TAILORING EFFECTIVE USE MODEL OF BIG DATA IN MANAGERIAL CONTEXT: INSIGHTS FROM AN EMPIRICAL STUDY IN ARMENIAN COMPANIES

https://doi.org /10.59982/18294359-24.15-te-07

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Abstract

This article explores the managerial dimensions of the big data phenomenon, focusing on the challenge of customizing an effective use model within companies. The central inquiry revolves around tailoring such a model to suit the specific needs of big data-user companies. To address this, the study adopts a conceptual framework proposed by Surbakti and his co-authors, which delineates the effective use of big data. The primary methodology involves quantitative analysis of data gathered from 211 surveys completed by Armenian industry professionals. Examination of the collected data through statistical analysis reveals the presence of two distinct cohorts within the realm of big data users: "novice users" and "advanced users." The main theoretical contribution that we aim for in this research is empirically proving the global validity of the studied model and demonstrating its flexibility of application in these two types of use cases of big data. While the conceptual model is found to be applicable to both types of users, its implementation varies significantly between the two groups. Therefore, from a managerial point of view, our results lead a manager to first think about the maturity of its company in terms of big data. Implementing a solution is not enough. By thinking in terms of novice vs. advanced, it creates two different managerial courses of action. Moreover, we propose the variables a manager has to analyze depending on this maturity.

Keywords: Big data, effective use of big data, novice user, advanced user, Armenian context, effective use.

Introduction

The question of how a company can effectively leverage big data today, that is, the "how" question, remains unanswered. To use big data effectively, companies face multiple challenges: technological [Falahat et al., 17], managerial [Liu et al., 362], societal [Ferreira et al., 1082], economic [Maroufkhani et al., 2]. These aspects potentially change the rules of the game related to the management and the effective use of big data by companies, making assessing the impact of big data a critical consideration. In this article, we focus on the managerial aspects of big data within companies located in Armenia. The question we aim to address here is: "How to tailor the model of effective use of big data to the companies in the Armenian context?"

To examine this question, we will first justify the application of the conceptual model of effective use of big data. In the second step, we will present our methodology. Finally, in the third step, we will discuss our results and highlight their implications.

Main body

To comprehend the foundations of big data, one can rely on the relationships established among the three categories: "Data – Information – Knowledge." **Data** are facts representing a certain reality, independent of whoever uses them. **Information** is the data to which an individual or a group has added meaning. The transition from information to **knowledge** occurs through a mechanism of cognition. Gartner defines big data as "data of large volume and wide variety generated at high speed, requiring specific processing for better understanding, innovative decision-making and cost-effective process automation". This includes various data characteristics such as Volume, Velocity, Variety, Veracity, Value, Variability, Visualization [Seddon, Currie, 303]. According to "The Economist 2017", the volume of data is expected to reach 180ZB in 2025, noting that 1 zettabyte is equivalent to 250 billion DVDs [Vassakis et al., 5]. The simplistic idea that "more data collected leads to better decision-making" is challenged by the need to convert data, due to its volume, into applicable knowledge robustly and reliably. Companies often find themselves in a "blind zone," a counterproductive effect of the increased volume of data, leading to a decline in the percentage of data they can process, understand and analyze.

Consequently, the effective use of big data is considered a crucial component in creating business value from the data. The literature review on the subject of value creation from big data reveals two important tracks. First, much of the literature is written by consultants and practitioners, resulting in a lack of theoretical foundations and empirical tests [Gupta, George, 1053]. Second, imitating "big data success stories" often leads companies to significant financial losses [Kiron, 64]. These two tracks, which are of interest to both researchers and decision-makers in the field, lead us to focus on the finer and more profound aspects that improve the understanding of the subject, aiming to empirically and in-depth study the effective use of big data at the organizational level and its integration into the entire process of value creation.

To achieve this, we studied the effective use of big data in Armenian companies through the conceptual model developed by Surbakti and his co-authors.

The model integrates 41 factors grouped into 7 themes: data quality; data privacy and security and governance; perceived organizational benefit; process management; people aspects; systems, tools and technologies; organizational aspects [Surbakti et al., 11], (Table 1). These factors were identified based on a systematic literature review and grouped into themes through content analysis. The use of 45 case studies by Marr in 2016 allowed grouping these themes into three categories: motivational, operational and supporting mechanisms, with interrelations whose influence on the effective use of big data must be considered [Marr]. This model, being the most recent and comprehensive, can serve as a tool to develop the theory of the effective use of big data.

