

Harnessing Big Data Analytics and Knowledge Sharing for Boosting Organizational Innovation in the Jordanian Insurance Industry

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Abstract. This research examines the role of big data analytics in driving organizational innovation within the Jordanian insurance industry, considering the intermediating function of knowledge management practices. Survey data collected from 270 employees across managerial roles and 15 firms reveals perceivable investments in data systems and knowledge exchange fostering measurable creativity. Regression analysis confirms big data use directly and indirectly influences innovation outcomes when coupled with intra-firm collaboration and information sharing, explaining over a third of variation. While data volumes, variety and processing velocity boost novelty of product or service offerings, concentrated cross-departmental coordinated efforts supplement the effect. As insurance sector grapples with pressures of increasing digitization, active data-driven knowledge management frameworks can provide strategic advantage.

Keywords: Big Data; Organizational innovation; Knowledge sharing; Jordanian Insurance companies

1. Introduction

The global Internet traffic will be more than 92 times greater than it was in previous years, starting in 2005, according to the expectations of the International Data Corporation (IDC). Data will be produced more than 44 times by the year 2023 compared to what it was in 2009, and this appeared with the introduction of big data, cloud computing, and the Internet of Things [1]. Moreover, because the word big data is widely used in Arab and Western societies, we must link the concept of data mining and analysis with the inclusion of scientific spaces and multidimensional technology. and according to the estimate of the International Data Company (IDC), where it is indicated that the amount of increase in data doubles every two years, as more data is produced online every second than previously stored [2]. Big data has a significant and efficient influence, and it has become essential in diverse business settings. These settings serve as crucial sources for producing structured, unstructured, and semi-structured data. Big data aids in decision-making and provides a competitive edge by fostering the creation of new businesses or advancing existing ones. The acquisition of meaningful information relies on the methodology employed to gather this data. Nevertheless, big data encounters numerous obstacles in terms of its magnitude, velocity, and the manner in which it is generated [3]. Based on the foregoing, technological development is considered one of the main factors to produce big data, and technological development is also an important element in the field of business technology because it is rapidly developing and helps business environments rely on data because it considers the infrastructure of big data itself considering the continuous technological development [4].

Billions of data have been produced around the world by the Internet of Things, smart home devices, and wearable devices, which has led to the inability of traditional technologies to process and store them because they contain unorganised forms, videos, and images [5]. In addition, McHugh et al. [4] e-commerce and social media are a large source of unorganised data production, and whenever any device is automatically connected to the Internet, new data accompanies it. Structured data is part of big data, while data collection for processing and analysis exceeds the amount of organised data within institutions, and the greater awareness of the organisation of technological development, the more It has increased the variety of data, both organised and unstructured, and when developing techniques for analysing this data, we may obtain structured data. The disparity and divergence in the big data suggests that this data was acquired and gathered from multiple sources, encompassing data in the form of photos or video clips. Hence, the tabulated data has been prearranged and labelled to assist the process of sorting. Images and audio are classified as unstructured data, making them challenging to categorise [6]. The data is highly varied and originates from diverse and intricate sources. Consequently, it necessitates the utilisation of a sophisticated analysis system, surpassing old methods, in order to effectively analyse the data and arrive at informed decisions. Organised data can be efficiently managed through the utilisation of databases [7].

Various data are generated in different forms from several sources, where the data sources are combined to obtain one basic source of the required data, and then these data are combined with each other to obtain useful information. Accordingly, when obtaining huge amounts of data from different sources, traditional methods of processing cannot be used because it contains a large amount of text, images, audio, and video, and this data cannot be arranged in tables directly, so it is placed in a relational database management system. This is because it is a large data area and increases the problems related to storage [2]. An example of the process of collecting and analysing data to obtain useful information is an application to monitor the weather and record forecasts. Data is received and obtained from various sources, such as sensors, for many weather parameters, namely temperature, rain, humidity, etc., and the application anticipates any possible changes that may occur in the weather from several geographical locations while providing some services, such as travel advice [8].

