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Assessment of challenges and potentials of Big Data Analytics for SMEs

-The case of Mongolia-

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- 몽골의 사례를 중심으로-

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Assessment of challenges and potentials of Big Data Analytics for SMEs: The case of Mongolia

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Abstract

Assessment of challenges and potentials of Big Data Analytics for SMEs

-The case of Mongolia-

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Small and medium enterprises (SMEs) are considered key players in any country's social and economic development. Adopting innovative technologies such as Big Data Analytics (BDA) can bring better performance and competitive advantage for SMEs, which is important for a country's economic growth. This study aims to assess the main challenges and potentials of BDA adoptions in SMEs and examine the impacts of its adoption into business performance for SMEs in developing countries aspect. To achieve the study's goal, a systematic literature review (SLR) is conducted regarding the adoption of BDA in SMEs. The most common SLR method among the researchers in information system research, which was initiated by

Kitchencham et al. (Kitchenham, Budgen, & Brereton, 2015) and Okoli et al.(Okoli & Schabram, 2010), is adapted in the study. In doing so, the SLR is focused on defining SMEs within various aspects and is directed to determine the most common influencing factors in BDA adoption in SMEs. In the result of the SLR, widely discussed 34 distinct influencing factors are identified in the adoption of BDA in SMEs from the previous literature. In addition, the hypotheses are developed based on the influencing factors, which show consensus among the researchers. After that, a conceptual framework is developed for developing the country aspect and control variables, and the moderating variables' effect is also estimated. To evaluate hypotheses and the conceptual framework, an online questionnaire is conducted among Mongolia SMEs which run businesses in various industries. The online questionnaire is distributed to decision-makers and information technology specialists in the firm. In total, 170 respondents participated in the online survey. Based on the survey result, hypotheses are tested. As a consequence, the collected data and proposed framework are analyzed by using Partial Least Squares (PLS). This is a method of Structure Equation Modeling (SEM) that allows investigating the inter-relationship between the latent and observed variables. In terms of statistical software tools, Smart PLS v3.3.3 was employed, which is one of the user-

friendly tools for data analysis. Finally, policies and recommendations are deployed based on the findings.

Keyword: Big Data Analytics, SME, Developing Country, Mongolia, SLR

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Chapter 1. Introduction

1.1. Background

Small and medium enterprises (SME) are considered key players in the economy of any country and are significant enablers in social and economic development (Tehrani & Shirazi Farid, 2014). Despite regional aspects, SMEs are defined differently in each country in terms of the number of employees and annual turnover, the economic role in micro and macro levels is resembled (Sen, Ozturk, & Vayvay, 2016b). Thus, the adoption of innovative technologies such as Big Data Analytics (BDA) can bring competitive advantages and better performance, which is important for a country's economic growth (Parisa Maroufkhani, Ismail, & Ghobakhloo, 2020) since it gives great potential and strategic value for businesses. However, capabilities and potential are still not fully exploited. Applications of BDA are very broad, and SMEs can have better performance having leveraged such technology. According to the Oxford economic survey report (2013) (Sen et al., 2016b), BDA is a significant instrument for SMEs' growth, and it brings strategic benefits. These benefits are the ability to analyze and predict market and customer behavior, anticipate customer preferences, and improve productivity (Sen et al., 2016b). Also, the collection and analysis of information regarding customers and other players in the market through the BDA can influence strategic decisions in a firm [4].

Even though Big Data is a key enabler in business, it has no benefits if it cannot generate valuable outcomes that can be applied to business operation (Jay Lee, Lapira, Bagheri, & Kao, 2013). However, SMEs face more difficulties in adopting new technologies than large companies. Consequently, there are many challenges for the adoption of BDA by SMEs in developing countries to sustainable competitiveness in the market. According to previous studies(Willetts, Atkins, & Stanier, 2020), the main challenges are the lack of technology availability, human resource, and government regulations. BDA adoption requires significant investment in hardware and software infrastructure, and most existing technologies in SMEs cannot support BDA (Willetts et al., 2020). Looking at both challenges and opportunities of BDA discussed earlier, studies have shown that the expectations of adopting BDA on business performance and productivity are higher. For instance: Corte Real et al.(C□rte-Real, Oliveira, & Ruivo, 2017) reveal that firms that adopt BDA in their business activities can show 5% more productivity and 6% profitability. Thus, many European firms tend to seriously invest in BDA technology(UK, 2013). Therefore, to successfully adopt BDA, it is highly critical to investigate the challenges and potentials before investing in a BDA project.

This study focuses on assessing the main challenges and potentials of BDA adoptions in SMEs, and the study case is chosen by Mongolian SMEs. In Mongolia, SMEs make significant contributions to the economy and employ 67% of the total workforce(Tuul & Bing, 2019). Mongolian SMEs also need to adopt such emerging technology into their business operations to improve their performance (Finance, 2012). According to the study result(Erdenebat & Kozsik), by 2025, around 80% of businesses in Mongolia will operate digital activities, and the government has already initiated a variety of projects under the "Digital Government," which are aimed to improve and expand the information and communication technology (ICT) field in Mongolia. Even though, "can Mongolian businesses adopt digital technologies into their business operations according to customer needs and demands?" and "what are the main challenges they face are still being under the question" (Erdenebat & Kozsik).

In the reviewed articles, found by the initial search term, the authors investigate Big Data, its applications, and related technological advances regarding many different aspects for various business and technological perspectives. Some studies inquire [13-15] big data's benefits and its availability to be implemented into traditional business fields such as health, supply chain, and agricultural industries within distinct theoretical frameworks, whereas others consider it a supporting analytical tool for sustainable business development.

This study aims to point out the main challenges and potentials in big data adoption in the case of Mongolian SMEs. To achieve the goal, the factors influencing the adoption of BDA in SMEs are explored and, further, the factors regarding the aspect of developing countries are identified. Thus, the following research questions are explored:

Q1: What are the challenges of the adoption of big data analysis by SMEs?

Q2: What are the challenges of the adoption of big data analysis by SMEs in developing countries?

Q3: What are the challenges of the adoption of big data analytics in Mongolian SMEs?

Q4: What are the key enablers toward a better big data analytic strategy in Mongolian SMEs?

The remainder of the article is organized as follows. Chapter 2 contains a detailed description of the background related to BDA applications and their adoption in SMEs. Chapter 3 reveals the methodology used for analysis, and Chapter 4 includes a model design drawn based on SLR findings. Next, Chapter 5 is designed to study the case of Mongolian SMEs, and Chapter 6 presents the conclusion, research contribution, and limitations.

Chapter 2. Background on Big Data Analytics Adoption

2.1. Definition of Big Data Analytics

Big data is one of the emerging technologies in the 4^{th} industrial evolution, and various researchers define big data through a few attributes: “volume,” which accounts for the enormously large number of data (e.g., exabyte and zettabyte); “velocity” that refers to the continuously generated data; and “variety” representing that data is produced by different sources having dissimilar formats (Belhadi, Zkik, Cherrafi, & Sha'ri, 2019), (Sagiroglu & Sinanc, 2013). Moreover, recent studies ((Zikopoulos, 2015) and (Younas, 2019)) adds the attributes “value” and “veracity” (Kepner et al., 2014) (see Figure 1) because the outcomes of big data are validated by a firm’s business performance, bringing monetary value and social value (Younas, 2019).

During the digitalization era, many human activities have highly depended on communication gadgets for social, personal, and professional tasks, generating a lot of data. Consequently, such intensive dependencies have originated novel challenges, including speed and variety in data management. This, in turn, made the big data term come out (Shoro & Soomro, 2015). On the other hand, the majority of data in the world has been generated within a few years and many technology companies, like Facebook, Google, Twitter, and Amazon, collect user data to identify the user's usage pattern for making better decisions for next service offerings. Added to that, a variety of sensors called the Internet of Things (IoT) generate enormous data, which is much more than data generated by humans. However, both types of data require an intensive analysis process, BDA, to obtain useful information (Henry & Venkatraman, 2015).

Organizations more and more rely on a variety of IT applications that aim to facilitate their daily business operations or deliver services and products to customers. Inconsequently, they collect and store customers' and partners' information in many different data types. During this process, they digitize many records such as customer complaints and business & private profile records (Henry & Venkatraman, 2015). BDA allows organizations to deeply inspect facts based on collected records, and this is also a potentially new, strong tool for the decision-making process (Villars, Olofson, & Eastwood, 2011). Thus, firms have been working on Big Data to investigate facts they did not observe before. Advanced analytics determines the current business situation and develops the next stages, such as customer behavior (Kambatla, Kollias, Kumar, & Grama, 2014).

To obtain precise outcomes (Tabesh, Mousavidin, & Hasani, 2019), which can contribute to business performance, firms need to implement a specific form of analytics, which is called advanced analytics, exploratory analytics and discovery analytics (Russom, 2011).

Figure 1.Big Data characteristics

Big data replaces random sampling (Hilbert, 2016). Especially, an individual' s behavior can be captured by BDA. For instance: the mobile phone generates the majority of data in the world (Raento, Oulasvirta, & Eagle, 2009) because that is penetrated by 95% worldwide, and its records can be used to infer an individual' s social, demographic and other behavioral treats.

2.2. Definition of SMEs

There is no concise definition of SMEs. The article (Stokes, Wilson, & Wilson, 2010) emphasizes that SMEs are defined based on annual turnover and the number of employees. (Berisha & Pula, 2015) reveals that economists are likely to classify the firms based on specific, measurable indicators, including the number of employees. For Mongolia, according to the Law, SMEs refer to legally registered business entities with up to 200 employees and with an annual turnover of up to MNT 1.5 billion (USD 833,000). In addition, SME definitions also vary from country to country, considering similar indicators such as headcount, sale income, and assets (Pandya, 2012). For example: in Egypt, SMEs are asked to have more than 5 and less than 50 employees, whereas, in Vietnam, an SME can comprise 10 – 300 employees. Inter–American Bank identified firms as SMEs if they do not employ more than100 people and have less than 3$ million in annual revenue. On the other hand, the definition of SME is regulated differently by national law and international institutional law. For instance: European Union defines that, to be included in the SME sector, a firm must ensure the quantitative criteria that the annual headcount is below 250 employees and that the annual turnover is less or equal than €50 million, while the Worldbank standard raises the accepted number of employees to 300 workers and the annual sales' income can only be up to 3$ million (Berisha & Pula, 2015).

2.3. The role of Big Data Analytics in SME

One of the main applications of BDA, which many researchers are interested in, is the use of BDA for decision-making at the managerial level (Tabesh et al., 2019). For instance, in the retail industry, this is implemented to predict customer preference based on accumulative records (Santoro, Fiano, Bertoldi, & Ciampi, 2019). BDA applied in the healthcare sector helps explore the risk and benefits of clinical treatment (Shan, Luo, Zhou, & Wei, 2019).

BDA is a process that analyzes and extracts valuable information from Big Data, which helps business processes. McKinsey Global Institute (Ying Liu, Anthony Soroka, Liangxiu Han, Jin Jian, & Min Tang, 2020) identifies the primary applications of BDA in SMEs to be forecasting the demand, planning the supply chain, supporting sales by developing products in the manufacturing industry, analyzing customer behaviors, and by optimizing prices, and improving distributions and logistics processes in the retail business.

Sen et al. (Sen et al., 2016b) imply that successful implementation of BDA in SMEs can bring significant change to the macro-economic level due to SMEs' contribution to the national economy. Seizing a novel technology and benefiting from that by saving costs on manufacturing and processing is considered one of the main objectives of businesses. However, BDA adoption has not been achieved for SMEs. The number of sources that generate data has even increased, requiring investments for processing the huge amount of data by SMEs. (Ardito, Scuotto, Del Giudice, & Petruzzelli, 2019). Although the role of big data in daily life increases, SMEs cannot benefit from advanced decision-making (Krause, 2012).

2.4. Characteristics of Developing Countries

There are several major characteristics for distinguishing developing countries. In terms of the economic aspect, World Bank renounces the level of development for the countries by estimating the Gross National Income (GNI) and the countries that have less than $1025 GNI per capita are grouped into low-income developing countries; the countries having GNI per capita between $1,026 and $3,995 are referred to as lower-middle-income developing countries; those with between $3,996 and $12,375 are identified as upper-middle-income countries and if more than $12,615 in income, those are recognized as high-income countries (World Bank, 2020). In addition, World Economic Situation and Prospects (WESP), which is a United Nations annual report, classifies all countries into three different categories based on their level of development that is identified by economic conditions such as developed economies, economies in transition, developing economies.

Except for the economic definition for the SMEs of the World Bank and the United Nations, there is another characteristic in developing countries(A. Arora & Gambardella, 2005). Developing countries are more likely to develop labor-intensive industries such as manufacturing and agriculture than human-capital-intensive industries such as software development and information technology that require skilled workforces (A. Arora & Gambardella, 2005). For instance: according to (Pandya, 2012), the study result shows that in Indonesia, 40 percentages of total SMEs run business in the manufacturing industry while 88 percentages out of total SMEs in the USA contribute to the service industry using technology advancement.

Chapter 3. Methodology and Model Design

3.1. Methodology used for analyzing Big Data Analytics Adoption in SMEs in developing countries.

We use systematic literature review (SLR) to reach the study's objective and there are several types of SLR approaches(Haneem, Kama, Ali, & Selamat, 2017). However, the methodologies introduced by Kitchenham et al.(Kitchenham et al., 2015) and Okoli et al.(Okoli & Schabram, 2010) are mostly adopted by researchers and practitioners in the field of information systems research(Haneem et al., 2017) (Okoli & Schabram, 2010). Therefore, we follow their research methods [38-39], and the following stages are performed.

In the first stage, we found a total of 251 (see Table 1) publications, including 18 from Google Scholar, 91 from Scopus, 8 from IEEE Xplore, 34 from Web of Science and 100 from Science Direct using keyword combinations such as "*big data,*" "*analytics,*" "*adoption,*" and "*SME.*" Those keyword terms were searched within title, abstract and author's keyword fields. Second, the inclusion criteria are applied, that is to include articles that were published after 2015 (2016, 2017, 2018, 2019 and 2020) because we found similar research work (S. Sun, Cegielski, Jia, & Hall, 2018) with our objective during the review of previous literatures. The article was designed to determine the influencing factor in BDA adoption using the SLR methodology. Therefore, we approach to update and support the previous article based on our research objective and questions. Then, 187 articles are retained, 72 articles are found in Scopus, 8 articles in IEEE Xplore, 68 articles in Science direct, 27 articles in Web of Science, and 12 articles on Google Scholar. Besides, there are study materials about the Mongolian SME industry, which were published by the Organization for Economic Co-operation and Development (OECD), Word bank(Milyutin, 2012), and other researchers (Buyantur & Nam, 2017; Erdenebat & Kozsik; Galindev et al., 2019; Lkhagvasuren & Xuexi, 2014; Tuul & Bing, 2019), which were reviewed to investigate current Mongolian current SMEs industry. Third, after cleaning the duplications, which are found by different databases having the same titles, authors and publication year, 165 articles remained (Table 1). Table 2 illustrates the proportion of article types found by the initial search. There are 5 book sections and 12 serial types of articles. In contrast, most findings are journal articles (122 articles) and 26 conference proceedings type articles. All articles are further investigated. Fourth, these 165 articles are sorted for different criteria. In terms of publication years (Figure 2), in 2020, the greatest number of articles was published (57 articles), while the least number of articles (17 articles) was found in 2017.

Table 1. Initial findings

Names	No. of results	Used keywords	Search within	No. of articles after inclusion criteria
Google Scholar	18	big data, analytics, SMEs	Title, abstract or author-specified keywords	12
Scopus	91	big data, analytics, SMEs		72
IEEExplore	8	big data, adoption,		8
Web of Science	34	big data, analytics, adoption,		27
Science direct	100	big data, analytics, adoption,		68
Total	251			187

Considering that 20 articles have been published in 2016, 40 articles in 2018, and 31 studies in 2019, it can be stated that the interest in this topic strongly increased during the past 6 years.

