | 4.39 |
| | Useful assessment system | 4.48 | 0.62 | 4.60 | 4.39 |
| | Assessment reports from the system can be further developed | 4.52 | 0.71 | 4.53 | 4.50 |
| | System is useful for organizational development | 4.52 | 0.57 | 4.60 | 4.44 |
| Usage | Modern and attractive design | 3.82 | 0.92 | 4.07 | 3.61 |
| | Easy to read and use | 4.27 | 0.84 | 4.47 | 4.11 |
| | Proper character size and font | 4.03 | 0.81 | 4.13 | 3.94 |

| Indicator | Details | Overall Mean | Overall SD | Mean of Executive Officers | Mean of Managers and Staffs |
|-----------------------|--|--------------|------------|----------------------------|-----------------------------|
| | Appropriate pattern of assessment | 4.27 | 0.57 | 4.47 | 4.11 |
| | Appropriate pattern of report | 4.24 | 0.87 | 4.47 | 4.06 |
| Data Security | Reliable system | 4.09 | 0.84 | 4.07 | 4.11 |
| | Secure setting up of username and password for logging in | 3.97 | 0.81 | 3.93 | 4.00 |
| | Terms are specified prior to usage | 4.09 | 0.95 | 4.33 | 3.89 |
| | Usage is controlled according to terms | 4.18 | 0.92 | 4.33 | 4.06 |
| | Data collection is accurate and secure | 4.03 | 0.91 | 4.13 | 4.06 |
| Perceived Usefulness | Useful to assess maturity level of Big Data | 4.39 | 0.61 | 4.40 | 4.39 |
| | Can be assessed and re-assessed online | 4.42 | 0.61 | 4.60 | 4.28 |
| | Able to comprehend weaknesses, strengths, and potential systematically | 4.48 | 0.62 | 4.40 | 4.56 |
| | Scoring reflects actual results depending on assessors | 4.27 | 0.63 | 4.33 | 4.22 |
| | System results can be assessed over time compared to technology and innovation | 4.39 | 0.66 | 4.47 | 4.33 |
| Perceived Ease of Use | Easily accessible and usable | 4.30 | 0.85 | 4.53 | 4.11 |
| | Clear and easy to use menu/directions | 4.36 | 0.74 | 4.47 | 4.28 |
| | Reporting system is clear and easy to comprehend | 4.39 | 0.61 | 4.47 | 4.33 |
| Intention to Use | Usage of system is proven useful | 4.39 | 0.61 | 4.40 | 4.39 |
| | Confident in the accuracy of assessment | 4.33 | 0.65 | 4.47 | 4.22 |
| | Feeling secure while using the system | 4.24 | 0.79 | 4.27 | 4.22 |

In terms of system efficiency, the average score of 4.52 for “Accurate systematic order”, “Assessment Reports” and “System is useful” was the highest. The factor of “Convenient and efficient” achieved a significantly lower average score of 4.30. Regarding the usage, the scores fairly differ with “Appropriate pattern of assessment” and “Easy to use” showing the highest average of 4.27, while “Modern and attractive design” achieved the lowest average score of 3.82. This open-end question shows that the

user interface should be redesigned for a better score of modern and attractive. In terms of data security, “Usage is controlled according to terms” achieved the highest average score of 4.18, whereas “Secure setting up of username and password for logging in” achieved the lowest average of 3.97. This insight shows that improvement is needed in the overall data security as its average score is significantly lower than the other five indicators.

The assessment of perceived usefulness achieved a relatively high score for “Able to comprehend weaknesses, strengths, and potential systematically” at 4.48, while achieving the lowest average of 4.27 for “Scoring reflects actual results depending on assessors”. The assessment of perceived ease of use also has a relatively high overall score, while the scores are barely dispersed for the Reporting system is clear and easy to comprehend” achieving the highest average of 4.39 points and “Easily accessible and usable” scoring the lowest average of 4.30. Regarding the intention to use, “Usage of system is proven useful” scored the highest average of 4.39, while “Confident in the accuracy of assessment” scored a lower mean of 4.33 and “Feeling secure while using the system” scored the minimum at 4.24.

Table 6. Pair Different Test Between Executive Officers Group and Managers and Staffs Group.

| Dimension | Mean | SD. | Significant level |
|-----------------------|--------|--------|-------------------|
| System Efficiency | .24400 | .18902 | 0.045** |
| Usage | .35600 | .10164 | 0.001** |
| Data Security | .13400 | .21686 | 0.239 |
| Perceived Usefulness | .08400 | .17644 | 0.347 |
| Perceived Ease of Use | .25000 | .14933 | 0.101 |
| Intention to Use | .10333 | .12858 | 0.299 |

The average of scoring for the executive officers’ group, which are top executives or business owners, compared to managers and staffs group shows that the executive officers group yields higher scores and indifferent for almost topics. The pair different test between two groups shows the indifferent of the mean (significant value higher than 0.05) of the perceived usefulness, perceived ease of use, intention to use, and data security. It means both groups have an indifferent opinion for all the above topics. However, the system efficiency and usage result of a significant value less than 0.05, which means both groups have a significantly different opinion. The top three topics, which executive officers group provides higher scores are “Convenient and Efficient”, “Modern and Attractive design”, and “Secure setting up of username and password for logging in”. This can be interpreted that they considered these three important. The “Able to comprehend weaknesses, strengths, and potential systematically” is the topic that the manager and staffs group gives a higher score, this might because they considered and satisfied the topic that related to their operation work.

5 Conclusion and Discussion

In this study, we proposed a BDMM for SMEs based on previous models and literature review to provide effective questions, domain, and results of assessment for SMEs. The model consists of the assessment of four domains, including OA, IT, AT, and PP. Our model, which was developed via LCA, could identify subgroups, and provide an insight into the behavior of multiple organizations during their assessment. In addition, the model provides an adaptive scoring, and it is dynamic in the sense that if more data becomes available or market behavior changes owing to the adoption of new technologies, the threshold of each level adapts based on the peers in a dynamic cluster. The BDMM of SMEs in terms of the mobile Web application was also developed considering the ease of use and ability to access from any mobile type. This allows SMEs to access their BDA status of each domain and review each question for implementing improvements. The technology acceptance model was applied to test the acceptance rate of the BDMM Web application by collecting data from 33 respondents. The result shows that the executive officers group provide higher mean scores for most of topics. Moreover, both groups show the statistically indifferent of attitude toward satisfaction of intention to use, perceived usefulness, perceived ease of use and data security. It shows that our application can be used for any level of staffs in SMEs. However, both groups confirm that the data security of the system and the user interface can be improved.

There are many possible use case scenarios for this BDDM mobile application for SMEs. We concluded that there are at least two possible customers for BDDMs: 1) End users take assessment themselves or consulting firms conduct an assessment for end-users and provide interpreting and consulting to their customers. This group of customers will use it for monitoring, controlling, or as a guideline to improve the capability of Big Data Analytics in SMEs. 2) Government Agency, who is responsible for promoting or supporting of digital technology to SMEs in Thailand, such as DEPA (www.depa.or.th) or OSMEP (www.sme.go.th). The Government Agencies can subscribe to the BDDM application and let SMEs measure their levels of competency. The Government Agencies can further provide proper support depending on SMEs' level of competency.

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