Big data analysis faces many challenges in terms of the storage space that accompanies the size and diversity of this data, in addition to privacy and security, as well as how to properly deal with different types of contradictions during the analysis process [9]. Ferraris et al. [10] demonstrated that companies

that established a greater number of Big Data Analytics (BDA) capabilities, both in terms of technology and management, saw improved performance. Additionally, they found that a Knowledge Management (KM) perspective played a key role in enhancing the impact of BDA capabilities. The research conducted by Shabbir & Gardezi [11] emphasised the significant significance, both strategic and practical, that decision making in organisations has for top management, especially in developing nations. This study aimed to enhance the existing literature by presenting original findings and providing valuable recommendations. These repercussions aided the upper-level executives in the crucial decision-making process and motivated practitioners who strive for a competitive edge by improving the performance of small and medium-sized enterprises (SMEs). Obitade [12] showed that organisations require sophisticated data analytics skills to efficiently utilise IT resources, enabling them to promptly and flexibly address cyber incidents, resulting in enhanced security of critical information assets. The results also yielded valuable insights for research and managerial practices.

Big data helps to increase human awareness and understanding of machines, because both are essential factors for data production, and in order to benefit from big data, it is necessary to understand the characteristics of this data in order to reach the true value of this data [5]. The difficulty of dealing with big data is due to its distinctions (size, speed, diversity, purpose, and value), and it is necessary that the process of producing data by means of sensors be useful because most cyber systems use part of this data. Therefore, a high-performance computing system is necessary to process data in a timely manner to obtain useful information for use in a disaster warning system, for example. Inconsistent sources and variable data formats are beyond the power of manual data fusion, analysis, and management. Information from big data analyses is considered valuable in disaster management because it also contributes to saving lives and property, reducing economic losses, and helping in facing similar disasters [13].

The real value of data is to bring real benefit to all operations within organizations. Value was considered one of the most important factors in big data, as it directly affects all operations, including decision-making, profit increase, etc. The real value of the data is found through careful analysis of this data, where the raw data is dealt with and processed, thus obtaining the highest benefit [6]. Knowing the value of data results in the awareness of individuals to enhance ideas derived through processing raw data. Considering the existence of a large amount of data, that does not necessarily mean that there is a great benefit from it [8].

When understanding the volume, diversity, and speed of big data, you can understand the fluctuations, the validity of the data, and the length of time to store it. The volatility of the data shows in this period, and when determining the actual time of the data, determining when the data is no longer relevant and can be applied by analysis Data must be available in some sources, while other sources may not have data, as this results in the need to understand data requirements, availability, and age. According to data standards, data is kept for decades until its importance is understood and when smooth operations within institutions are carried out. Set rules and organisation for this data [14].

Big data is large and somewhat complex data that the traditional processing system cannot analyse. The analysis process is confusing in terms of previously used processing methods such as filtering and change. This process is complicated by the multiplicity of sources that generate data for decision-making, and when managing this data properly, that enhances its value and allows access to it in an easy way to decide.

For example, disaster data is a challenge facing civil defence, the police, and any organisation responsible for disasters with large amounts of processed and stored data. What matters to these organisations is the real-time processing of this data as quickly as possible so that interaction and coordination can take place with high efficiency [15].

Ghasemaghaei and Calic [16] stated the impact of big data with the main characteristics such as volume, variety, and velocity on firms' innovation performance. To investigate this study, data was

collected from 239 managers from different firms and empirically examined the relationships in the proposed model. The result indicated that variety and velocity have a positive impact on firm innovation performance, while data volume has no significant impact. Further, the findings reveal that velocity plays an important role in firm innovation performance.

Del Vecchio et al. [17] discussed the bid data for innovation in small and medium enterprises (SMEs) and large and stressed that "big data" has acquired a high level of attraction from scholars and practitioners because it contributes to increasing the innovation level in the business environment. Finally, this study highlights the need to bridge the gap in the lack of overviews of the use of bid data for open innovation strategies.