Table 2. Number of articles types

№.	Types	Quota	References
1	Book section	5	(Banica & Hagiu, 2016; Dawei, Anzi, & Gen, 2018; Ponsard, Majchrowski, & Goeminne, 2018; Poulin, Thompson, & Bryan, 2016; Rakesh Kumar et al., 2019)
2	Conference Proceedings	26	(Agarwal, 2020; Aldinucci et al., 2018; Ardagna, Ceravolo, & Damiani, 2016; Beesley, 2020; Black et al., 2019; Cazzanti, Davoli, & Millefiori, 2016; Creslovnik, Košmerlj, & Ciavotta, 2018; Fong, 2017; Goerke-Mallet et al., 2020; Karim, Al-Tawara, Gide, & Sandu, 2017; Llave, Hustad, & Olsen, 2018; Martinez et al., 2018; Martino, Angelo, & Esposito, 2017; Mbassegue, Escandon-Quintanilla, & Gardoni, 2016; Mirzaei, Ranganathan, Kearns, Airehrour, & Etemaddar, 2019; Mohamed & Weber, 2020; Noonpakdee, Phothichai, & Khunkornsiri, 2018; Pile, 2018; *Proceedings of the 11th European Conference on Information Systems Management, ECISM 2017*, 2017; Rajabion, 2018; Shah, Soriano, & Coutroubis, 2018; Silva et al., 2019; Syed Thajudeen, 2018; Tan & Haji, 2017; Ulrich, Becker, Fibitz, Reitelsh□fer, & Schuhknecht, 2018; Willetts et al., 2020)
3	Journal Article	122	(Aboelmaged & Mouakket, 2020; Aggarwal, Aggarwal, & Aggarwal, 2018; Ahmad, Ismail, & Othman, 2019; Akpan, Udoh, & Adebisi, 2020; Al Tawara & Gide, 2016; Allam & Dhunny, 2019; Amankwah-Amoah & Adomako, 2019; Anejionu et al., 2019; Antoncic, Antoncic, Grum, & Ruzzier, 2018; Ariyaluran Habeeb et al., 2019; S. K. Arora, Li, Youtie, & Shapira, 2020; Arunachalam, Kumar, & Kawalek, 2018; Aysan, Disli, Ng, & Ozturk, 2016; Babiceanu & Seker, 2016; Baharuden, Isaac, & Ameen, 2019; Barham & Daim, 2020; Becciani & Petta, 2019; Belhadi, Kamble, Zkik, Cherrafi, & Touriki, 2020; Belhadi, Zkik, Cherrafi, Yusof, & El fezazi, 2019; Bertello, Ferraris, Bresciani, & De Bernardi; Biesialska, Franch, & Munt□s-Mulero, 2020; Bilal et al., 2016; Braganza, Brooks, Nepelski, Ali, & Moro, 2017; Britzelmaier, Graue, & Sterk, 2020; Cabrera-S□nchez & Villarejo-Ramos, 2020; Chang, 2018; Choi, Kim, & Yang, 2018; Cochran, Kinard, & Bi, 2016; Coleman, 2020; S. Coleman et al., 2016; Cuquet & Fensel, 2018; Dam, Le Dinh, & Menvielle, 2019; Das & Rangarajan; Di

No.	Types	Quota	References
			Porto & Ghidini, 2020; Dong & Yang, 2020; El Alaoui & Gahi, 2020; El Hilali, El Manouar, & Janati Idrissi, 2020; Ferraris, Mazzoleni, Devalle, & Couturier, 2019; Flick et al., 2018; Flynn, 2017; Frizzo-Barker, Chow-White, Mozafari, & Ha, 2016; Gaffney, 2020; Gao, Wang, Yuan, & Lin, 2020; Gauzelin & Bentz, 2017; Ge, Bangui, & Buhnova, 2018; Guerreiro, Costa, Figueiras, Graça, & Jardim-Gonçalves, 2019; S. Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018; Heberle, Lowe, Gustafsson, & Vorrei, 2017; Holland, Thornton, & Naudé, 2020; Horick, 2020; Hua, Wang, & Wang, 2016; Hung, He, & Shen, 2020; Hunter, 2019; Irani et al., 2018; Kho, Lee, & Zhong, 2018; Kim, Choi, & Byun, 2020; Kızıltan, 2018; Kshetri, 2016; J. Lee, Bagheri, & Jin, 2016; J. H. Lee & Dong, 2018; Liu, Li, Tang, Lin, & Liu, 2019; Ying Liu et al., 2020; Y. Liu, A. Soroka, L. Han, J. Jian, & M. Tang, 2020; Lozada, Arias-Pérez, & Perdomo-Charry, 2019; Lundqvist, 2019; S. K. Mangla, Raut, Narwane, Zhang, & Priyadarshinee, 2020; Mantelero, 2018; Marinakis et al., 2020; Parisa Maroufkhani, Tseng, Iranmanesh, Ismail, & Khalid, 2020; P. Maroufkhani, Wan Ismail, & Ghobakhloo, 2020; Marriott & Robinson, 2017; Meunier et al., 2017; Michna & Kmieciak, 2020; Mikalef, Boura, Lekakos, & Krogstie, 2019; Mikalef, Krogstie, Pappas, & Pavlou, 2020; Mohd Selamat, Prakoonwit, Sahandi, Khan, & Ramachandran, 2018; Mourtzis, Vlachou, & Milas, 2016; Nasrollahi, Ramezani, & Sadraei, 2020; Navaz, Serhani, Al-Qirim, & Gergely, 2018; O'Connor & Kelly, 2017; Ogoh & Ben Fairweather, 2019; Papakonstantinou & de Hert, 2020; Papanagnou & Matthews-Amune, 2018; Parasol, 2018; Perakis et al., 2020; Pramanik, Lau, Demirkan, & Azad, 2017; Rialti, Zollo, Ferraris, & Alon, 2019; Sahal, Breslin, & Ali, 2020; Saleem, Li, Ali, Mehreen, & Mansoor, 2020; Saleem et al.; Sargut, 2019; Sen, Ozturk, & Vayvay, 2016a; Shabbir & Gardezi, 2020; Shadroo & Rahmani, 2018; Shamim, Zeng, Shariq, & Khan, 2019; Sharmeen, Ahmed, Huda, Kocer, & Hassan, 2020; Shirdastian, Laroche, & Richard, 2019; Singh, 2020; Sivarajah, Irani, Gupta, & Mahroof, 2020; Sivarajah, Kamal, Irani, & Weerakkody, 2017; Smith, Coleman, Bacardit, & Coxon, 2019;

№.	Types	Quota	References
			Soroka, Liu, Han, & Haleem, 2017; W. Sun, Zhao, & Sun, 2020; Suoniemi, Meyer-Waarden, Munzel, Zablah, & Straub, 2020; Tanev, 2019; Tang, Srivastava, & Liu, 2020; Tian, Hassan, & Razak, 2018; van Rijmenam, Erekhinskaya, Schweitzer, & Williams, 2019; Vitale, Cupertino, & Riccaboni, 2020; F. Wang, Ding, Yu, & Zhao, 2020; F. Wang, Li, Mei, & Li, 2020; S. Wang & H. Wang, 2020; Y. Wang, 2016; Yichuan Wang, Kung, & Byrd, 2018; Yichuan Wang, Kung, Wang, & Cegielski, 2018; Weilnhammer et al., 2019; Wu & Lin, 2018; Yadegaridehkordi et al., 2020; Yuan & Wang, 2019; Zaki, Theodoulidis, Shapira, Neely, & Surekli, 2017; Zhang, Ren, Liu, & Si, 2017; R. Y. Zhong, Newman, Huang, & Lan, 2016)
4	Serial	12	("3rd International Conference of Reliable Information and Communication Technology, IRICT 2018," 2019; "4th International Conference on Future Network Systems and Security, FNSS 2018," 2018; "17th IFIP WG 6.11 Conference on e-Business, e-Services, and e-Society, I3E 2018," 2018; "18th International Conference on Business Process Management, BPM 2020," 2020a; "18th International Conference on Business Process Management, BPM 2020," 2020b; Dittert, H□rting, Reichstein, & Bayer, 2018; Montalvo-Garcia, Quintero, & Manrique-Losada, 2020; Naeem, Moalla, Ouzrout, & Bouras, 2016; Nemati & Khajeheian, 2018; Riehle et al., 2020; Tien, Ali, Miskon, Ahmad, & Abdullah, 2020; Ud Din, Henskens, Paul, & Wallis, 2018)
Total		165	

Fifth, the articles found in the first search process have been further explored with respect to the academic databases (e.g., Emerald Insights, IEEE Xplore, Oxford academic database and Science Direct), in which they appeared. The highest number of articles have been published in ScienceDirect, totally, 71 articles. Among those papers, there are 5 book sections and 66 journal articles. The second-highest number of articles has been found in the Scopus Database, comprising 15 conference proceedings, 25 journal articles, and 12 serial-type articles. Expect for Scopus and ScienceDirect, only a few journal articles have been found in the databases of Emerald Insight, IEEE Xplore, Ingenta Connect, Oxford Academic, ProQuest, Research Square, Springer, SSRN, Taylor&Francis, and minor databases. The minor databases are the university library database, "IOP Science," "IOS press," "Europe PMC," and "World Scientific." They are referred to as " other" in Table 2. IEEE Xplore and Springer also contain 8 and 2 conference proceedings.

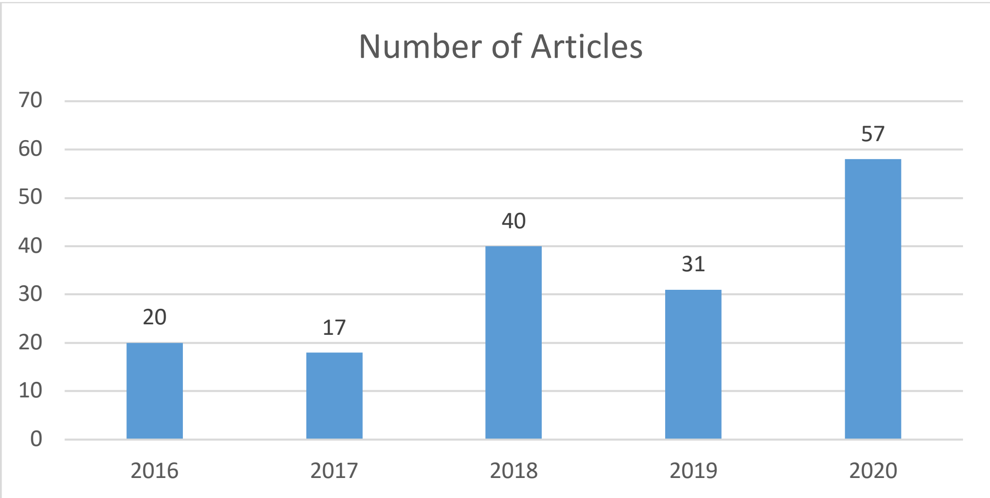

Figure 2. Number of Articles over time

Sixth, the inclusion criteria, which were designed to find the most relevant articles with respect to the research objective, are applied. The inclusion criteria are the publication date of the research article, the research questions laid out, and the language in which the research article is written. Besides, the current literature review presented focuses additionally on SMEs and developing countries aspect

Table 3. Number of Papers by Journal

Database Name	Book Section	Conference Proceedings	Journal Article	Serial	Total
Emerald Insight			6		6
IEEE Xplore		8	3		11
Ingenta Connect			1		1
Oxford Academic			2		2
ProQuest			1		1
ResearchSquare			1		1
ScienceDirect	5		66		71
Scopus		15	25	12	52
Springer		2	2		4
SSRN			1		1
Taylor&Francis			1		1
Other		1	13		14
Total	**5**	**26**	**122**	**12**	**165**

while updating the previous study to achieve the research questions. Furthermore, the criterion that the review article should be relevant with respect to the research questions is applied. All studies selected contribute to at least one of the research questions stated in the introduction. In addition to this, due to the study case of Mongolian SMEs, articles written in Mongolian or English are reviewed. However, only research articles written in English are considered. All research articles have been collected and managed with EndNote[x9].

After screening the titles, abstracts, and introductions of the 165 research works according to the inclusion criteria, 11 articles have been identified as being relevant for answering one of the research questions on BDA adoption by SMEs in developing countries. The remaining 154 articles have not been considered for a detailed analysis. Those articles investigate only a particular business sector from a technical perspective. Relevance indicates that the study selected contributes to addressing at least one of the research questions stated in the review protocol.

Table 4 lists the selected 11 papers. The articles are found from various academic databases, including Emerald Insight, IEEE Xplore, Ingenta Connect, Oxford Academic, ProQuest, Research Square, Science Direct, Scopus, Springer, SSRN and Taylor&Francis. The articles *(S. K. Mangla et al., 2020; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Shamim et al., 2019)* were published in the "Information and Management" journal, while the rest of them *(S. Coleman et al., 2016; Lozada et al., 2019; P. Maroufkhani et al., 2020; Nasrollahi et al., 2020; Silva et al., 2019; Tan & Haji, 2017; Willetts et al., 2020; Yadegaridehkordi et al., 2020)* were published in different journals and international conferences. In terms of the research context, the studies (Silva et al., 2019; Tan & Haji, 2017; Yadegaridehkordi et al., 2020) focused on BDA adoption in marketing, education, and hotel industries, and *(S. Coleman et al., 2016; Lozada et al., 2019; S. K. Mangla et al., 2020; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; P. Maroufkhani et al., 2020; Nasrollahi et al., 2020; Shamim et al., 2019; Yadegaridehkordi et al., 2020)* examined BDA adoption factors in different countries, comprising Iran, Malaysia, China, Columbia and India. The two studies (Silva et al., 2019; Tan & Haji, 2017) identified adoption factors in general. All 11 articles concisely determine different influencing factors in BDA adoption in SMEs using various theoretical backgrounds.

Table 4. Selected 11 papers

№	Database	Journal	Journal Subject Area and Category	Type study	Country	Title	Context	Theory
1	Scopus	Journal of Science and Technology Policy Management	Business, Management and Accounting; Decision Sciences;	Journal article	Iran	Big data analytics adoption model for small and medium enterprises(P. Maroufkhani et al., 2020)	General	TOE framework and Resource Based View (RBV)
2	Science Direct	Electronic Commerce Research and Applications	Business, Management and Accounting; Computer Science	Journal article	Malaysia	The impact of big data on firm performance in hotel industry. (Yadegaridehkordi et al., 2020)	Hotel industry	TOE framework Human-Organization-Technology fit
3	ACM	BDIOT2017: Conference on Big Data and Internet of Thing	Big Data and IoT research	Conference Paper	Not Specified	Big data educational portal for small and medium sized enterprises (SMEs) (Tan & Haji, 2017)	Education	Design Science
4	ScienceDirect	Information & Management	Business, Management, and Accounting; Computer Science; Decision Sciences	Journal article	China	Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view (Shamim et al., 2019)	Management challenges	Dynamic Capability theory

№.	Database	Journal	Journal Subject Area and Category	Type study	Country	Title	Context	Theory
5	ScienceDirect	information & Management	Business, Management, and Accounting; Computer Science; Decision Sciences	Journal article	Iran	Big data analytics adoption: Determinants and performances among small to medium-sized enterprises (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020)	General	TOE model, DOI, and RBV
6	Scopus	information & Management	Business, Management, and Accounting; Computer Science; Decision Sciences	Journal article	Indian	Mediating effect of big data analytics on project performance of small and medium enterprises (S. K. Mangla et al., 2020)	Project performance	Not Specified
7	ScienceDirect	Heliyon	Multidisciplinary	Journal article	Columbia	Big data analytics capability and co-innovation: An empirical study (Lozada et al., 2019)	Co-Innovation	Resource-Based Theory by Barney (1991)
8	Scopus	Quality and Reliability Engineering International	Decision Sciences; Engineering	Journal article	Not Specified	How Can SMEs Benefit from Big Data? Challenges and a Path Forward (S. Coleman et al., 2016)	General	Not Specified

№.	Database	Journal	Journal Subject Area and Category	Type study	Country	Title	Context	Theory
9	IEEE	2020 Fourth International Conference on Intelligent Computing in Data Sciences (ICDS)	Intelligent Computing; Its applications including Data Mining, Natural language processing, Image/Video Processing, data pre-processing, sampling and reduction	Conference Paper	UK	Barriers to SMEs Adoption of Big Data Analytics for Competitive Advantage (Willetts et al., 2020)	General	Not Specified
10	Springer	International Conference on Data Mining and Big Data	Data Mining; Algorithms; Big Data;	Conference Paper	Not Specified	Factors Affecting the Big Data Adoption as a Marketing Tool in SMEs (Silva et al., 2019)	Marketing	UTAUT
11	ORCID	Research Square		Journal article	Iran	The impact of Big Data Adoption on SMEs Performance (Nasrollahi et al., 2020)	General	Not Specified

3.2. Model Design

3.2.1. Factors

During the next step of the evaluation process of the 11 articles, factors, which have been emphasized as impacting BDA adoption by SME, have been identified, not considering aspects related to developed countries and developing countries. Factors are merged if they are named differently but express the same meanings. For instance, "Top Management Support" is presented as "the degree to which managers comprehend and embrace the technological capabilities of a new technology system" in (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020), whereas (Shamim et al., 2019) defines "Leadership Focus on Big Data" as an effective way of top managers in the company to development and reconfiguration. After merging factors with the same meanings, 34 unique factors are identified (see Table 6). The following Table 5 shows a summary of the focus of the studies with respect to developed countries vs. developing countries and specific industry sectors vs. all industry.