To address the proposed research question, our primary objective is to develop and apply a coherent methodological approach to empirically test the conceptual model developed by these authors. Our main approach involves gathering quantitative data through a survey of 211 professionals in the field, representing 16 Armenian companies that use big data. This quantitative study enables us to operationalize the variables of the model and conduct the necessary testing.

For collecting quantitative data, we have devised an instrument based on the bibliometric method to measure the effective use of big data. We analyzed 40 papers to identify scientifically sound measurement scales for assessing the 41 factors of the conceptual model. Additionally, eight professionals in the field and one academician were engaged to adapt the survey instrument to the research context and conduct a pilot study. To ensure the reliability of the structures, we retained an internal consistency coefficient of Cronbach's Alpha ≥ 0.9 (0.93) [Hair et al., 96].

Table 1

Theme	**Factor**
F1: Perceived organizational benefit	f1.1: Perceived value f1.2: Perceived risk f1.3: Perceived usefulness f1.4: Perceived ease of use f1.5: Intention to use f1.6: Perceived observability f1.7: Cost–benefit analysis
F2: Process management	f2.1: Process orientation f2.2: IT business process integration f2.3: Data management
F3: Data privacy and security and governance	f3.1: Data privacy and security f3.2: Data governance
F4: Data quality	f4.1: Data quality and information quality f4.2: Data completeness f4.3: Data currency f4.4: Data access f4.5: Data relevance f4.6: Data accuracy f4.7: Data consistency
F5: People aspects	f5.1: People's knowledge and skills f5.2: Trust f5.3: Champions f5.4: Employee engagement f5.5: User participation f5.6: Individual Characteristic
F6: Organizational aspects	f6.1: Organizational cultural competence f6.2: Talent management f6.3: Change management program f6.4: Strategic alignment f6.5: Project management f6.6: Performance management f6.7: Organizational structure and size f6.8: Interdepartmental collaboration f6.9: Communication f6.10: Top management support f6.11: Environmental effect f6.12: Clear goals f6.13: Focus on innovation
F7: Systems, tools and technologies	f7.1: System quality f7.2: IT infrastructure f7.3: Vendor support

Themes and factors of the conceptual model

The main study targeted professionals involved in the processing and use of big data, including Data Scientists, Data Analysts, Data Engineers and Big Data Processing Project Managers. When constructing the sample, we followed the guidelines of Bryant and Yarnold and "the law of 100" [Bryant, Yarnold, 99–136] due to the nature of our research, which required adapting non-probability sampling [Bidan, 187].

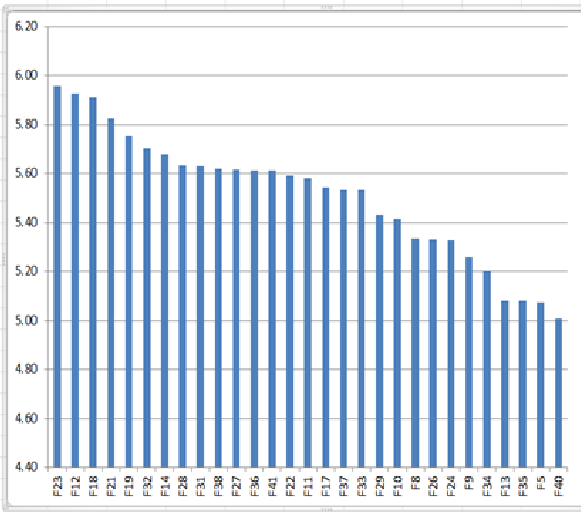
We statistically analyzed the 211 usable questionnaires according to the guidelines of Raguseo, which involve ranking and prioritization based on an order of variables according to their average values [Raguseo, 189]. To conduct this analysis, we utilized Excel software with its "Data Analysis" function and XLSTAT.

The initial processing step involved ensuring the reliability of comparisons by calculating the coefficient of variation (CV) for each factor, where CV= σ/μ or CV= s/x. For all factors studied, the coefficient fell within the zone where $CV < 0.15$, confirming the representativeness of the means. Subsequently, rankings were calculated based on the size of the company, its sector of activity, and the company's relationship with big data. An analysis of variance test (ANOVA) revealed a statistically significant difference for the two groups of respondents (where SSBW<SSWG, with a $p<0.05$ value), corresponding to the feature of the respondent's company's relationship with the exploitation of big data. This led us to later propose names for these two groups of companies: "novice user" and "advanced user". Through a third stage of the analysis process, we established two lists of the most significant factors contributing to the effective use of big data for each type of user.