Zheng et al. [18] showed in the digital era, organisations can generate a large amount of data from the business process, which is considered valuable for many advantages, such as competition and innovation. In China, small and medium enterprises can get radical innovation through investing in big data. In total, 297 managers in small and medium enterprises were involved in this study using the Mplus 7.4 approach.

The sample shows that big data use is directly and indirectly related to radical innovation, and then knowledge sharing moderates the link between big data and innovation.

Taleb and Serhani [19] examined the relationship between the application of big data analytics (ABDA) and organisational performance (OP) in SMEs in Pakistan. Furthermore, this study tests the mediating of knowledge management practice (KMP) in relation to ABDA and OP. Data was collected from respondents through a developed questionnaire and using the Baron-Kenny approach to examine the mediation. The result indicated that ABDA had a positive impact on OP, and KMP had practically mediated the relationship between ABDA and OP in the mentioned enterprises.

The research presented aims to investigate the influence of Big Data on organisational innovation in Jordanian insurance companies, with a particular focus on the intermediary function of knowledge exchange. The study recognises the significant impact that Big Data, cloud computing, and the Internet of Things can have, given the rapid increase in worldwide Internet traffic and data generation. The study highlights the difficulties related to the large amount, rapidity, and varied characteristics of Big Data, particularly considering the unorganised forms produced by sources including the Internet of Things, smart devices, e-commerce, and social media. This research emphasises the essential role of technical advancement in enabling the utilisation of Big Data and emphasises the importance of comprehending the various aspects of Big Data, such as its magnitude, velocity, variety, purpose, and worth. The study examines the challenges of analysing data that includes text, images, audio, and video, highlighting the importance of advanced analytic methods. In addition, the study explores the difficulties related to storage capacity, confidentiality, protection, and the significance of data in the context of Big Data analysis. The current body of literature, as referenced, provides additional evidence for the importance of examining the connections between Big Data, knowledge sharing, and organisational innovation. Previous research has shown that the effects on innovation performance range across various types of organisations. The research seeks to enhance the current knowledge by focusing on the Jordanian insurance industry and elucidating the intermediary function of knowledge sharing in the connection between Big Data and organisational innovation.

2. Theoretical Background

2.1 Ways for big data processing

All treatment frameworks are compared according to the state of the available data, without the need to classify them according to their sources into three groups.

- 1. Processing data processing (batch)**

It refers to a set of data collected over a specific period. When collecting data over a specific period,

it requires uploading it to some kind of storage, database, or file system to be processed and bulk processing is used because it is large amounts of data. When there is a large amount of data in groups, the batch processing includes operating on large and static data, and the results are retrieved later, and when there is a need to access a complete set of records, the batch processing is the most appropriate solution [20].

2. Flow processing systems

Systems that work on processing the flow to calculate the data when it enters the system deal with the data that is generated continuously, and they convert the huge data into fast data in which the data is entered into an analysis department such as a system called PHOTON [21].

3. Hybrid treatment

Here, mixed processing frameworks are used at work when projects require it, and the most common mixed frameworks are Apache Link and Apache Spark. Hybrid processing frameworks provide a comprehensive solution for data processing. They also provide integrated services for data processing due to their tools [22].

2.2 Organizational innovation

The term “organisational innovation” refers to the mechanism that is applied by organisational management to achieve many advantages, such as competitiveness, technological advancement, market share, techniques, systems, etc. On the other hand, organisational innovation means the ability of the organisation itself to develop new products or services and its success in bringing those products or services to market [23].

To be clearer, the difference between creativity and organisational innovation is very useful. Where creativity is the production of new ideas, in addition, innovation is the successful realisation of innovation ideas within the organisation.

Organisational innovation, a central tenet of contemporary management literature, is a dynamic and multifaceted concept that encompasses a wide array of practices and strategies aimed at enhancing an organisation's competitiveness and adaptability in today's rapidly changing business landscape. Drawing from the resource-based view of the firm, organisations are increasingly recognising innovation as a key driver of sustained competitive advantage. Innovations in organisational structures, processes, and cultures, often influenced by external factors such as technological advancements and market disruptions, have gained prominence. Recent research also underscores the significance of leadership and knowledge management as critical drivers of organisational innovation, emphasising the role of top management in fostering a culture of innovation [24].