Table 5 shows that 6 articles[134, 139, 147, 154, 164, 187] discussed the developing country aspect regardless of industry type (General). Besides, Coleman et al.*(S. Coleman et* *al., 2016)* investigate non−specified countries and industry types, whereas 2 articles (Silva et al., 2019; Tan & Haji, 2017) investigate the industry types with general aspect. Additionally, Mangle et al., *(S. K. Mangla et al., 2020)* study the developing country aspect as indicating the industry type, while the remaining study *(Willetts et al., 2020)* identified influencing factors of BDA adoption in terms of the general industry type within developed countries.

Table 5. Country development level vs. Industry type

Area \ Literature		P. Maroufkhani et al. (2020)	Yadegaridehkordi et al. (2020)	(Tan & Haji, 2017)	Shamim et al. (2019)	Parisa Maroufkhani, Ming−Lang Tseng, et al. (2020)	S. K. Mangla et al. (2020)	Lozada et al. (2019)	S. Coleman et al. (2016)	Willetts et al. (2020)	Silva et al. (2019)	Nasrollahi et al. (2020)
Country	Developing country	+	+		+	+	+	+				+
	Developed country									+		
	General			+					+		+	
Industry	Industry−specific			+			+				+	
	General	+	+		+	+		+	+	+		+

3.2.2. Theories

Technological-Organizational-Environment (TOE) framework (Tornatzky, Fleischer, & Chakrabarti, 1990), Unified Theory of Acceptance and Use of Technology (UTAUT) (Pickrahn et al., 2017), Dynamic Capability (Teece, Pisano, & Shuen, 1997), Resource Based-View (Barney, Ketchen Jr, & Wright, 2011) theories were employed by the studies. A few studies among the 11 articles adapted combined theoretical backgrounds such as TOE with RBV and TOE with Human-Organizational-fit (Nasrollahi et al., 2020). A variety of studies (Chau & Tam, 1997; Gibbs & Kraemer, 2004; Iacovou, Benbasat, & Dexter, 1995) that investigate technology adoption at the organizational level emphasize that the TOE framework is one of the common theories to assess the organizational acceptance in novel technology (Lippert & Govindarajulu, 2006). The TOE framework describes the influencing factors in three contexts: technological context, organizational context, and environmental context. In terms of RBV, this identifies the resources which ensure long-term development for a firm. Moreover, RBV explains that an organization exists based on various resources, including tangible and intangible, which determine their competitive advantages in the market (Wernerfelt, 1984). In terms of Dynamic Capability theory, this theory is an extension of RBV and explains that a firm is a collection of activities that deliver services and products, in which it focuses on a firm's competitive advantage in a rapid-changing market by identifying organizational processes such as integration and reconfiguration to match a changing environment (Chowdhury & Quaddus, 2017). In contrast, UTAUT theory is developed by Venkatesh et al. (Im, Hong, & Kang, 2011), which consists of eight distinct factors explaining a user's technology acceptance. These are performance expectancy, effort expectancy, social influence, facilitating conditions, gender, age, experience, and voluntariness of use (Im et al., 2011).

The TOE framework, which was introduced by Tornatzky and Fleischer (1990) (Tornatzky et al., 1990), is selected for the in-deep analysis and model design. The reason behind that is that first, the TOE framework brings the ability to investigate the adoption of technology in an organization. Second, The TOE framework is considered one of the most common theories to assess the organizational acceptance of novel technology (Lippert & Govindarajulu, 2006). Third, according to our objective of study and questions, we focus on assessing the influencing factors of BDA adoption at the firm level. Other theories are less discussed than the TOE framework and investigate the factors at the individual level (Lippert & Govindarajulu, 2006). For instance: UTAUT focuses on individuals prospective and does not consider organizational culture (Im et al., 2011), while RBV and Dynamic capability theories evaluate the technology adoption process in aspect of the firm's competitive advantage in the market, in which how firms are changed due to rapid-changing market to keep competitive advantage (Chowdhury & Quaddus, 2017).

The identified factors are grouped into 3 contexts (see Table 7) based on their influential aspects in the technology adoption, including technological, organizational, environmental contexts in the TOE framework since it is selected as a theoretical explanation. "Relative Advantage," "Compatibility," "Complexity," "Risks and Insecurity," "Trialability," "Observability," "Effort Expectancy," "Cost of adoption," "Performance Expectancy" are assigned to technical context because those factors are described in a technology-related context. In detail, the "Effort Expectancy" factor is referred to as how the technology is easy to learn and use (M. A. H. Al-Hagery, 2016) and "Performance Expectancy" refers to as the perception of the performance that is given by the technology (Pickrahn et al., 2017) with the UTAUT model. Also, "Relative Advantage," "Compatibility," "Complexity," "Risks and Insecurity," "Trialability," "Observability" are explained in a technological context (Alshamaila, Papagiannidis, & Li, 2013; Priyadarshinee, Raut, Jha, & Kamble, 2017; Ramdani, Chevers,

& Williams, 2013). “Cost of adoption” implies technological expense that a firm incurs to sustain big data usage and future scalability (Park, Kim, & Paik, 2015; Verma & Bhattacharyya, 2017). For the organizational context, “Top Management Support,” “Organizational Resource”, “Organizational Size,” “Organizational Readiness,” “Organizational culture,” “Collaboration and Explorative Learning,” “Project Success,” “Project Performance of SMEs,” “Resistance to Use, “Lack of Intuitive Software,” “Different Venture Concept,” “Financial barriers,” “Lack of Knowledge," “Social Responsible” and “In-house data analyst” factors are considered because these factors explain the impact and barrier in organizational internal resource and intention to use the technology into their process. For instance, “Resistance to Use” is referred to as opposition of employees to use the new technology, which is caused by failed experience [247-249] while “Collaboration and Explorative Learning,” “Project Success,” “Project Performance of SMEs,” “Lack of Intuitive Software,” “Different Venture Concept” factors in past literature (S. K. Mangla et al., 2020) are adopted into organizational context because those factors explain internal influencing factors in SMEs (S. K. Mangla et al., 2020). In terms of environmental context, external resources such as government regulation, market competitiveness, and social influence are impacted by the environmental context. These are "Government Regulations," "Social Influence," "Labor market," "Lack of business cases," "External Pressure," "External Support," "Non-transparent Software Market," "Green Purchasing," "Project Operational Capabilities," "Project Complexity."

Table 6. Identified factors

№	Factors	Sun et al.(S. Sun et al., 2018)	Maroufkhani et al. 2020 (P. Maroufkhani et al., 2020)	Yadegaridehkordi et al. 2020 (Yadegaridehkordi et al., 2020)	Tan et al. 2017 (Tan & Haji, 2017)	Shamim et al. 2019 (Shamim et al., 2019)	Tseng et al. 2020 (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020)	Mangla et al. (S. K. Mangla et al., 2020)	Lozada et al. 2019 (Lozada et al., 2019)	Coleman et al. 2016 (S. Coleman et al., 2016)	Willetts et al. 2020) (Willetts et al., 2020)	Silva etl al. 2019) (Silva et al., 2019)	Nasrollahi et al. 2020 (Nasrollahi et al., 2020)	**Count of Use by Literature**
1	Relative Advantage	✓	+	+			+				+		+	**5**
2	Compatibility	✓	+	+			+						+	**4**
3	Complexity	✓	+	+			+				+			**4**
4	Risks And Insecurity	✓	+	+			+			+				**4**
5	Trialability	✓	+				+						+	**3**
6	Observability	✓	+				+						+	**3**
7	Effort Expectancy		+											**1**
8	Cost Of Adoption											+		**1**
9	Performance Expectancy			+										**1**
10	Top Management Support	✓	+	+		+		+		+	+		+	**7**
11	Organizational Resource	✓		+		+		+	+		+	+		**4**
12	Organizational Size	✓		+									+	**2**
13	Organizational Readiness	✓	+				+				+		+	**4**
14	Organizational Culture	✓				+				+			+	**3**
15	Collaboration And Explorative Learning	✓						+						**1**

№.	Factors	Sun et al. (S. Sun et al., 2018)	Maroufkhani et al. 2020 (P. Maroufkhani et al., 2020)	Yadegaridehkordi et al. 2020 (Yadegaridehkordi et al., 2020)	Tan et al. 2017 (Tan & Haji, 2017)	Shamim et al. 2019 (Shamim et al., 2019)	Tseng et al. 2020 (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020)	Mangla et al. (S. K. Mangla et al., 2020)	Lozada et al. 2019 (Lozada et al., 2019)	Coleman et al. 2016 (S. Coleman et al., 2016)	Willetts et al. 2020) (Willetts et al., 2020)	Silva etl al. 2019) (Silva et al., 2019)	Nasrollahi et al. 2020 (Nasrollahi et al., 2020)	**Count of Use by Literature**
16	Project Success							+						1
17	Project Performance Of Smes							+						1
18	Resistance To Use	✓										+		1
19	Lack Of Intuitive Software									+				1
20	Different Venture Concept	✓								+				1
21	Financial Barriers									+				1
22	Government Regulations		+				+			+	+		+	5
23	Social Influence	✓										+		1
24	Labor Market									+				1
25	Lack Of Business Cases	✓								+	+			2
26	External Pressure	✓	+	+			+							3
27	External Support	✓	+	+			+				+		+	5

№.	**Factors**	Sun et al.(S. Sun et al., 2018)	Maroufkhani et al. 2020 (P. Maroufkhani et al., 2020)	Yadegaridehkordi et al. 2020 (Yadegaridehkordi et al., 2020)	Tan et al. 2017 (Tan & Haji, 2017)	Shamim et al. 2019 (Shamim et al., 2019)	Tseng et al. 2020 (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020)	Mangla et al. (S. K. Mangla et al., 2020)	Lozada et al. 2019 (Lozada et al., 2019)	Coleman et al. 2016 (S. Coleman et al., 2016)	Willetts et al. 2020) (Willetts et al., 2020)	Silva etl al. 2019) (Silva et al., 2019)	Nasrollahi et al. 2020 (Nasrollahi et al., 2020)	**Count of Use by Literature**
28	Non-Transparent Software Market									+				**1**
29	Green Purchasing							+						**1**
30	Project Operational Capabilities							+						**1**
31	Project Complexity							+						**1**
32	Lack Of Understanding & Knowledge	✓			+					+	+			**2**
33	Social Responsibility							+						**1**
34	In-House Data Analytic Expertise	✓		+		+			+	+	+		+	**6**
	Count Of Factors By A Study		12	11	1	4	10	9	2	12	10	4	11	

3.2.3. Classification of factors into the categories

From a technological perspective, 9 factors were found in the primary studies, which impact BDA adoption by SMEs. These are "Relative Advantage," "Compatibility, "Complexity," "Risks and Insecurity," "Trialability," "Observability," "Effort Expectancy," "Cost of adoption," "Performance Expectancy." "Relative advantage" and "Compatibility" factors have a positive impact on BDA, according to (Nasrollahi et al., 2020; Yadegaridehkordi et al., 2020). However, Maroufkhani et al.(P. Maroufkhani et al., 2020) and (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020) found that these factors have no significant impact. Similarly, (P. Maroufkhani et al., 2020) and (Willetts et al., 2020) found that "Complexity" has a negative impact, whereas (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020) and (Yadegaridehkordi et al., 2020) conclude that it has an insignificant impact. Besides, the "Risks and Insecurity" factor is evaluated as a positive impact on BDA by (Nasrollahi et al., 2020), while the factor impacts insignificantly by (S. Coleman et al., 2016; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; P. Maroufkhani et al., 2020; Yadegaridehkordi et al., 2020). For the remaining factors in the technological category, there is consensus, in which "Trialability", "Observability", "Performance Expectancy" factors lead to positive impact (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; P. Maroufkhani et al., 2020; Nasrollahi et al., 2020; Silva et al., 2019). On the other hand, "Effort Expectancy" and "Cost of Adoption" factors negatively influence BDA adoption and intention of Big Data to use in a firm (Silva et al., 2019; Yadegaridehkordi et al., 2020).

In terms of organizational factors, the analysis shows that factors, such as "Top Management Support, "Organizational Size, "Organizational Readiness," "Organizational Culture," "In-house Data Analytic Expertise", "Project Success," and "Performance of SMEs" are agreed upon to having a positive impact BDA (S. Coleman et al., 2016; S. K. Mangla et al., 2020; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; P. Maroufkhani et al., 2020; Nasrollahi et al., 2020; Shamim et al., 2019; Willetts et al., 2020; Yadegaridehkordi et al., 2020). Contrary to that, "Resistance to Use," "Lack of Intuitive Software," "Different Venture Concept," "Financial Barriers," "Social Influence" negatively impact BDA adoption (S. Coleman et al., 2016; Nasrollahi et al., 2020; Silva et al., 2019; Willetts et al., 2020). For the remaining organizational factors, "Organizational Resources" have a positive impact on BDA adoption and firm's decision-making level (Lozada et al., 2019; Silva et al., 2019; Willetts et al., 2020; Yadegaridehkordi et al., 2020), whereas Mangla et al. (S. K. Mangla et al., 2020) conclude that "Organizational Resource" and "Collaboration and Explorative Learning" have an insignificant impact on BDA adoption. Also, the "In-House Data Analytic Expertise" factor positively affects BDA adoption, "Decision-making effectiveness," "Capability and Co-innovation" (S. Coleman et al., 2016; Lozada et al., 2019; P. Maroufkhani et al., 2020; Nasrollahi et al., 2020; Willetts et al., 2020; Yadegaridehkordi et al., 2020). In contrast, the factor "Lack of Understanding & Knowledge" has a negative impact according to Coleman et al. (S. Coleman et al., 2016), (Tan & Haji, 2017), (Willetts et al., 2020) and (Lozada et al., 2019), while the "Social Responsibility" factor is evaluated as insignificant impact in this context by (S. K. Mangla et al., 2020).

The environmental category includes the factors "Government Regulations," "Social Influence, "Labor Market," "Lack of Business Cases," "External Pressure, "External Support," "Non-transparent Software Market," "Green Purchasing," "Project Operational Capabilities", and "Project Complexity. Nasrollahi et al. (Nasrollahi et al., 2020), (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020), (S. Coleman et al., 2016), (Silva et al., 2019), Yadegaridehkordi et al. (Yadegaridehkordi et al., 2020), (S. K. Mangla et al., 2020), and Willetts et al. (Willetts et al., 2020) assent to "Government Regulations, "Social Influence, "External Pressure, "Green

Purchasing, “Project Operational Capabilities” having a positive impact on BDA adoption in SME. (S. Coleman et al., 2016), (S. K. Mangla et al., 2020), and (Willetts et al., 2020) determine that “Labor Market, “Lack of Business Cases, “Non-transparent Software Market,” “Project Complexity” influence negatively. Controversially discussed is the impact of the factor “External Support. (S. Coleman et al., 2016) conclude that the factor negatively impacts BDA adoption, while (P. Maroufkhani et al., 2020), (Yadegaridehkordi et al., 2020), (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020), and (Nasrollahi et al., 2020) say that it has a positive impact on BDA adoption in SME.