Figure 1

1	5.9578	F23	1 Intention to use
2	5.9276	F12	2 Trust
3	5.9121	F18	3 Data governance
4	5.826	F21	4 Perceived usefulness
5	5.7519	F19	5 Perceived value
6	5.7051	F32	6 Strategic alignment
7	5.6801	F14	7 Employee engagement
8	5.6353	F28	8 Data management
9	5.63	F31	9 Change management program
10	5.6206	F38	10 Top management support
11	5.6166	F27	11 IT BP integration
12	5.6125	F36	12 Interdepartmental collaboratio
13	5.6117	F41	13 Focus on innovation
14	5.5914	F22	14 Perceived ease of use
15	5.5827	F11	15 Peoples knowledge and skills
16	5.5442	F17	16 Data privacy and security
17	5.535	F37	17 Communication
18	5.5324	F33	18 Project management
19	5.431	F29	19 Organizational cultural compet
20	5.4139	F10	20 Data consistency
21	5.3339	F8	21 Data relevance
22	5.3303	F26	22 Process orientation
23	5.3275	F24	23 Perceived observability
24	5.2572	F9	24 Data accuracy
25	5.2013	F34	25 Performance management
26	5.0818	F13	26 Champions
27	5.0797	F35	27 Organizational structure and siz
28	5.0749	F5	28 Data Completeness
29	5.0085	F40	29 Clear goals

5.96	Intention to use
5.93	Trust
5.91	Data governance
5.83	Perceived usefulness
5.75	Perceived value
5.71	Strategic alignment
5.68	Employee engagement
5.64	Data management
5.63	Change management program
5.62	Top management support
5.62	IT BP integration
5.61	Interdepartmental collaboratio
5.61	Focus on innovation
5.59	Perceived ease of use
5.58	Peoples knowledge and skills
5.54	Data privacy and security
5.54	Communication
5.53	Project management
5.43	Organizational cultural compet
5.41	Data consistency
5.33	Data relevance
5.33	Process orientation
5.33	Perceived observability
5.26	Data accuracy
5.20	Performance management
5.08	Champions
5.08	Organizational structure and siz
5.07	Data Completeness
5.01	Clear goals



The most important factors that contribute to the effective use of big data for a "novice user"

The statistical analysis of quantitative data enables us to categorize respondents into two distinct groups. The first group comprises 117 respondents (55.45%) who have implemented a necessary and tailored infrastructure for big data. The second group consists of 94 respondents (44.55%) who use big data alongside their primary activities without a specifically adapted infrastructure. Both groups effectively harness big data: the first group's core activities and business model revolve around data, whereas the second group integrates big data into their existing activity. An analysis of variance test (ANOVA) reveals a statistically significant difference between these two groups: the first group is labeled as "advanced users," while the second group is termed "novice users," a distinction that will be elaborated upon further.

Our study yields two key findings. **Firstly,** among companies leveraging big data in Armenia, there are distinct user types: "novice user" and "advanced user." This dichotomy influences how big data is effectively used within these companies.

Secondly, each user type requires a tailored adaptation of the model. A "novice user" perceives effective use of big data through motivational factors such as organizational interest and aspects related to human and organizational dynamics. Such companies adopt infrastructure to extract value from big data in alignment with the DITMG model (Driver-Information-Technology-Methods-Goal) [Surbakti, 3]. Consequently, effective use of big data among "novice users" in the Armenian context relies on 29 out of 41 factors outlined in the model (Figure 1).

On the other hand, for "advanced users," operational factors and support mechanisms play a pivotal role in maximizing the benefits of big data (Table 2).

Table 2

Advanced user			
(f) code	**Mean**	**Rang**	**Factor**
F2	6.3442	1	Infrastructure IT
F6	6.0167	2	Data Currency
F9	6.0127	3	Data accuracy
F11	6.0001	4	Peoples knowledge and skills
F18	5.8663	5	Data governance
F28	5.8597	6	Data management
F8	5.81	7	Data relevance
F5	5.6859	8	Data Completeness
F10	5.6809	9	Data consistency
F3	5.5243	10	Vendor Support
F12	5.4691	11	Trust
F1	5.3647	12	System Quality
F32	5.1702	13	Strategic alignment
F4	5.1033	14	Data Quality
F39	5.0779	15	Environmental effect
F17	5.0051	16	Data privacy and security

The most important factors that contribute to the effective use of big data for an "advanced user"

These companies, built around a data-centric business model, using big data primarily to enhance their core operations. Hence, effective use of big data among "advanced users" depends on 16 out of the 41 factors in the model.