Additionally, the concept of ambidexterity, which involves simultaneously exploiting existing capabilities and exploring new ones [25], has emerged as a pivotal framework for understanding how organisations can balance the tension between operational efficiency and innovation. As organisations grapple with the imperative of staying innovative in an increasingly competitive landscape, academic inquiry into the dynamics and determinants of organisational innovation remains an area of continued exploration and importance.

2.3 Knowledge sharing

Knowledge sharing can be seen as the process through which individuals exchange their knowledge and experience related to work with their colleagues at work, and this concept includes the use of individuals' knowledge and experience to solve work problems and develop new ideas, policies, and procedures [26].

Adopt Sharing knowledge depends on the ability of the individual who possesses the knowledge to transfer his apparent knowledge and experiences to others, on the one hand, and on the other hand, it depends on the ability of the recipient to absorb, understand, and apply the knowledge he learns from

its sources. Some see that sharing knowledge is a transfer of knowledge, as it includes acquiring new knowledge through the process of learning and applying knowledge by the recipients of knowledge, and this is done by providing information about the implementation of tasks, helping others, and directing them in solving business problems that they perform [27].

Some have talked about two approaches to clarifying the sharing of knowledge: the perceptual approach, which explains how to easily exchange virtual knowledge from one person to another, while the second constructive approach talks about social interactions, which considers that knowledge is a social formation that depends on experience and social interactions. Some believe that with the knowledge sharing strategy, customer knowledge is transferred from the customer to the employees and then to the organisation to take advantage of the cumulative experience that the customers have gained because of their use of the products and services provided by the organization. The mediating variable: Sharing knowledge: It is the process of exchanging ideas, knowledge, skills, experiences, and expertise among workers with the aim of helping others solve work problems and develop their skills through many means, including discussions, directives, and seminars [28].

Knowledge sharing aims to improve the organisation's ability to exploit its knowledge resources and employ them to raise the level of workers' skills in helping them achieve their goals. The most important goals of knowledge sharing can be summarised in the following [23].

1. Improving the abilities and skills of workers to perform their work.
2. Knowledge sharing is an educational process through which knowledge is transferred and new knowledge is created.
3. It leads to activating innovation and design and improving the level of quality in the completion of work.
4. It reduces training costs.
5. Reducing production costs and reducing the percentage of errors in work'

Regarding knowledge sharing requirements, there is no doubt that the knowledge-sharing process includes various activities related to the existence of an appropriate environment for participation. The most important requirements for knowledge sharing can be summarised as follows:

- i. The ability and desire of those who possess knowledge to transfer it to others depends on the individual's desire to help and guide others in solving work problems, and this is often linked to the existence of material or moral incentives that encourage the individual to generate knowledge and transfer it to others. The availability of the ability to transfer knowledge to others depends on his skill in teaching others and directing them at work.
- ii. The availability and motivation of the recipient of knowledge to receive knowledge through questioning, follow-up, and interaction with others to benefit from their experiences in solving work problems and their interest in developing their knowledge and skills continuously.
- iii. The availability of an appropriate physical environment such as the arrangement of offices, buildings, and technological means, as there is a suitable arrangement of offices better than others for the cooperation of individuals and the sharing of knowledge, and modern organisation patterns such as work teams are among the facilitating factors for sharing relationships, and technological means such as intranets, extranets, groupware, and conferencing Remote data warehouses, expert systems, and other knowledge sharing aids.
- iv. Availability of the appropriate moral environment for knowledge sharing, and it includes encouraging the organisation's management for employees to share knowledge and taking knowledge sharing into account when evaluating the performance of employees. The availability of trust between employees is an important element to encourage the transfer and sharing of knowledge, and the positive evaluation of employees who contribute to the transfer of their

knowledge to others and motivate them This work is an important component of encouraging knowledge sharing.

3. Methodology

The study aimed to examine the impact of big data on organizational innovation, through knowledge sharing as a mediator in the Jordanian insurance companies. The following hypotheses were built to explain the relationship between the three variables:

Ha1: there is a statistically significant impact of big data on organizational innovation.