Table 7. Identified factors by impact

Category	Factors	Impact			impact on	Country (Developed or Developing Country)
	Name	Positive	Negative	Insignificant		
Technological	Relative advantage	Yadegaridehkordi et al. (2020), Nasrollahi et al. (2020)		Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020, pp. 43-46) (P. Maroufkhani et al., 2020)	big data adoption	Iran, Malaysia, General
	Compatibility	Yadegaridehkordi et al. (2020), Nasrollahi et al. (2020)		Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020) P. Maroufkhani et al. (2020)	big data adoption	Iran, Malaysia, General
	Complexity		Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020), Willetts et al. (2020)	Yadegaridehkordi et al. (2020), P. Maroufkhani et al. (2020)	big data adoption	Iran, Malaysia, UK, General
	Risks and Insecurity	Nasrollahi et al. (2020)	Yadegaridehkordi et al. (2020), P. Maroufkhani et al. (2020) Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020), Coleman et al.(S. Coleman et al., 2016)		big data adoption	Iran, General

Category	Factors	Impact			impact on	Country (Developed or Developing Country)
	Name	Positive	Negative	Insignificant		
	Trialability	Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020),P. Maroufkhani et al. (2020),			big data adoption	Iran, General
	Observability	Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020), P. Maroufkhani et al. (2020), Nasrollahi et al. (2020)			big data adoption	Iran, General
	Effort Expectancy			Silva et al. (2019)	the Intention to Use of Big Data	General
	Cost of adoption			Yadegaridehkordi et al. (2020)	big data adoption	Malaysia, + General
	Performance Expectancy	Silva et al. (2019)			the Intention to Use of Big Data	General
Organizational	Top Management support	P. Maroufkhani et al. (2020),Yadegaridehkordi et al. (2020),.Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020),S. K. Mangla et al. (2020), Nasrollahi et al. (2020) Shamim et al. (2019), S. Coleman et al. (2016), Willetts et al. (2020)			big data adoption	Iran, China, UK, General

Category	Factors	Impact			impact on	Country (Developed or Developing Country)
	Name	Positive	Negative	Insignificant		
	Organizational resource	Yadegaridehkordi et al. (2020), Silva et al. (2019) Lozada et al. (2019); Willetts et al. (2020)		S. K. Mangla et al. (2020),	big data adoption, BDA adoption, firm's big data decision-making capability	India, China, UK, Colombian
	Organizational Size	Yadegaridehkordi et al. (2020) Nasrollahi et al. (2020)			big data adoption	Malaysia, General
	Organizational Readiness	P. Maroufkhani et al. (2020), Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020),Nasrollahi et al. (2020),. Willetts et al. (2020)			big data adoption	Iran, Malaysia, UK, General
	Organizational culture	Shamim et al. (2019), Nasrollahi et al. (2020),.S. Coleman et al. (2016),			firm's big data decision-making capability.	UK, Chinese
	Collaboration and Explorative Learning			S. K. Mangla et al. (2020),	BDA adoption	India
	Project Success	S. K. Mangla et al. (2020),			BDA adoption	India
	Project Performance of SMEs	S. K. Mangla et al. (2020),			BDA adoption	India

Cate gory	Factors	Impact			impact on	Country (Developed or Developing Country)
	Name	Positive	Negative	Insignificant		
	Resistance to Use		Silva et al. (2019)		the Intention to Use of Big Data	General
	Lack of intuitive software		S. Coleman et al. (2016), Willetts et al. (2020)		BDA adoption	General
	Different venture concept		S. Coleman et al. (2016)		BDA adoption	General
	Financial barriers		S. Coleman et al. (2016), Nasrollahi et al. (2020)		BDA adoption	General
	Social Responsibility			S. K. Mangla et al. (2020)	BDA adoption	India
	In-house data analytic expertise	Yadegaridehkordi et al.(Yadegaridehkordi et al., 2020) Lozada et al.(Lozada et al., 2019), Nasrollahi et al.(P. Maroufkhani et al., 2020), Coleman et al.(S. Coleman et al., 2016), Shamim et al.(Shamim et al., 2019) Willetts et al.(Willetts et al., 2020)			big data adoption, capability and Co-innovation	Malaysia, Colombia, UK
	Lack of understanding & knowledge		S. Coleman et al. (2016), Tan and Haji (2017),Lozada et al. (2019), Willetts et al. (2020)		BDA adoption BDA capability & Co-innovation	UK, Colombian

Cate gory	Factors	Impact			impact on	Country (Developed or Developing Country)
	Name	Positive	Negative	Insignificant		
Envi ron ment al	Government Regulations	Maroufkhani, Wan et al. (P. Maroufkhani et al., 2020), Nasrollahi et al. (2020), Maroufkhani, Tseng et al.Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020), S. Coleman et al. (2016), Willetts et al. (2020)			big data adoption	UK, General
	Social Influence	Silva et al.(Silva et al., 2019)			the Intention to Use of Big Data	General
	Labour market		S. Coleman et al. (2016)		BDA adoption	General
	Lack of business cases		.S. Coleman et al. (2016), Willetts et al. (2020)		BDA adoption	General, UK
	External Pressure	P. Maroufkhani et al. (2020) Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020), Yadegaridehkordi et al. (2020),		-	big data adoption	General
	External Support	P. Maroufkhani et al. (2020).Yadegaridehkordi et al. (2020), Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020), Nasrollahi et al. (2020)		S. Coleman et al. (2016),	BDA adoption	General Iran, Malaysia, + General
	Non-transparent software market		S. Coleman et al. (2016),		BDA adoption	General

Cate gory	Factors	Impact			impact on	Country (Developed or Developing Country)
	Name	Positive	Negative	Insignificant		
	Green Purchasing	S. K. Mangla et al. (2020)			BDA adoption	India
	Project operational capabilities	S. K. Mangla et al. (2020)			BDA adoption	India
	Project Complexity		S. K. Mangla et al. (2020)		BDA adoption	India

3.2.4. Impact on Developing Countries

Table 7 (last column) describes the countries for which the studies are conducted. However, some studies did not specify the country context. P. Maroufkhani et al. (2020), Shamim et al. (2019), Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020), S. K. Mangla et al. (2020), and Nasrollahi et al. (2020) focus on developing country aspects such as China, India, Malaysia, Iran, Columbia. Furthermore, (Willetts et al., 2020) consider the barriers of BDA adoption in SMEs in the United Kingdom while Yadegaridehkordi et al. (2020), Tan and Haji (2017), Lozada et al. (2019), S. Coleman et al. (2016), and Silva et al. (2019) examine the adoption of BDA in the general context.

There are 24 factors determined for the context of developing countries. These are "Relative Advantage," "Compatibility," "Complexity, "Risks and Insecurity," "Trialability," "Observability," "Cost of Adoption," "Top Management Support," "Organizational Resource," "Organizational Size," "Organizational Readiness," "Organizational Culture," "Collaboration and Explorative Learning," "Project Success," "Project Performance of SMEs," "Government Regulations," "Lack of Business Cases," "External Support," "Green Purchasing," "Project Operational Capabilities," "Project Complexity," "Lack of

Understanding & Knowledge," "Social Responsibility," and "In-house Data Analytic Expertise." Moreover, 12 factors such as "Trialability," "Observability," "Top Management Support," "Organizational Readiness," "Organizational Culture," "Project Success," "Project Performance of SMEs," "Government Regulations," "Green Purchasing," "Project Operational Capabilities" are identified as having a positive impact on BDA adoption in SMEs in developing country. In contrast, there are also 6 negatively influencing factors. These are "Cost of Adoption," "Collaboration and Explorative Learning," "Lack of Business Cases," "External Support," "Project Complexity," and "Lack of Understanding & Knowledge." Moreover, there are 7 factors found as diverse impacts among the evaluated 11 articles result, including "Relative Advantage," "Compatibility," "Complexity," "Risks and Insecurity," "Organizational Resource," Organizational Size," and "In-house data analytic expertise," whereas "Social Responsibility" factor has insignificant impact on BDA adoption in SMEs in developing countries. In terms of remaining factors which determined by S. Coleman et al. (2016) Tan and Haji (2017), Willetts et al. (2020) and Silva et al. (2019) are not considered as developing country aspect because they didn't specify any country during the study.

Analysis of studies illustrates that there are consensus and contrasts among the authors regarding the factors that influence BDA adoption in SMEs. The reason behind this is that the literatures are conducted in different contexts. In detail, S. Coleman et al. (2016) investigate the challenges that SMEs encounter with the benefits from BDA in their business operations in UK and United States situation. Especially in the United States, lack of human resource capability is emphasized as becoming a problem in the labor market while according to the UK e-skill survey S. Coleman et al. (2016), 57% of recruiters in the UK state that filling data analysis positions is difficult. On the other hand, Nasrollahi et al. (2020) assess the influencing factors of BDA adoption in SMEs in developing countries with a lack of infrastructures and human resources Nasrollahi et al. (2020). They found that the "External Support" factor is expected to have a positive impact, while (S. Coleman et al., 2016) identified an insignificant impact on BDA adoption in SMEs. The reason for these distinct results is that S. Coleman et al. (2016) conducted a survey and analyzed its result among SMEs in UK and United States, which are leading economies in the world and business environment is well-established Todaro and Smith (2012) compared to developing countries such as Iran where Nasrollah et al. (Nasrollahi et al., 2020) investigates. Conversely, Yadegaridehkordi et al. (2020), Silva et al. (2019), and Shamim et al. (2019) evaluate the "Organizational Resource" factor to positively impact BDA adoption, while S. K. Mangla et al. (2020) say that it has an insignificant impact on BDA adoption. Furthermore, Shamim et al. (Shamim et al., 2019) consider the antecedents and influences in BDA decision-making capacities for decision-making quality in Chinese SMEs by using Dynamic Capability theory. On the other hand, in the study of Mangla et al.(S. K. Mangla et al., 2020), the influencing factors in the adoption of BDA are identified as mediating effects enhancing project performance in SMEs in the context of the Indian economy were one of important players in the IT off-shore outsourcing (Budhwar, 2009). Though, Silva et al. (2019) intent is to identify to influencing factor of BDA in the aspect of marketing tool, using the UTAUT model even though Shamim et al. (2019) assume that human resource and leadership which focus on Big Data are significant impacts by adapting Dynamic capability theory and Yadegaridehkordi et al. (2020) investigate only hotel industry as grounding on TOE(Tornatzky et al., 1990) and HOT-fit(Sallehudin et al., 2019) models. This variation in results can be justified by the authors' distinct research method, study objectives and assumptions.

3.2.5. Impact on Different Industry Sectors

According to the research questions Q1 and Q2, the goal of SLR is to identify the challenges in the adoption of BDA in developing countries' SMEs. Considering the 34 factors, SMEs' challenges are transversal, complex, and multifaceted in various dimensions (S. Coleman et al., 2016). Also, several studies were conducted focusing on specific industry sectors. Yadegaridehkordi et al. (2020) considers the hotel industry for Malaysian SMEs. In the study, the authors approach to develop a specific framework that can be applied to the Malaysian hotel industry, and the result shows that the significant influencing factors are "Relative Advantage," "Management Support," "IT Expertise," and "External Pressure" in the technological, organizational, human, and environmental contexts which grounded at TOE(Tornatzky et al., 1990) and HOT-fit(Sallehudin et al., 2019) models. Furthermore, Silva et al. (2019) focus on the context of marketing of SMEs using the technology acceptance model called Unified Theory of Technology Adoption and Use of Technology(Im et al., 2011) (UTAUT). The study(Silva et al., 2019) results show that technical infrastructure is a crucial influencing factor in implementing BDA in a firm's marketing activity. Even though most studies focus on the overall effect of BDA on firm performance. Also, Mangla et al.(S. K. Mangla et al., 2020) studies mediating of the effect of BDA adoption in the context of SMEs in terms of project management perspective. The study result shows that BDA adoption contributes to manufacturing, sustainability, and project performance in SMEs. Moreover, they (S. K. Mangla et al., 2020) identify that BDA can impact management with respect to supporting better decision-making (e.g., by visualizing data that has been collected during organizational business activities).

3.2.6 Theoretical Background and Hypothesis Development

According to the SLR, we found 34 factors that influence BDA adoption. Among those factors, there are 10 factors, which are widely discussed in the studies. Moreover, there is consensus in those studies regarding the impact of these 10 factors on BDA adoption. Other factors are least discussed in the literatures, and most of them resulted in contradictory conclusions. In other words, there is no consensus between the studies that these factors have an impact on BDA adoption. Therefore, we excluded those factors in our framework.

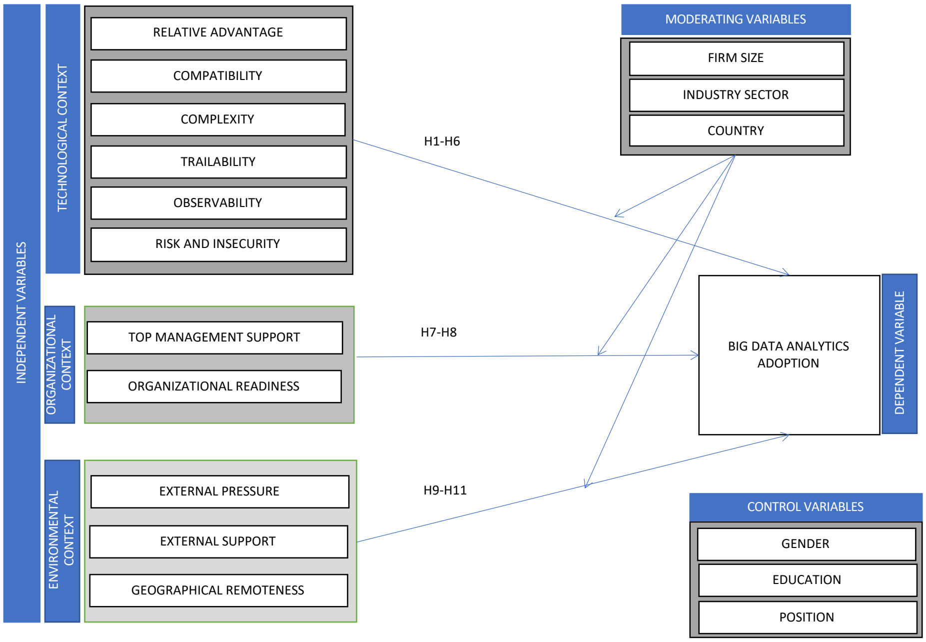

Figure 3. Proposed Framework

Additionally, there is a more relevant factor in the Mongolian context, namely "Geographical remoteness." This factor takes into account the geographical location of SMEs in Mongolia. Because of that, the geographical area of Mongolia is ~1.5million km square, and population density is the least in the world (wikipedia.org, 2021). The statistics show that ~30% of SMEs in Mongolia are located in rural areas [6], and according to the study (Wamba & Carter, 2013), firms in the metropolitan area tend to be more innovative operating their businesses.

Since the beginning of the study, the present study approaches to identify the influencing factors of BDA adoption in SMEs according to the research questions. 24 factors are ignored among identified 34 factors in conceptual framework due to these factors have no consensus and the diverse impact resulted according to SLR outcome. Some factors such as "Collaboration and Explorative Learning," "Project Success," "Project Performance of SMEs," "Social Responsibility," "Green Purchasing," "Project operational capabilities," "Project Complexity" are discussed in Indian SMEs while other factors "Effort Expectancy," "Cost of adoption," "Performance Expectancy," "Organizational resource," " Organizational Size," "Organizational Culture," " Collaboration and Explorative Learning," "Project Success," " Project Performance of SMEs," "Resistance to Use," "Lack of intuitive software," "Different venture concept," "Financial barriers," "Social Responsibility," "Lack of understanding & knowledge," "Social Influence," "Labor market," "Lack of business cases," and "Non-transparent software market" are less discussed among the selected 11 literatures than 10 factors which selected for the conceptual framework. On the other hand, those factors' impact on the adoption of BDA is evaluated in various countries' SMEs regardless of the economic development level, including Iran, Chinese, Colombia, Malaysia, and the UK. The identified factors in the proposal model are categorized depending on their influential dimensions: technological context , organizational context, and environmental context. (Lippert & Govindarajulu, 2006). As stated in Section 4.2, the theoretical foundation of the resulting model is based on the TOE framework (Tornatzky et al., 1990), and Figure 3 illustrates the theory used and the 10 factors which are elaborated on in previous chapters. Moreover, the factor related to the Mongolian context and moderating variables and control variables are adapted in the conceptual framework. Consequently, we initiate 11 hypotheses according to the conceptual framework. There are 8 positive impacts and 3 negative impacts that are expected to adopt BDA in SMEs in the developing country aspect.

3.2.7. Technological context

Technological context considers the exogenous and endogenous influence of technology in a firm (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020). The factor "Relative advantage" is one of the crucial elements in the context, which refers to "the degree to which an innovation can bring benefits to an organization" (Rogers, 2003). Also, Ghobakhloo et al. (Ghobakhloo, Arias-Aranda, & Benitez-Amado, 2011) state that SMEs are likely to adopt novel technology if they believe that the technology advantage exceeds the advantage of existing technology (Table 5). Consequently, we believe that "Relative

Advantage" brings positive impacts on BDA adoption. As such, we propose the following hypothesis.

H1: Relative advantage positively impacts BDA adoption.

Another important factor is "Compatibility," which refers to the degree to which an innovation is consistent with existing business processes, practices, and value systems [273]. Chen et al. [208] consider it one of the main critical factors that significantly influence technology adoption in a firm. Similarly, Verma and Bhattacharyya (2017) emphasize that compatibility is an important driver to BDA adoption. On the other hand,Parisa Maroufkhani, Ming-Lang Tseng, et al. (2020) indicate that SMEs are willing to adopt BDA for different parts in their internal business operations as they believe BDA adoption can be compatible with existing procedures. So that, we believe that higher compatibility leads SMEs to become more willing to adopt and implement if they perceive that adoption of BDA is compatible with its existing systems such as operation procedures and compliances. Based on that, the following hypothesis is developed.