Conclusion

The aforementioned outcomes provide insight into adapting the conceptual model of big data developed by Surbakti and his co-authors to companies in Armenia. Understanding the company's relationship with big data technology is crucial, as it reveals two distinct user types: novice and advanced. Each user type necessitates a nuanced application of the conceptual model. This finding underscores the potential for a more generalized model and its variations tailored to specific contexts and perspectives on big data.

Consequently, our research contributes to empirically validating the global applicability of the studied model. We urge researchers to further test the model across diverse cases to advance the theory of effective use of big data. From a managerial perspective, understanding the maturity level of a company in terms of big data is paramount. Mere implementation of solutions is insufficient, instead, managers should adopt distinct strategies based on whether their company falls into the novice or advanced user's category.

References

1. Bidan, M. (2020). *Chapitre 16. Une introduction aux méthodologies quantitatives.* In Produire du savoir et de l'action, pp. 183-195. https://doi.org/10.3917/ems.peret.2020.01.0183
2. Bryant, F. B. and Yarnold, P. R. (1995). *Principal-components analysis and exploratory and confirmatory factor analysis.* In L. G. Grimm & P. R. Yarnold (Eds.), Reading and understanding multivariate statistics, pp. 99–136. American Psychological Association.
3. Falahat, Mohammad, Phaik Kin Cheah, Jayamalathi Jayabalan, Corrinne Mei Jyin Lee, and Sia Bik Kai (2023). *"Big Data Analytics Capability Ecosystem Model for SMEs"*. Sustainability 15, no. 1: 360, pp. 1-23. https://doi.org/10.3390/su15010360
4. Ferreira, C., Merendino, A. Meadows, M. (2023). *Disruption and Legitimacy: Big Data in Society.* Inf Syst Front 25, pp. 1081–1100. https://doi.org/10.1007/s10796-021-10155-3
5. Gupta, M. and George, J. F. (2016). *Toward the development of a big data analytics capability.* Information and Management, 53(8), pp. 1049–1064. https://doi.org/10.1016/j.im.2016.07.004
6. Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2010). *Multivariate Data Analysis.* 7th Edition, Pearson, New York, 816 p.
7. Kiron, D. (2017). *Lessons from Becoming a Data-Driven Organization.* MIT Sloan Management Review, 58(2), pp. 60-68.
8. Liu, Y., Wang, W. and Zhang, Z.(J). (2022). *"The dual drivetrain model of digital transformation: role of industrial big-data-based affordance"*. Management Decision, Vol. 60 No. 2, pp. 344-367. https://doi.org/10.1108/MD-12-2019-1664
9. Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W. and Khalid, H. (2020). *Big data analytics adoption: Determinants and performances among small to medium-sized enterprises.* International Journal of Information Management. Volume 54, pp. 1-15. https://doi.org/10.1016/j.ijinfomgt.2020.102190
10. Marr, B. (2016). *Big Data in Practice. How 45 Successful Companies Used Big Data Analytics to Deliver Extraordinary Results.* Hoboken, 320 p. https://doi.org/10.1002/9781119278825
11. Raguseo, E. (2018). *Big data technologies: An empirical investigation on their adoption, benefits and risks for companies.* International Journal of Information Management, 38(1), pp. 187-195. https://doi.org/10.1016/j.ijinfomgt.2017.07.008
12. Jonathan J.J.M. Seddon and Wendy L. Currie (2017). *A model for unpacking big data analytics in high-frequency trading.* Journal of Business Research, vol. 70, issue C, pp. 300-307. https://doi.org/10.1016/j.jbusres.2016.08.003
13. Surbakti, F. P. S. (2020). *What is Effective Use of Big Data? The Consensual Definition of Effective Use of Big Data.* IOP Conference Series: Materials Science and Engineering, Volume

847, 12th ISIEM (International Seminar on Industrial Engineering & Management): "Industrial Intelligence System on Engineering, Information, and Management" 17-19 March 2020, Batu, Malang - East Java, Indonesia, pp. 1-8. https://doi.org/10.1088/1757-899X/847/1/012003

14. Surbakti, F. P. S., Wang, W., Indulska, M. and Sadiq, S. (2019). *Factors influencing effective use of big data: A research framework.* Information and Management, 57(1), pp. 1-16. https://doi.org/10.1016/j.im.2019.02.001

15. Vassakis, K., Petrakis, E. and Kopanakis, I. (2018). *Big Data Analytics: Applications, Prospects and Challenges. Mobile Big Data.* Lecture Notes on Data Engineering and Communications Technologies, Springer, Cham, 10, pp. 3–20. https://doi.org/10.1007/978-3-319-67925-9_1

Ներկայացվել է՝ 20.03.2024թ.
Ուղարկվել է գրախոսման՝ 07.05.2024թ.