Ha2: there is a statistically significant impact of big data on knowledge sharing.

Ha3: there is a statistically significant impact of knowledge sharing on organizational innovation.

Ha4: there is a statistically significant impact of big data on organizational innovation through knowledge sharing as a mediator.

Figure (1) shows the 3 variables and the types of relationships between them.

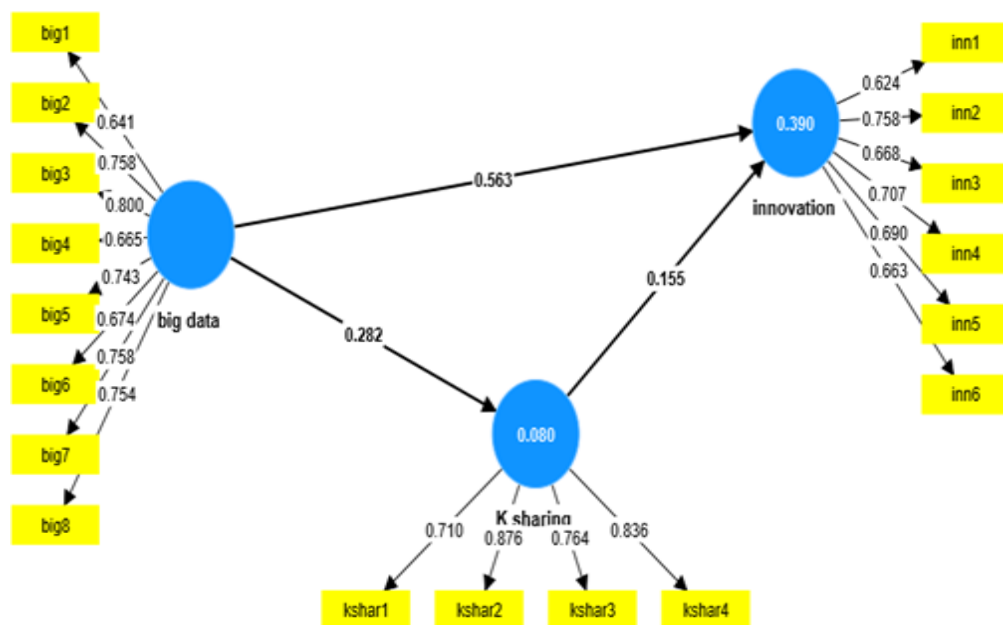


Fig. 1: The study structural model

Regarding the study population and sample, the study population consisted of Jordanian insurance companies. According to the records of the Jordanian Ministry of Industry and Trade, there are a total of 21 companies. Out of the 21 companies, 15 participated in the study. From each company, a sample of 18 employees from all managerial positions was selected randomly. The researchers relied on this sampling method because it is the most suitable for this type of study. Random sampling makes it possible to collect data without any bias, taking into consideration all positions. which enhances the credibility and comprehensiveness of the collected data. 270 questionnaires were distributed electronically. (248) were recovered and statistically analysed. with a response rate of 92%.

On the other hand, the study relied on the questionnaire for collecting data. The questionnaire was developed to measure first the demographic information of the sample (gender, age, education, and experience). The second part of the questionnaire measures the independent variable (the big data) based on [8]; [21]; and [7]. While the third part measures the dependent variable (organisational innovation)

based on [8], [7], The fourth part measures the mediator variable (knowledge sharing) based on [21]. The Likert 5 scale of agreement was utilised in parts 2, 3, and 4 questions.

4. Results and discussion

The reliability and validity of the questionnaire were tested using Cronbach's alpha, composite reliability, and the AVE test. The results in Table 1 show that all the values of the reliability results are > 0.70 . And the results of (AVE) are > 0.50 . According to Hair et al. [29], this means that the questionnaire is reliable and valid.