H2: Compatibility positively impacts BDA adoption.

(Rogers, 2010) also define that the higher complexity of new technology may cause the failure of adoption for a firm. Complexity refers to "the degree to which an innovation is difficult to use" (Budhwar, 2009; Tornatzky et al., 1990). The new technology must be easy to be implemented into existing business processes, and employees need to immediately acquire knowledge regarding the technology [207]. Especially, SMEs face significant difficulties in adopting the new technology such as lack of infrastructure, political issues, and social and cultural barriers (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020). Particularly developing countries' SMEs run their businesses at a low level of technological adoption (Kapurubandara & Lawson, 2006). Therefore, we consider that the technology's higher complexity might negatively impact BDA adoption in SMEs. Thus, the following hypothesis is proposed:

H3: A higher level of complexity negatively impacts BDA adoption.

The trialability factor is defined as "the degree to which an IT innovation is promising to be tried" (Sallehudin et al., 2019). Especially early adopters, including SMEs, consider trialability important, giving firms the chance to benefit from new technology from the initial stage (Barney et al., 2011; Sallehudin et al., 2019). According to study (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020), as employees in SMEs quickly acquire knowledge about the technology, SMEs have a higher chance of reducing uncertainty, which can be caused by technology adoption. So that, we believe that trialability gives an opportunity for employees of SMEs to gain knowledge. In addition, it is a crucial opportunity for innovative firms to reduce uncertainty that might be faced in the commercial market (Tornatzky et al., 1990). Based on these statements, we perceive that trialability is referred to as a positively influencing factor to BDA adoption and the following hypothesis is proposed:

H4: Trialability positively impacts BDA adoption.

Observability is referred to as "the process by which companies observe the success factor of other firms that have already adopted big data" by .F. Wang, Ding, Yu, and Zhao Moreover, Roger defines observability as "the degree to which the results of an innovation are visible to others." As such, there is no standard definition regarding observability among researchers. However, Kapoor et al. [276] propose observability as a key driver of innovative technology adoption for firms. In the same context, Sallehudin et al. (2019) and Siew, Rosli, and Yeow (2020) empirically tested that observability significantly impacts BDA adoption. In addition, study result (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020) shows that SME owners are more likely to adopt the technology into their business operations if a success case is observed, which is related to the technology adoption in the market. Therefore, we propose:

H5: Observability positively impacts BDA adoption.

According to Alshamaila et al. (2013), insecurity is considered a risk which may accompany technology adoption. Similarly, Asiaei and Rahim (2019) define risk and insecurity as the most common issue in data-related innovation. For instance, cloud computing technology is highly dependent on the issue. Many researchers highlight risk and insecurity-related issues linked to cloud computing and data-related innovation as a predictor of adoption for a firm(Rogers, 2003; Teece et al., 1997). In this regard, there are two types of concerns. First, business owners concern the risk that comes out from third-party tools that provide BDA adoption assistance. Second, there is a risk that SMEs that lack In-house Data Analytic Expertise tend to outsource entire jobs related to the technology adoption process [278]. In both cases, a firm implementing BDA in their business faces the security and privacy issue that they need to allow third-party to access the data, and there are risks and insecurity of losing control of their own critical information. Therefore, we believe that risk and insecurity negatively impact BDA, and we hereby propose the following hypothesis.

H6: Risk and Insecurity negatively impact BDA adoption.

3.2.8. Organizational context

In this context, Top management support and organizational readiness factor are categorized. Top management support refers to "the degree to which managers comprehend and embrace the technological capabilities of a new technology system" (Bruque & Moyano, 2007; Chiu, Chen, & Chen, 2017).

Mostly, in the SMEs, the top management team is the decision-makers, and their support for any innovative technology adoption can bring change in their business operation and strategy. Furthermore, in the developing countries' SMEs such as Malaysia, due to the lack of qualified management team, they are hindered from adopting a new technology that can expand their business activities(Ng & Kee, 2012). Consequently, this is considered a crucial factor (Navaz et al., 2018). Similarly, many researchers emphasize that the top management team as the main point between individuals and the technology adoption process in the organization because they lead employees and define the corporate strategy (Barney et al., 2011). Also, decisions are made in by a centralized number of persons in SMEs (Bruque & Moyano, 2007). Hence, in this context, top management support is assumed as it positively impacts BDA adoption. Based on that, the following hypothesis is developed.

H7: Top management support positively impacts BDA adoption.

The following factor in the organizational context is organizational readiness which refers to "the extent to which a firm's technology and business resources are adequate to support adoption" (S. H. Wang & H. Wang, 2020). Even SMEs are hindered in the technology adoption process due to its impediments caused by internal barriers in the organization (Kapurubandara & Lawson, 2006). So that, it is vital to comprehend the influence of the factors that SMEs inhibit in developing countries. According to the study result (Priyadarshinee et al., 2017), technical infrastructure, platform, and standards applied to a new process are necessary to successfully adopt innovation in a firm. Therefore, technological readiness in the organization is an essential factor that influences BDA adoption (Alshamaila et al., 2013). Additionally, business behavior in the company is influenced by readiness and adequacy in existing technical and financial resources (Ahlemeyer-Stubbe & Coleman, 2014). Furthermore, Hsu, Kraemer, and Dunkle (2006) say that interpretation of in-house IT expertise means that firms have sufficient personnel with the knowledge and technology-related experience to implement the technology adoption. Typically, this factor is revealed by the availability of experienced and knowledgeable staff in the organization (Silva et al., 2019). Thus, in this regard, human resource is considered into organizational readiness. Especially, SMEs in developing countries face various challenges that are specified in comparison with developed countries (Kapurubandara & Lawson, 2006). For example, the lack of internal experts who handle the technology adoption process is more pronounced here. In doing so, sufficient levels of competent human resource and technology readiness significantly impact BDA adoption (Teo, Lin, & Lai, 2009), and we propose the following hypothesis.

H8: Organizational Readiness positively impacts BDA adoption.

3.2.9. Environmental context

There are three factors determined in this context; these are external support, external pressure factors, and geographical remoteness. According to the study(Kapurubandara & Lawson, 2006), these factors are identified as strong influencing factors which are beyond the SMEs' control. External support is indicated as "the extended support from a vendor or third-party to encourage firms to innovate and be able to adopt an innovation" (Rogers, 2003). Many researchers found that a firm receiving external support from vendors and the government can build substantial attributes on BDA adoption. Because they expand innovation capabilities by studying from the vendor and available open-source platforms [(Rogers, 2003). In this context, government regulations, tend to prohibit the disclosure of personal data. On the other hand, particular regulations support and encourage firms to implement novel technologies (Nemati & Khajeheian, 2018). The study result (Kapurubandara & Lawson, 2006) shows that in the environmental context, legislation and regulations are necessary to be directly paid attention from the government in developing countries for SMEs. Thus, the higher degree of existence of external support such as regulation and vendor support positively impacts BDA adoption in SMEs. Then, we propose the following hypothesis. Therefore, the following hypothesis is proposed.

H9: External support positively impacts BDA adoption.

Second, within the environmental context, external pressure refers to the burden coming to the firm from the customers, suppliers and competitors (Vidal, Marle, & Bocquet, 2011) in the market. (Chau & Tam, 1997) reveal that impact, which is influenced by the external environment, prompts SMEs to use BDA in their business operations. In consequence, Ghobakhloo et al. (2011) and Agrawal (2015)] conclude that firms that run a business under pressure to compete tend to adopt new technology. Similarly, we expect that external pressure positively impacts BDA adoption.

H10: External Pressure positively impacts BDA adoption.

Lastly, there is a more relevant factor with the context of Mongolia, namely "Geographical remoteness." This factor takes into account the geographical location of SMEs in Mongolia. The geographical area of Mongolia is ~1.5million km square, and population density is the lowest in the world (wikipedia.org, 2021). Moreover, statistics show that ~30% of SMEs in Mongolia are located in rural areas [6], and according to the study(Wamba & Carter, 2013), firms in the metropolitan area tend to be more innovative operating their business. Therefore, we believe that geographical remoteness can bring other challenges from the perspective of infrastructure and other resources to adopt technology in SMEs. Consequently, we set out that it has a significant impact on BDA adoption in the case of Mongolia.

H13: Geographical remoteness negatively impacts BDA adoption.

Despite the fact that the defined factors in the three main contexts such as technology, environment and organization, control variables and moderating variables are determined in the conceptual model, moderating variables have a fundamental role "which act like a catalyst in a regression relationship" while control variables are referred to as "independent variables which are not part of the research study, but their influence can be overlooked" ().

3.2.10. Moderating Variables

A Business takes a distinct attitude for innovative technology adoption depending on the industry type (Chiu et al., 2017). For example, Hsu et al. (2006) found that firms in the manufacturing industry tend to be more willing to implement innovative technology in their businesses in comparison with firms in distribution and financial industries. But, Teo et al. (2009) show a different result that there is no difference among the industry types, and different attitudes in firms may occur in various size organizations. Consequently, we employ three factors such as firm size, industry type and the country as moderating variables in BDA adoption in our study.

In detail, the study (Teo et al., 2009) states that the influencing factors in the technology adoption in SMEs can result in diverse outcomes due to the number of employees in the firm. The reason behind that, the firm which has a higher number of employees tends to have more ability to receive higher risk than companies that have a smaller number of employees. A technology adoption itself demands SMEs to have the potential to tolerate risks that can be caused by the technology adoption process (Zona, Zattoni, & Minichilli, 2013). Thus, we consider the "firm size" as moderating variable in the conceptual framework.

The conceptual framework is designed based on SLR that covered SME and developing country aspects. It can be applicable to general concepts because the TOE framework that we adapted for theoretical background explains a technology adoption process in general concept within a firm level (Zona et al., 2013). So that, the country is adapted as moderating variable due to the technology adoption process in SMEs varies from country to country depending on their economic development (Martin & Matlay, 2001). Moreover, we found that some literature, such as Yadegaridehkordi et al. (2020) and Tan and Haji (2017), emphasizes specific industry types. They identify the influencing factor in BDA adoption in the hotel industry(Yadegaridehkordi et al., 2020) and education sector(Tan & Haji, 2017). Due to these industry-based concerns, this study also expects that distinct outcome depending on the industry type in which the firm operates its business. Consequently, the industry type is adapted as moderating variable.

3.2.11. Control variables

The respondents' education level, gender and position in the company are considered as control variables because BDA can be a strong tool in the firm's strategical decision-making process(Villars et al., 2011), and according to the study (Hambrick & Mason, 1984), an individual's demographic characteristics such as position, gender, and education background level are directly influencing factors in the innovative Information technology champion behavior. In addition, the study result (T.-C. Lin, Ku, & Huang, 2014) shows that a higher position of manager in a firm has a higher degree of information technology absorptive capability and is highly involved in information technology use. Based on these findings, we assume that position in the company is control variables BDA adoption in Mongolian SMEs.

Moreover, researchers have credit on gender difference if the study investigates individual level (Deshwal, 2016). In such case, gender (female and male) is considered a biological variable (Deshwal, 2016), which affects study outcomes because females' satisfaction is initiated on their negative emotion while males' satisfaction is dependent on initial positive emotion (Deshwal, 2016). However, present study uses the gender of respondents as a control variable because our study focuses on assessing factors of technological adoption at a firm level.

Similarly, education background is one of the influencing factors on customer satisfaction for individual assessment. The reason for that is that it can be a representative factor for respondents' income and life quality (Deshwal, 2016). Yet, we assume that demographic factors, such as an individual's education background have no direct impact () because our study objective approaches to assess the firm level's technology adoption. In addition, this is one of the common factors in control variables (Ruigrok, Peck, & Tacheva, 2007). Based on these statements. The education background of respondents is included in the control variables.

Chapter 4. Framework for Mongolian Case

4.1. Mongolia

The total population of Mongolia reached 3,238,479 people in 2018, up by 60,580 people (1.91 percent) compared to the previous year. The number of children born in 2018 was 78,444. 63.77% of the total population is under 35 years of age. In terms of economy, the Mongolian economy is highly reliant on the mining industry (94%) by the report of the National Statistical Office (Office, 2021). According to the Wordbank report 2019, Mongolia GNI per capita for 2019 was $3,780, a 4.13% increase from 2018. In Mongolia, SME refers to legally registered business entities with 199 or fewer employees and with an annual turnover of up to MNT 1.5 billion (USD 833,000). The SME Law also differentiates sectors regarding the number of employees and annual turnover (Buyantur & Nam, 2017). (Erdenebat & Kozsik) reveals that among the Mongolian organizations, one of the reasons for that slow progress in technology transition is a lack of support from executives and employers.

4.2. Data collection

For the data collection, we developed the online questionnaires (see Appendix 1) by using the Google Form Platform. An online survey was sent to Mongolian SMEs across the various industry sectors. The survey' s answers had choices that five-point Likert scale with anchors ranging from 1 that refers to as "strongly disagree" to 5 that refers to as "strongly agree". An online survey was prepared in the Mongolian and English languages. In addition, the survey development process had two-three stages. The first stage was the initial creation of instruments that can represent each factor determined in the conceptual framework, including moderating and control variables. In the second stage of the survey development, we asked two researchers to review whether instruments are coherently and articulately stated.

Table 8: Demographic information

Characteristic		**Frequency**	Percentage
Gender	Female	42	25%
	Male	128	75%
Education	PhD Degree	2	1%
	Master Degree	51	30%
	Bachelor degree	107	63%
	Associate degree (college of two years)	1	1%
	Primary school	1	1%
	Secondary school	3	2%
	No formal education	5	3%

Characteristic		Frequency	Percentage
Position	Senior Executive	13	8%
	Executive	18	11%
	Director	7	4%
	Senior Manager	15	9%
	Manager	31	18%
	Senior Staff	28	16%
	Intermediate level staff	55	32%
	Associate level staff level staff	3	2%

The questionnaires were improved based on the feedback given by those reviewers and sent again with the same procedure but to different reviewers. Finally, two rounds of preliminary reviewing process for individual instruments were sent by email to Mongolian SMEs. We targeted to get a response with the online survey from IT specialists or senior-level staff in firms across the diverse industries. Before sending the email, general information and the purpose of the questionnaires were introduced by phone call. From 500 potential respondents, we have collected 170 responses. Table 8 shows that the majority (75%) of respondents are male, while 25% of the total are female. In addition, to identify basic knowledge about Information technology (IT) and Big Data in survey participants, we prepared additional two questions, which were interpreted by a five-point Likert scale with anchors ranging from 1 that refers to as "no expertise" to 5 that refers to as "expert". In terms of knowledge rate about IT and Big data technology (Table 10), median values are the same in both genders (male and female), while female survey participants showed a higher mean value (3.931) in the general IT knowledge in comparison with males (3.802). However, in the Big Data knowledge, male respondents show a slightly higher value (3.311) than females (3.276).

Table 9. Knowledge about IT and Big Data

Area	Mean	Median	Gender
Knowledge about IT	3.931	4	Female
	3.802	4	Male
Knowledge about Big Data	3.276	3	Female
	3.311	3	Male

4.3. Basic understanding on moderating effects

To understand how the main model and interaction effects modeling, consider the following Figure 4. In order to compute this model effects, first, we apart from the main effect model, which follows the simple linear regression effect(Fassott, Henseler, & Coelho, 2016) with the following equation:

$$\mathcal{Y} = \mathcal{B}'_0 + \mathcal{B}'_1 * \mathcal{X} + \mathcal{B}'_2 * \mathcal{M}$$

$\mathcal{X}$ represents the independent variables, and $\mathcal{M}$ represents the moderating variables. $\mathcal{B}'_0$ is referred to as intercept, and $\mathcal{B}'_1$, and $\mathcal{B}'_2$, are referred as to slopes of $\mathcal{X}$ and $\mathcal{M}$ in Figure 4, the moderating effect is represented by $\mathcal{B}_3$, symbolized by an arrow pointing to the relationship between X and Y, which is hypothesized to be moderated. So that, the following equation(Fassott et al., 2016) is formulated:

$$Y = B'_0 + B'_1{*}X + B'_2{*}M + B'_3{*}\,(X\,{*}M)$$

Here simple moderating effects are estimated, such as the strengthening of the relationship between X and Y. In addition, B_1 is expected to change by the size of B_3 if the level of moderators is escalated.

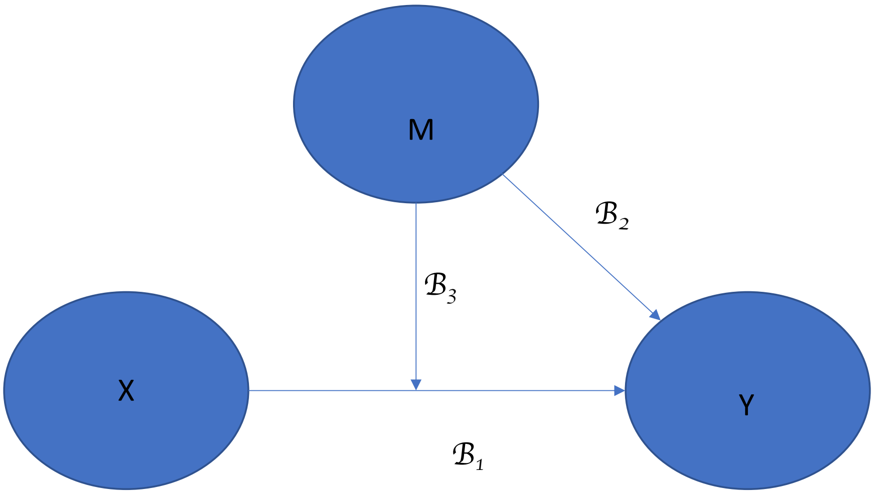

Figure 4: Simple moderating effect model

4.4 Data analysis

First, we aggregated the indicators in moderating variables which was gathered by an online questionnaire to comply with the classification that is declared by the Law of SME in Mongolian (Info, 2021). MV1 instruments' responses were aggregated into 1-9, 10-49, 50-199 and more than 200 classifications which defined by the number of employees in the firm (6), whereas MV2 instruments were aggregated based on annual turnover, which is defined by the Mongolian SME law (Info, 2021). Moreover, the industry sectors that SMEs run their business activities have been classified as four main economic sectors defined by Kenessey (Kenessey, 1987), such as the primary, secondary, tertiary and quaternary.

Second, after the data preparation, the data were analyzed using partial least squire (PLS), a method of structural equation modeling (SEM). This technique allows investigating the inter-relationship between the latent and observed variables (Sarstedt & Cheah, 2019). As well, the PLS-SEM method is a casual predictive approach to SEM, which indicates the prediction in estimating statistical models that have a variety of variables, indicators and constructs(Sarstedt & Cheah, 2019). In terms of statistical software tools, we employed the SmartPLS v3.3.3, which is a user-friendly tool for data analysis (Hair, Risher,

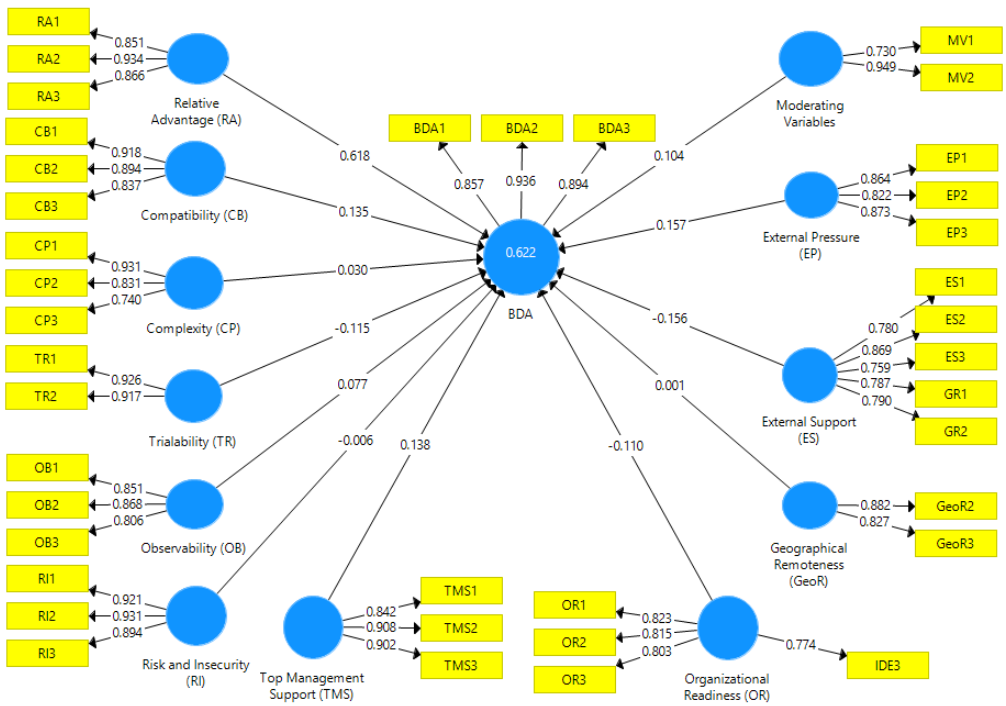

Figure 5. Main Effect Model

Sarstedt, & Ringle, 2019). Since we have considered the moderating variables' effect in the conceptual framework, we analyzed the collected data in two variances. First, the main model effect was analyzed (Figure 5). Second, data is evaluated with an interaction effect model. The factor analysis, path analysis and hypotheses testing are performed using the statistical tool for the model's evaluation process.

4.5. Results

4.5.1 Reliability and validity

For the reliability evaluation, we employed Cronbach's Alpha (CA) measure, in which the reliability values between 0.60 and 0.70 are referred to as "acceptable in exploratory research", between 0.70 and 0.90 range from "satisfactory to good" (Hair et al., 2019). In addition, Composite Reliability (CR) and Average Variance Extracted (AVE) are used to validity test, and AVE value is accepted as higher than 0.5 and lower than composite reliability (CR). Table 6 shows the values in the test results, including CA value, CR and AVE.

In the main effect model (Figure 5), the coefficient of determination, $R^{2,}$ is 0.622 for the dependent variable, in which other variables such as Relative Advantage (RA), Compatibility (CB), Complexity (CP), Trialability (TR), Observability, Risk and Insecurity (RI), Top Management Support (TMS), Organizational readiness (OR), External Pressure (EP), External Support(ES), Geographical Remoteness (GeoR) are explained as 62.2% of the variance in BDA adoption. Especially, the strongest effects are found on Relative Advantage (RA) with 0.618 (61.8%) and followed by External Pressure (EP) with 0.157 (15.7%), and Top Management Support (TMS) with 0.138 (13.8%) and Top

Management Support (TMS) with 0.136 (13.6%). In terms of Observability (OB) and Complexity (CP), they resulted in significant effects with 0.077 (7.7%), 0.030(3.0%), respectively. For other variables such as Trialability (TR) −0.115 (−11.5) Geographical Remoteness (GeoR) −0.001(−1%), Risk and Insecurity (RI) −0.006 (−3%), Organizational readiness (OR) −0.110 (−11.0%) and External Support (ES) −0.156 (−15.6%) suggested the weak effect on the Adoption of BDA.

In Table 11, the factor loadings values of the Adoption of the BDA construct are above the given criteria. However, there were indicators estimated as under the threshold in the main effect model(Hair et al., 2019). Therefore according to the guideline(Bido & Silva, 2019), those indicators are eliminated from reliability assessment.

Conventionally, CA is estimated to evaluate the internal consistency reliability in the research. However, we measure it as both methods, including CA and CR. Table 11 shows that each construct has a higher value than 0,6 in which constructs demonstrated high internal consistency reliability.

To confirm the convergent validity, we tested the AVE measure. Again, Table 11 demonstrates that each construct has a greater acceptable threshold of 0.5, in which convergent validity is confirmed.

Table 10. Convergent Validity

Constructs	Factors Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Adoption of Big Data Analytics (BDA)	0.857	0.878	0.924	0.803
	0.936			
	0.894			
Relative Advantage (RA)	0.851	0.860	0.915	0.782
	0.934			
	0.866			
Compatibility (CB)	0.918	0.860	0.914	0.781
	0.894			
	0.837			
Complexity (CP)	0.931	0.822	0.875	0.702
	0.831			
	0.740			
Trialability (TR)	0.926	0.822	0.918	0.849
	0.917			
Observability	0.851	0.795	0.880	0.709
	0.868			
	0.806			
Risk and Insecurity (RI)	0.921	0.903	0.915	0.782
	0.931			
	0.894			
Top Management Support (TMS)	0.842	0.860	0.915	0.782
	0.908			
	0.902			
Organizational readiness (OR)	0.823	0.820	0.880	0.647
	0.815			
	0.803			
	0.774			
External Pressure (EP)	0.864	0.813	0.897	0.637
	0.822			
	0.873			

Constructs	Factors Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
External Support (ES)	0.780	0.859	0.897	0.637
	0.869			
	0.759			
	0.787			
	0.790			
Moderating Variables (MV)	0.857	0.646	0.832	0.716
	0.936			
	0.894			
Geographical Remoteness (GeoR)	0.882	0.634	0.844	0.731
	0.827			

In terms of discriminant validity, which is referred to as "the extent to which construct is empirically distinct from other constructs in structural model" (Hair et al., 2019), it asks the AVE value of each construct to be higher than squire root correlation values(Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020). Thus, Table 12 illustrates those results of discriminant validity for each construct. For example, EP' s AVE value is 0. 853 (see Table 11); hence its square root becomes 0.924(see Table 12). The calculated value (0.924) is larger than the correlated values. In doing this, similar estimation was executed in other constructs, and the results showed that discriminant validity is well established.

Table 11. Discriminant Validity

	BDA	CB	CP	EP	ES	GeoR	MV	OB	OR	RA	RI	TMS	TR
BDA	0.896												
CB	0.576	0.884											
CP	0.357	0.416	0.838										
EP	0.390	0.445	0.437	0.853									
ES	0.205	0.377	0.507	0.684	0.798								
GeoR	0.396	0.467	0.437	0.600	0.528	0.855							
MV	0.143	0.016	0.006	0.118	0.175	0.121	0.846						
OB	0.516	0.622	0.495	0.551	0.481	0.520	0.074	0.842					
OR	0.364	0.448	0.587	0.636	0.556	0.567	0.077	0.607	0.804				
RA	0.743	0.647	0.498	0.467	0.352	0.557	0.024	0.614	0.537	0.885			
RI	0.450	0.525	0.493	0.532	0.346	0.563	0.027	0.580	0.661	0.577	0.915		
TMS	0.563	0.676	0.385	0.561	0.486	0.506	0.026	0.677	0.530	0.606	0.579	0.884	
TR	0.394	0.606	0.452	0.496	0.468	0.597	0.092	0.579	0.506	0.586	0.571	0.503	0.921

4.5.2 Structural Model Analysis

The following step assessed the structural model using the PLS analysis method because PLS model analysis is the most suitable method for a small number of sample analyses (Riskinanto, Kelana, & Hilmawan, 2017). Thus, the bootstrap resampling technique (Riskinanto et al., 2017) was employed, and 5000 iterations were tested to ensure validity test(Chin, 1998). This technique analyzes hypotheses and the relationship of constructs based on path analysis(Riskinanto et al., 2017). According to the analysis results (See Table 13), H2, H3, H4, H5, H6, H8, H10 and H11 were unsupported due to the *p-value* < 0.05 and *t value* is resulted below than standard threshold (1.96) while H1 (t value = 8.131, p-value > 0.05 and β = 0.629), H7 (t value = 1.984, p-value > 0.05 and β = 0.162) and H9(t value = 2.308, p-value > 0.05 and β = -0.179) were supported with structural model analysis.

Table 12. Structural Model Analysis

Hypotheses	Relationships	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T-value	P-value	Result of analysis
H1	Relative Advantage (RA) -> Adoption of Big Data Analytics (BDA)	0.629	0.631	0.077	8.131	0.000	Accepted
H2	Compatibility (CB) -> Adoption of Big Data Analytics (BDA)	0.131	0.134	0.079	1.666	0.096	Rejected
H3	Complexity (CP) -> Adoption of Big Data Analytics (BDA)	0.046	0.042	0.058	0.797	0.046	Rejected
H4	Trialability (TR) -> Adoption of Big Data Analytics (BDA)	-0.008	-0.006	0.079	0.101	0.919	Rejected
H5	Observability (OB) -> Adoption of Big Data Analytics (BDA)	0.064	0.065	0.075	0.847	0.397	Rejected
H6	Risk and Insecurity (RI) -> Adoption of Big Data Analytics (BDA)	-0.008	-0.006	0.079	0.101	0.919	Rejected
H7	Top Management Support (TMS) -> Adoption of Big Data Analytics (BDA)	0.162	0.160	0.081	1.984	0.047	Accepted
H8	Organizational readiness (OR) -> Adoption of Big Data Analytics (BDA)	-0.113	-0.107	0.072	1.558	0.119	Rejected
H9	External Support (ES) -> Adoption of Big Data Analytics (BDA)	-0.179	-0.160	0.078	2.308	0.021	Accepted

Hypotheses	Relationships	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T-value	P-value	Result of analysis
H10	External Pressure (EP) -> Adoption of Big Data Analytics (BDA)	0.156	0.145	0.082	1.907	0.057	Rejected
H11	Geographical Remoteness (GeoR) -> Adoption of Big Data Analytics (BDA)	-0.009	-0.009	0.058	0.160	0.873	Rejected

4.5.3 Moderating variables' effect

In terms of moderating effects, the articles(Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; P. Maroufkhani et al., 2020) discuss various aspects such as industry type, firm size in different countries. The present study also considers the moderating effects in the conceptual framework because researchers emphasize that different business outcomes are depending on the firm's size as implementing the innovative technologies in their business operations. For instance, small-sized firms run operations with more flexible decision-making processes compared to the bigger companies. So, BDA can bring more performance changes for them(P. Maroufkhani et al., 2020). Thus, in this section, moderating variables effect is evaluated. The interaction effect model is evaluated by using the productive-indicator approach, which is mostly used in a variety of studies (Ramayah, Cheah, Chuah, Ting, & Memon, 2018). This method involves "multiplying each indicator of the exogenous construct with each indicator of the moderator" (Ramayah et al., 2018). In the interaction effect model analysis (Figure 5), a change in R^2 value indicates that the substantive impact on the interaction model is computed (Figure 4) when the specific construct is omitted (Sarstedt, Ringle, & Hair, 2017). This estimation method is referred as to f^2 or effect size which follows:

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

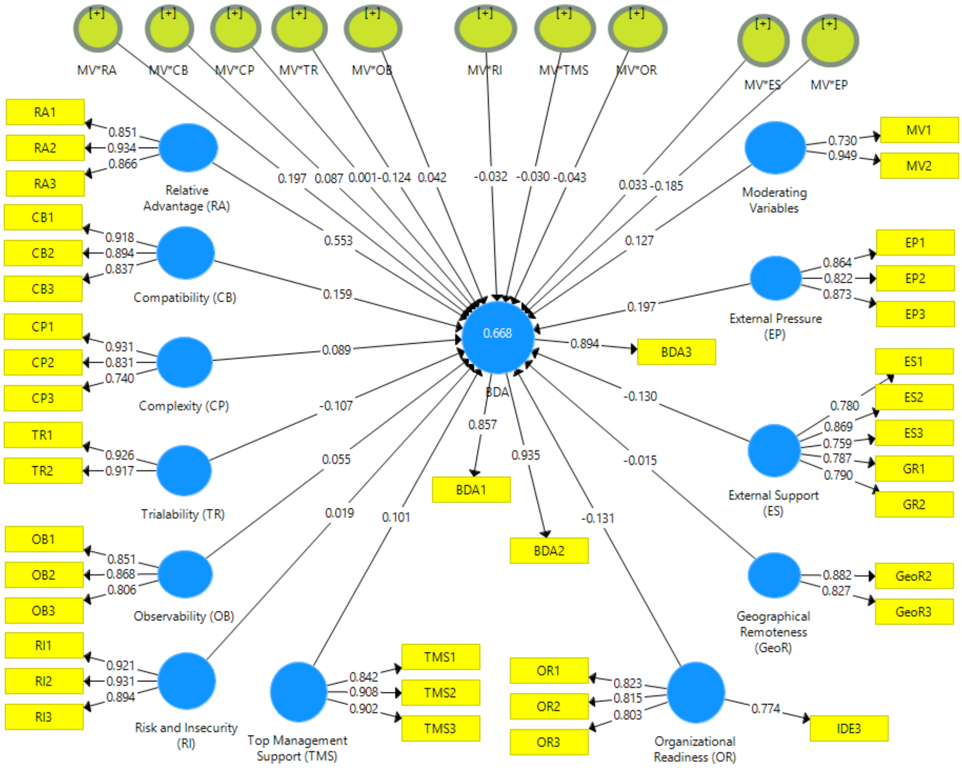

Figure 6. Interaction Effect Model

The change of R^2 is considered important in the interaction effect model analysis. Table 14 presents that the main model effect is 0.622 while the interaction model effect results in 0.668. The change of R^2 was indicated as 0.018, which is referred as to f^2.

According to Cohen (Cohen, 1988), the effect size is determined between 0.02 and 0.15 as small, between 0.15 and 0.35 as medium and more than 0.35 as large effect size. Based on that, the analysis result illustrated that effect size is less than given intervals (0.018) in which the data analysis result indicated that the overall effect size is insignificant.

Table 13. Main effect model vs. Interaction model effect

	Moderating variables for Adoption of BDA		f^2 effect size
	excluded	Included	
R−Squired	0.622	0.668	0.018

Chapter 5. Conclusion

5.1. Discussion

This research work sought to extend previous studies in BDA adoption in SMEs. The objective of the study is to identify the influencing factors in the BDA adoption of SMEs in developing countries. The SLR was conducted to achieve the goals. Accordingly, various types of factors are identified. Moreover, the TOE framework(Tornatzky et al., 1990) is identified as the most common theory for technology adoption in a firm-level and the most frequently discussed factors which positively impact are "Top Management support" and "External Supports" with researchers while "Risks and Insecurity" and "Lack of Understanding & Knowledge" are considered as widely discussed negatively impacting factors on the adoption of BDA in SMEs in developing country aspect. "Top Management Support", "Organizational Readiness" factors are categorized into organizational context according to the TOE framework(Tornatzky et al., 1990). This reveals that in the context, high-level decision maker's support in a firm and internal resource is the most critical factors to implement the technology in business process among SMEs whereas "Risks and Insecurity" are considered as most negatively impacted factor into BDA adoption in SMEs because data collection and data processing may itself be an intrusion in critical information which is highly related with the business process in the firm. In addition, "Lack of Understanding & Knowledge" is widely discussed by authors as a negatively impacted factor in the topic due to any kind of technological implementation into the business demands to be competent in the area from employees in a firm.

5.1.1 Technological context

The online survey was conducted among the SMEs across various industry sectors in Mongolia. The result of the analysis is discussed in terms of TOE theoretical framework contexts, including technology, organization and environmental contexts.

In the technological context, 6 hypotheses were tested. The study result shows that only a hypothesis was supported. Other 5 hypotheses were rejected. "Relative Advantage" is one of the commonly discussed influencing factors across the IT adoption process at a firm level (S. Sun et al., 2018) in the technological context. According to the result of the analysis the "Relative Advantage," which was hypothesized in H1 as a positive impact on BDA adoption in SMEs, was supported. Because BDA adoption can bring a significant advantage regardless of the firm size for the business (P. Maroufkhani et al., 2020). Furthermore, H2 (Compatibility) that was expected positive impact and H3 (Complexity) expected to negatively impact BDA adoption, are rejected. The reason could be that the BDA has already become easily accessible to anyone with low cost regardless of the region with support services (Marr, 2016). The H4 was rejected because the "Trialability" factor is insignificant in BDA adoption in Mongolian SMEs. Since we targeted to retain the analysis result from IT specialists or decision-makers in the SMEs in Mongolia, The present study result, which related to the "Trialability" factor, is in consensus with Nikou et al. (Nikou, 2019) result. They identified that trialability has no direct impact on intention to use the technology for decision-makers and experienced respondents in the field. In the same way, the "Observability" factor hypothesized in H5 to have a positive impact on BDA adoption was not supported according to the analyzed result. Reason behind that, according to previous literature (Finance, 2012), one of the reluctances in Mongolian SMEs is a adoption novel technology which can extent business activity and then, the result indicates that there is insufficient number of influential success cases which benefit from BDA in the market. Therefore, "Risk and Insecurity" factor which was hypothesized in H6 as negative impact on BDA adoption in SMEs was rejected. That means practitioners in this context do not concern the insecurity issue of BDA adoption.

5.1.2 Organizational context

In this context, there are two hypotheses (H7 and H8) assumed. Among them, H7 (Top Management Support), which was assumed positive effect on BDA adoption in SMEs, was supported according to the result of the analysis. On the other hand, H8(Organizational readiness) was rejected due to it was identified as an insignificant impact on BDA adoption with the analysis result. In this regard, the internal technical infrastructure, existing technology use for BDA and human resources are considered. So we can conclude that initial infrastructure and computing systems are solved by cloud infrastructure offered by vendors(Marr, 2016), and respondents answered that the technology does not require higher readiness from firms.

5.1.3 Environmental context

In the environmental context, 3 hypotheses (H9, H10 and H11) are discussed, and H9 was supported while H10 and H11 were rejected according to the data analysis. In detail, the "External Pressure" factor does not significantly impact BDA adoption in SMEs, as H10 was rejected. Mongolia is one the least populated countries globally, which creates less competitiveness in the market (Network, n.d.). Similarly, H11 was rejected because the factor “Geographical Remoteness” that corresponds to the Mongolian context doesn’t significantly influence BDA adoption in the context of the result. A reasonable cause of this is Mongolia is the country which fully covered of the whole area with an internet connection (Network, n.d.), so that the SMEs are not hindered as geographical remoteness of the company to adopt BDA.

Last but not least,

5. 2. Contributions

The study is expected to help SMEs look into the key challenges and enablers to consider for their big data strategy. It’s also expected to provide policymakers with a good foundation for setting up policies that can help SMEs implement BDA, including infrastructure, connectivity, regulations, etc. Such policies can have a greater impact on a country’s economy and give SMEs the power to grow fast and compete on a larger scale. Especially, we aim to analyze the current state of adoption of BDA in Mongolian SMEs. Study outcome is recommended to be considered by managerial perspective in SMEs of Mongolian to set up strategy regarding BDA adoption.

Last but not least, this paper analyzed the current state of potentials and challenges of adoption of BDA in Mongolian SMEs. According to the survey result, general knowledge about BDA is sufficient in table 9. However, in the result of analysis, respondents need to improve security and data privacy concern because the factor related to "risk and insecurity" concerns resulted in an insignificant impact on this technology. In addition, legal environmental is concerned as part of external support factors. According to the SLR result, insufficient government regulation can cause reluctance in novel technologies adoption among Mongolian SMEs. Thus, government regulation improvement related to a technology adoption that can support SMEs is one of the most critical recommendations. Policy-makers in the Mongolian government should implement policies that can support and promote a technology adaption as delivering public services using technology advancement for entities. Also, the key driving power behind the business operation of any SME is a high revenue stream with lower cost and high return. So that, the study found out that BDA can be one of the technological accelerators for decision-making level in Mongolian SMEs.

5.3. Policy implication

The study would be helpful to decision-makers within developing countries and scholars who are majoring in the adoption of BDA in various industries. The study aimed to investigate the main challenges and potentials of adopting BDA as grounding on the TOE framework and try to explain substantial evidence with their relationships with SMEs business performance. Firstly, the study findings with SLR indicate that most influencing factors discussed three contexts, including technology and organization and environment contexts (TOE). In terms of policy-maker, the legal environment should be considered critical because "External Support" indicates one of the biggest influencing factors by analysis. On the other hand, in the firm level, managerial perspective, the "Top Management Support" factor should be paid attention to rather than concern on technology-related complexity and observability because there various are solutions for adoption BDA to implement regardless of the geographical location of the firm. In addition, BDA is identified as an accelerator for business performance according to previous literature, and managers in the firm should be concerned with having a clear vision and goals for implementation of BDA. Their great interest in BDA is crucial to cultivate the organizational culture that uses evidence-based decision-making by implementing BDA.

5.4. Limitations and Outlook

There are several limitations to this study. First, the sample population was taken in a limited number of SMEs in Mongolia, one of the least populated countries (3). Hence, even if we assume that the proposed conceptual model can be applicable to the general concept, further studies are needed to expand the population sample. Also, comparative research work is necessary to further research because analyze of the statistical sample of different countries is helpful to fill the existing research gaps in BDA adoption and its policy implication for technological and management perspective to build baseline in BDA adoption of SMEs in developing countries. Second, this study was conducted during the period when firms were running their activities under restricted situation due to the Covid-19 outbreak, resulting in an economic crisis all over the world (Nicola et al., 2020). This onslaught of the Covid-19 has impacted a firm's operation and financial performance, requiring immediate policy intervention rather than implementing a new technology adoption(Juergensen, Guim□n, & Narula, 2020).

Appendix.1

	Name of Variable	Instrument (Question)	Answer Range	Used in Literature (References)	Comment
Dependent Variable	Status of Adoption of Big Data Analytics (BDA)	"At what stage of BDA adoption is your organization currently engaged?"	• Not considering BDA at all • Currently evaluating (e.g., in a pilot study) • Have evaluated BDA, but do not plan to adopt this technology • Have positively evaluated BDA and plan to adopt this technology • Have already adopted services, infrastructure, or platforms of BDA	(Oliveira, Thomas, & Espadanal, 2014; Thiesse, Staake, Schmitt, & Fleisch, 2011)	The instrument is modified to fit our scenario from the original, which is "At what stage of cloud computing adoption is your organization currently engaged"
		"If you're anticipating that your company will adopt BDA in the future. When do you think it will happen?"	• Never • In more than 5 years. • Between 2 and 5 years • Between 1 and 2 years. • In less than 1 year • Have already adopted services, infrastructure, or platforms of BDA	(Oliveira et al., 2014; Thiesse et al., 2011)	The instrument is modified to fit our scenario from the original, which is "If you're anticipating that your company will adopt cloud computing in the future. How do you think it will happen?"
		"BDA is considered as …."	• Mandatory. • Complicated but necessary	(Ramachandran & Chang, 2014;	The instrument is modified to fit our

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
				for business improvement • Time-consuming and expensive for business improvement. • Not needed.	Thiesse et al., 2011)	scenario from the original, which is "Cloud computing is considered as …" ,
Independent Variable	Technological Context "Technological context is one of the most important aspect that drives the SME' s final decision to adopt the technology(Ramachandran & Chang, 2014). Technological context describes both the internal and external	Relative Advantage	"BDA reduces costs."	Likert Scale 1-5	(Chen, Preston, & Swink, 2015; Ghobakhloo et al., 2011; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Premkumar & Roberts, 1999)	
			"BDA improves customer satisfaction."		(Chen et al., 2015; Ghobakhloo et al., 2011; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Premkumar & Roberts, 1999)	
			"BDA adoption helps to identify new products, services, and opportunities."		(Chen et al., 2015; Ghobakhloo et al., 2011; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Premkuma	

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
					r & Roberts, 1999)	
		Compatibility	"Using BDA is consistent with our business."		(Chen et al., 2015; Ghobakhloo et al., 2011; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Thong, 1999; Tornatzky & Klein, 1982)	
			"Using BDA fits our organizational culture."		(Chen et al., 2015; Ghobakhloo et al., 2011; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Thong, 1999; Tornatzky & Klein, 1982)	
			"It is easy to incorporate" BDA into our organization."		(Chen et al., 2015; Ghobakhloo et al., 2011; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Thong, 1999; Tornatzky & Klein, 1982)	
		Complexity	"Learning to use BDA is difficult for		(Lai, Sun, & Ren, 2018; Parisa	

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			employees."		Maroufkhani, Ming-Lang Tseng, et al., 2020; Xu, Ou, & Fan, 2017)	
			"BDA is difficult to maintain."		(Lai et al., 2018; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Xu et al., 2017)	
			"BDA is difficult to operate compared to traditional system"		(Moore & Benbasat, 1991; Vluggen, 2005; Xu et al., 2017)	The instrument is modified to fit our scenario from the original, which is "ERP is difficult to operate compared to traditional system"
		Trialability	"Our Company could have a free BDA trial before making the decision to adopt BDA."		(Etsebeth, 2012; Limthongchai & Speece, 2003; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Moore & Benbasat, 1991)	The original instrument has slightly been modified, to improve the meaning.
			"Our company has an opportunity to try several BDA applications before		(Etsebeth, 2012; Limthongchai & Speece, 2003; Parisa Maroufkhani, Ming-	

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			making a decision and try out BDA software packages on sufficiently large scale."		Lang Tseng, et al., 2020; Moore & Benbasat, 1991)	
			"Our company does not need a BDA trial, because the start-up cost for using BDA is low."		(Etsebeth, 2012; Limthongchai & Speece, 2003; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Moore & Benbasat, 1991)	The instrument is modified to fit our scenario from the original, which is "The start-up cost for using BDA is low. "
		Observability	"Many competitors or business partners in the market have started using BDA."		(Limthongchai & Speece, 2003; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Moore & Benbasat, 1991)	
			"Using BDA helps my company to connect with both domestic and international business partners."		(Limthongchai & Speece, 2003; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Moore & Benbasat, 1991)	
			"There are many computers that people		(Limthongchai & Speece, 2003;	The instruments are modified to

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			in the company can use to access BDA applications."		Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Moore & Benbasat, 1991)	fit our scenario from the original, which is "There are many computers that people in the company can access to BDA."
		Risk and Insecurity	"The need to outsource BDA creates concerns on data security and privacy."		(Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Salleh & Janczewski, 2016; Dong-Hee Shin & Shin, 2011)	
			"The need to outsource BDA creates vulnerability in access control of the organization' s information asset."		(Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Salleh & Janczewski, 2016; Dong-Hee Shin & Shin, 2011)	
			"The need to outsource BDA creates risks through excessive dependency on vendor."		(Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Salleh & Janczewski, 2016; Dong-Hee Shin & Shin, 2011)	
	Organizational	Top Managem	"Our top management supports		(Chen et al., 2015; Lai et al.,	

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
		ent Support	BDA initiatives within the organization."		2018; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Priyadarshinee et al., 2017)	
			"Our top management promotes BDA as a strategic priority within the organization."		(Chen et al., 2015; Lai et al., 2018; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Priyadarshinee et al., 2017)	
			"Our top management is interested in the news about using BDA."		(Chen et al., 2015; Lai et al., 2018; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Priyadarshinee et al., 2017)	
		Organizational readiness	"Lacking capital and financial resources have prevented my company from fully exploiting BDA."		(Chen et al., 2015; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020)	The instruments is modified to fit our scenario from the original, which is "lacking capital/financial resources has prevented my company from fully exploit Big Data

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
						Analytics lacking needed.”
			“Lacking IT infrastructure has prevented my company from exploiting BDA”		(Chen et al., 2015; Parisa Maroufkhani, Ming–Lang Tseng, et al., 2020)	The instruments is modified to fit our scenario from the original, which is “Lacking needed IT infrastructure has prevented my company from exploiting Big Data Analytics.”
			“Lacking analytics capability prevent the business fully exploit BDA.”		(Chen et al., 2015; Parisa Maroufkhani, Ming–Lang Tseng, et al., 2020)	
		In–house Data Analytic Expertise	“Our company has in–house analytics experts, who have sufficient experience in Big Data related systems”		(Parisa Maroufkhani, Ming–Lang Tseng, et al., 2020; Powell & Dent-Micallef, 1997)	
			“We have sufficient human resource capability, to handle the problems that are related with		(C.–Y. Lin & Ho, 2011; Maduku, Mpinganjira, & Duh, 2016)	The instrument is modified to fit our scenario from original, which is “Our employees would be capable of

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			adoption of BDA"			using mobile marketing to solve our marketing problems easily" "
			"Our company needs to cooperate with a third-party on BDA adoption"			Instrument has been designed by ourselves.
		Organizational Culture	"Our company perceives our workplace culture to be highly organized and feel that goals and objectives are clear-cut and reasonable."		(Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Melitski et al., 2010)	
			"Our company perceives that individual workgroup are adequately informed about issues and priorities facing the organization."		(Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Melitski et al., 2010)	
			"Our company managers actively plan their efforts, and their department gets		(Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Melitski et al., 2010)	

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			cooperation and assistance from other departments,”			
	Environmental Context “Any kind of business, external environment such as market competitiveness and regulations applied by government bring strong impact on the intention to adopt the innovative technology (Gassmann & Keupp, 2007). Consequently, environmental	Government Regulation	“The governmental policies encourage companies, to adopt new information technology (e.g., BDA).”		(M. Gupta & George, 2016; Lai et al., 2018; Li, 2008; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020)	
			“The government provides companies with incentives for using BDA in government procurements and contracts such as offering technical support, training, and funding for BDA use.”		(M. Gupta & George, 2016; Lai et al., 2018; Li, 2008; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020)	The instruments is modified to fit our scenario from the original, which is “The government provides incentives for using big data analytics in government procurements and contracts such as offering technical support, training, and funding for big data analytics us”
			“There are some business laws to deal with the security and		(M. Gupta & George, 2016; Lai et al., 2018; Li, 2008; Parisa Maroufkha	

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			privacy concerns over the Big Data Analytics technology”		ni, Ming-Lang Tseng, et al., 2020)	
		External Pressure	“Our choice to adopt BDA would be strongly influenced by what competitors in the industry are doing.”		(Ifinedo, 2011; Tiago Oliveira & Maria Fraga Martins, 2010; Tiago Oliveira & Maria F Martins, 2010; Oliveira et al., 2014)	
			“Our company is under pressure from competitors to adopt BDA.”		(Ifinedo, 2011; Tiago Oliveira & Maria Fraga Martins, 2010; Tiago Oliveira & Maria F Martins, 2010; Oliveira et al., 2014)	
			“Our company would adopt Big Data Analytics in response to what competitors do.”			Instruments is designed.
		External Support	“Community agencies or BDA vendors can provide		(Ghobakhloo et al., 2011; Li, 2008; Parisa Maroufkhani, Ming-	The instruments are modified to fit our scenario from the original,

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			required training for BDA adoption."		Lang Tseng, et al., 2020)	which is "Community agencies/vendors can provide required training for Big Data Analytics adoption."
			"Community agencies and BDA vendors can provide effective technical support for BDA adoption."		(Ghobakhloo et al., 2011; Li, 2008; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020)	The instruments is modified to fit our scenario from the original, which is "Community agencies/vendors can provide effective technical support for Big Data Analytics adoption."
			"Vendors actively market BDA adoptions"		(Ghobakhloo et al., 2011; Li, 2008; C.-Y. Lin & Ho, 2011; Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020)	
		Geographical Remoteness	"Our company has difficulties to adopt BDA due to its geographical location."			Based on study, statements (C[illegible]rte-Real et al., 2017; Tuul & Bing, 2019; Wamba & Carter, 2013), instruments
			"We can access BDA			

	Name of Variable		Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			applications in rural area."			are designed.
			"Metropolitan area gives us more opportunity to adopt or implement BDA."			
Moderating Variable	Firm Size		"What is the number of employees in your company?"	1.1–5 2.6–9 3.10–50 4.51 – 100 5.101–199 6.200–249 7.250–300 8.More than 300		The instrument has been designed to cover the different definitions of the EU, Worldbank, Egypt, US (Bank, 2021; EU, 2021).
			"What is the annual turnover of your company"	1.Up to US$ 150,000 2.Between US$ 150,000 and US$ 500,000 3.Between US$ 500,000 and US$ 833,000 4.Between US$ 833,000 and US$ 1.2 Million 5.Between US$ 1.2Million and US$ 3 Million 6.Between US$ 3 Million and US$ 55 Million		The instrument has been designed to cover the different definitions of the EU, Worldbank, Egypt, US (Bank, 2021; EU, 2021)

	Name of Variable	Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			7.More than US$ 55 Million		
		"In which country are you working for your company?"	*Afghanistan, …, Zimbabwe*		195 countries are listed, referring to the United Nation country list (Nation, 2021).
		"In which country does your company conduct most of its business?"	*Afghanistan, …, Zimbabwe*		195 countries are listed, referring to the United Nation country list (Nation, 2021).
		"In which country is the headquarter of your company?"	*Afghanistan, …, Zimbabwe*		195 countries are listed, referring to the United Nation country list (Nation, 2021).
	Industry Sector	"To what industry sector does your company belong to?"	1.Wholesale Trade Retail Trade 2.Transportation and Warehousing, and Utilities 3.Information & media 4.Finance and Insurance, and Real Est 5.Professional, Scientific, and Management, and Administrative 6.Waste Management Services 7.Educational Services,		Instrument and answer options are designed based on the Global Industry Classification Standard (GICS) (standard, 2021) and The North American Industry Classification System (NAICS)) ((NAICS), 2021).

	Name of Variable	Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			and Health Care and Social Assistance 8. Arts, Entertainment, and Recreation, and Accommodation and Food Services 9. Energy (Energy Equipment, Oil, 10. Gas & Consumable Fuels) 11. Materials (Chemicals, Construction Materials, Containers & Packaging, Metals & Mining, Paper & Forest Products) 12. Industrials (Building Products, Construction & Engineering, Electrical Equipment, Machinery) 13. Consumer Discretionary (Automobiles & Components)		
Control Variable	Education	"What is your Education"	1. No formal education	(Parisa Maroufkhani, Ming-Lang	Added more options from

	Name of Variable	Instrument (Question)	Answer Range	Used in Literature (References)	Comment
			2.Primary School Degree 3.Secondary School Degree 4.Associate Degree (college of two years) 5.Bachelor Degree 6.Master Degree 7.PhD Degree	Tseng, et al., 2020; Tiago Oliveira & Maria Fraga Martins, 2010; Oliveira et al., 2014)	(Duverger, 2012)
		"Please rate your expertise in information technology."	1 (no expertise) to 5 (expert)		Instrument has been designed by the authors.
		"Please rate your expertise in Big Data."	1 (no expertise) to 5 (expert)		
		"How many percent per workday do you use your computer for work purposes?"	1 (0%) to 5 (100%)		
	Position	"What is your position in the company?"	1.Senior executive 2.Executive 3.Senior Director 4.Senior Manager 5.Manager 6.Senior Staff 7.Intermediate level staff 8.Associate level staff	(Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020; Tiago Oliveira & Maria Fraga Martins, 2010; Oliveira et al., 2014)	Adapted from (Parisa Maroufkhani, Ming-Lang Tseng, et al., 2020) and added more options from (Careers, 2012).

	Name of Variable	Instrument (Question)	Answer Range	Used in Literature (References)	Comment
	Gender	"What is your Gender"	1. "Female" 2. "Male"		Instrument is designed

Apendix.2

Category	Factors	Description
Technological	Relative advantage	"the degree to which an innovation is perceived as being better than the idea it supersedes" . (Rogers, 2003) (Alshamaila et al., 2013; Priyadarshinee et al., 2017; Ramdani et al., 2013)
	Compatibility	"the degree to which the innovation is perceived as consistent with the existing values, past experiences, and needs of the potential adopter" (Agrawal, 2015; Chen et al., 2015; Tornatzky et al., 1990)
	Complexity	According to Lee (2004), " the degree to which an innovation is perceived as relatively difficult to understand and use" (Jungwoo Lee, 2004), (Chen et al., 2015), (Alshamaila et al., 2013; Rogers, 2010)
	Risks and Insecurity	"The degree to which the results of incorporating an innovation in an organization might be insecure"(Benlian & Hess, 2011) (Alshamaila et al., 2013; Priyadarshinee et al., 2017)
	Trialability	"as the degree to which an innovation may be experimented with on limited basis." (Salleh & Janczewski, 2016) (Priyadarshinee et al., 2017)
	Observability	"The degree to which the results of an innovation are visible to others" (Jeyaraj, Rottman, & Lacity, 2006; Lu, Quan, & Cao, 2009; Rogers, 2010)
	Effort Expectancy	Refers to how easy it is to learn and use what this new technology will be. According to UTAUT, Big Data will be used more or less depending on how easy or difficult it is (M. A. H. Al-Hagery, 2016)
	Cost of adoption	"The expense that a firm incurs to sustain big data usage and future scalability" (D-H Shin & Bohlin, 2020), (Park et al., 2015; Verma & Bhattacharyya, 2017)
	Performance Expectancy	"Refers to the perception of the performance that the technology will have" (Pickrahn et al., 2017)
Organizational	Top Management support	"Ramdani and Kawalek (2007) define top management support as the degree to which managers comprehend and embrace the technological capabilities of a new technology system" (Ramamurthy, Sen, & Sinha, 2008; S. Sun et al., 2018)

Category	Factors	Description
	Organizational resource	"The extent to which a firm's technology, and business resources are adequate to support adoption" (Hong & Zhu, 2006; S. Sun et al., 2018)
	Organizational Size	"The firm's annual revenue and number of employees that could support the adoption of big data" (Hong & Zhu, 2006; Park et al., 2015; Verma & Bhattacharyya, 2017)
	Organizational Readiness	"According to Premkumar and Roberts (1999), organizational readiness refers to the extent to which the required organizational resources are available to utilize technology like BDA" (Asiaei & Rahim, 2019; Gangwar, 2018; Taxman, Henderson, Young, & Farrell, 2014)
	Organisational culture	"Refers to the set of norms, values, attitudes and pattern of behaviours that defines the core organisational identity, influences leadership styles, working climates, strategy formulations, management processes and organisational behaviours "(Denison, 1984; Laforet, 2017; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012; Saffold III, 1988)
	Collaboration and Explorative Learning	"Complex manufacturing projects often have inter-related and inter-dependent tasks which are sometimes interorganizational. The collaboration of project actors is a must for decision making and problem-solving" (Dubey et al., 2019; Sachin K Mangla, Raut, Narwane, & Zhang, 2020)
	Project Success	"Traditionally project success was compliance with cost, time, and scope objective. Further strategic dimensions such as the impact on the customer, project efficiency, business success, preparedness for the future, and impact on the team were categorized as project success. In recent times social and environmental dimensions of sustainability have been incorporated" (Martens & Carvalho, 2016) ((M. M. d. Carvalho & Rabechini Junior, 2015)
	Project Performance of SMEs	To monitor strategic alignment, the project manager needs to gather information about project performance. Long term and short-term project performance can be enhanced through BDA. (Biedenbach & M�ller, 2012; Hermano & Mart�n-

Category	Factors	Description
		Cruz, 2016; Narwane, Raut, Gardas, Kavre, & Narkhede, 2019)
	Resistance to Use	"the use of many new technologies has failed because of the opposition of users to their implementation" (M. A. Al-Hagery, Alfaiz, Alorini, & Althunayan, 2015; Amelec & Alexander, 2015; Ban et al., 2015)
	Lack of intuitive software	Solutions with both an intuitive user interface and a strong analytical potential are rare. IBM's Market analysts emphasise the need for predictive analytics software with intuitive user interfaces and a shorter learning curve (Probst, Frideres, Demetri, Vomhof, & Lonkeu, 2014)
	Different venture concept	Venture perspective creates the idea that business is only dependent on the way they excel in such dimensions, eventually overlooking other resources at their disposal, as well as new opportunities to improve and diversify their activity (Shirley Coleman et al., 2016)
	Financial barriers	SMEs have less access to debt finance than larger companies, particularly because of imperfect or asymmetric information between financial institutions and SMEs (Bartlett & Bukvič, 2001; Fuller-Love, 2006; B. Zhong, 2008)
	Social Responsibility	"Social responsibility comprehends external population, internal human resources, macro social performance, the participation of stakeholder, occupational health and standards such as ISO 14001, ISO/CD 45001, and OHSAS 18001:2007. ISO 26000 gives principles of social responsibility, whereas OHSAS 18000 elaborates safety and health principles. BDA capabilities can ensure the commitment of all stakeholders of manufacturing SMEs to social responsibility" (Labuschagne & Brent, 2005; Ren et al., 2019)
	In-house data analytic expertise	"The interpretation of IT expertise is that organization has adequate personnel with the enough knowledge of IT to adopt big data" (K. Lee & Ha; Maduku et al., 2016; Powell & Dent-Micallef, 1997)
	Lack of understanding & knowledge	The e-skills UK survey highlights an extremely low understanding of big data analytics by SME representatives, whereas among the representatives of larger organisations, around 30% to 40% claim to have good or very good

Category	Factors	Description
		understanding of big data analytics (UK, 2013), (Vossen, Lechtenb□rger, & Fekete, 2015)
Environmental	Government Regulations	“Tornatzky et al. (1990) asserted that sometimes government regulations for the adoption of technology require businesses to have some preconditions, such as some specialized standards, in place that may impose higher transaction costs on firms to adopt a favourable technology.” (Das & Rangarajan).
	Social Influence	“has been used to measure the effect of the influence perceived by the users regarding what others –friends, family– think concerning the use of a technology. In a business environment, it is also important what leaders and colleagues think” (Ban et al., 2015; Khanali & Vaziri, 2017)
	Labour market	There is a growing shortage of qualified data analysts on the labour market (Manyika et al., 2011), (UK, 2013)
	Lack of business cases	Although guidelines and examples exist, for example, in Ahlemeyer–Stubbe et al., stimulating and trend–setting big data SME usage cases are not widely available services (Ahlemeyer–Stubbe & Coleman, 2014; Vossen et al., 2015)
	External Pressure	"Refers to influences from the external environment that prompt the organization to use BDA” (Oliveira et al., 2014) (Tsai, Lai, & Hsu, 2013).
	External Support	A major part of consulting services used by SMEs concerns the operational level, for example, accounting or hardware–related and software–related IT issues. Management and business analytic consulting is less considered by SMEs services (Ahlemeyer–Stubbe & Coleman, 2014; Vossen et al., 2015) “External support has been defined as the extent to which vendors or third–parties can provide technological support for companies to adopt important innovation” (Navaz et al., 2018) “availability of support for implementing and using an information system” (Premkumar & Roberts, 1999).
	Non–transparent software market	Plenty of business analytics software solutions exist on the market. For users with little or no expertise, it is hard to select a product with a good price–performance ratio and to separate the wheat

Category	Factors	Description
		from the chaff. The existing comparison and evaluation platforms are strongly vendor biased. Independent evaluations and selection schemes are hard to find (Shirley Coleman et al., 2016)
	Green Purchasing	"Green procurement in project management is still in the nascent phase. The selection of subcontractors that will provide green manufacturing service is associated with high cost and uncertainty. BDA can assist in supplier selection, cooperation and involvement. Regulatory and customer pressures are the external factors that can play a crucial role in green purchasing in manufacturing project management. SMEs must select suppliers based on sustainability criteria" (Azadeh, Zarrin, & Salehi, 2016; M. M. Carvalho & Rabechini Jr, 2017; Wamba et al., 2017)
	Project operational capabilities	"Project operational capabilities enable manufacturers to upgrade existing processes and products. Also, new processes and products can be developed for "first-of-its-kind" projects through different assets and procedures". (Hermano & Mart□n-Cruz, 2016; Labuschagne & Brent, 2005)
	Project Complexity	"Project complexity is the property of a project which makes it difficult to understand, foresee and keep under control its overall behaviour, even when given complete information about the project system." Project complexity can be categorized as organizational and technological. Organizational complexities are prominent, which involves environmental aspects, diversity of objectives, and complexity of tasks (He, Luo, Hu, & Chan, 2015; Vidal et al., 2011)

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Abstract in Korean

중소기업 (SME)은 모든 국가의 사회 및 경제 개발에서 핵심적인 역할을 하고 있는 것으로 간주된다. 빅 데이터 분석 (BDA)과 같은 혁신적인 기술의 채택은 국가 경제 성장에 중요한 역할을 하는 있는 중소기업에 더 나은 경영 성과와 경쟁력을 가져올 수 있다. 본 연구는 중소기업에서 BDA 채택하는 데에 있는 주요 과제와 잠재력을 평가하고 개발 도상국 측면에서 BDA 채택은 중소기업의 경영 성과에 대한 영향을 조사하는 것을 목표로 한다. 본 연구의 목표를 이루기 위해 우선 SME 에서 BDA 채택과 관련한 문헌검토(systematic literature review (SLR))를 하였다.

정보 시스템 연구자들 중에 Kitchencham et al [1]과 Okoli et al. [2]에 의해 시작된 정보 시스템 연구는 가장 일반적인 SLR 방법이라고 할 수 있다. 이 방법은 본 연구에 적용됩니다. 본 연구는 문헌검토를 통해서 다양한 측면에서 SME 를 정의하는 데 초점을 맞추고 있으며 SME 에서 BDA 채택의 가장 일반적인 영향 요인을 밝혔다 . 문헌 검토한 결과를 보면, 선행 연구에서 SME 의 BDA 채택에 있어서 34 개의 뚜렷한 영향 요인을 논의했다는 것을 확인되었다.

본 연구의 가설은 연구자들의 일치한 관점을 보여주는 영향 요인을 기반으로 설정하였다. 그 다음에 개발 도상국을 위한 개념의 체계를 세우고 통제 변인과 조절 변인의 영향도 추정하였다. 가설과 개념 체계를 평가하기 위해 본 연구는 몽골의 다양한 사업을 운영하고 있는 중소기업을 대상으로 온라인 설문조사를 실시하였다. 온라인

설문조사의 참여자는 회사의 주요 의사 결정자 및 정보 기술 전문가였다. 이를 통해 수집 된 데이터와 제안 된 체계를 PLS (Partial Least Squire)를 사용하여 분석하였다. 이 방법은 잠재 변수와 관찰 변수 간의 상호 관계를 조사 할 수있는 구조 방정식 모형 (SEM) 방법이다. 통계 소프트웨어 도구 측면에서는 접하기가 쉬운 데이터 분석 도구 중 하나인 SmartPLS v3.3.3 을 이용하였다. 마지막으로, 본 연구는 분석한 결과를 기반하여 정책 및 제안을 제시하였다.

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Assessment of challenges and potentials of Big Data Analytics for SMEs

By Enkhbaatar Batbayar

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