Table 1: Reliability and validity of the current study

| Variables | Cronbach's alpha | Composite reliability | Average variance extracted (AVE) |
|-------------------|------------------|-----------------------|----------------------------------|
| Big data | 0.872 | 0.880 | 0.527 |
| Innovation | 0.783 | 0.784 | 0.671 |
| Knowledge sharing | 0.809 | 0.813 | 0.639 |

Most of the sample are males, with 58.9% having university degrees and mostly young; the majority have more than 5 years' experience. This indicates a degree of education and practical experience that enables them to answer the survey questions accurately. Table (2) shows the sample demographic features (gender, age, education and experience).

Table 2: Sample features

| Variable | Frequency (248) | Percentage 100% |
|-------------------|--------------------|--------------------|
| Gender | | |
| Male | 146 | 58.9 |
| Female | 102 | 41.1 |
| Age | | |
| Less than 30 | 113 | 45.5 |
| 30- less than 40 | 52 | 21 |
| 40- less than 50 | 47 | 19 |
| 50-or more | 36 | 14.5 |
| Education | | |
| Diploma | 24 | 9.7 |
| Bach | 162 | 65.3 |
| Master | 50 | 20.2 |
| Ph.D | 12 | 4.8 |
| Experience | | |
| Less than 5 years | 38 | 15.3 |
| 5-less than 10 | 86 | 34.7 |
| 10- less than 15 | 91 | 36.7 |
| 15 years and more | 33 | 13.3 |

The researchers computed the means and standard deviations for the three-variable questions. The results in Table 3 indicate a high level of agreement among the sample members on the questions since all the means are > 3.67 . This finding aligns with previous studies highlighting the increasing trend of insurance companies investing in big data analytics [21-22]. These companies are actively engaged in the collection, organization, and analysis of vast amounts of data, storing them in comprehensive databases for informed decision-making and strategic planning [24]. Moreover, the observed high levels

of creativity and innovation, as evidenced by the means in the table, underscore the proactive stance of Jordanian insurance firms towards service enhancement and diversification [25-26]. This resonates with the literature on organizational innovation, which emphasizes the importance of fostering a culture conducive to continuous improvement and adaptation [23]. The means of knowledge sharing, and transfer further validate the significance of teamwork, collaboration, and group dynamics in fostering creativity and innovation within organizations [28-29].

Table 3: Descriptive statistics results

| Variables | Means | Standard Deviation |
|----------------------------------|-------|--------------------|
| Big data | | |
| Q1 | 4.47 | .516 |
| Q2 | 4.31 | .615 |
| Q3 | 4.33 | .682 |
| Q4 | 4.35 | .651 |
| Q5 | 4.32 | .561 |
| Q6 | 4.33 | .549 |
| Q7 | 4.15 | .699 |
| Q8 | 4.17 | .739 |
| Organizational Innovation | | |
| Q1 | 4.15 | .666 |
| Q2 | 4.23 | .581 |
| Q3 | 4.29 | .646 |
| Q4 | 4.02 | .954 |
| Q5 | 4.09 | .909 |
| Q6 | 4.25 | .770 |
| Knowledge Sharing | | |
| Q1 | 3.73 | .858 |
| Q2 | 3.81 | 1.050 |
| Q3 | 3.70 | .748 |
| Q4 | 3.90 | .910 |

Regarding hypotheses testing results, the Smart PLS (4) programme was utilised to test the study's hypotheses. Figures (2) and (3) show the values of t for the three variable connections and the values of t sig. As it is manifested, the values of t are > 1.96 , the tabulated value of t. And the values of t sig < 0.05 . Based on Hair et al. [29], these results indicated a statistically significant impact of the independent variable on the dependent. The results of Ha1 indicated a statistically significant impact of big data on organisational innovation. The results of Ha2 indicated a statistically significant impact of big data on knowledge sharing.

The results of Ha3 indicated a statistically significant impact of knowledge sharing on organisational innovation. While the results of Ha4 indicated a statistically significant impact of big data on organisational innovation through knowledge sharing as a mediator, as shown in Table 4 (the value of the total indirect effect). But based on the results in Table 4, it is a partial mediation since all the effects between the 3 variables are statistically significant.

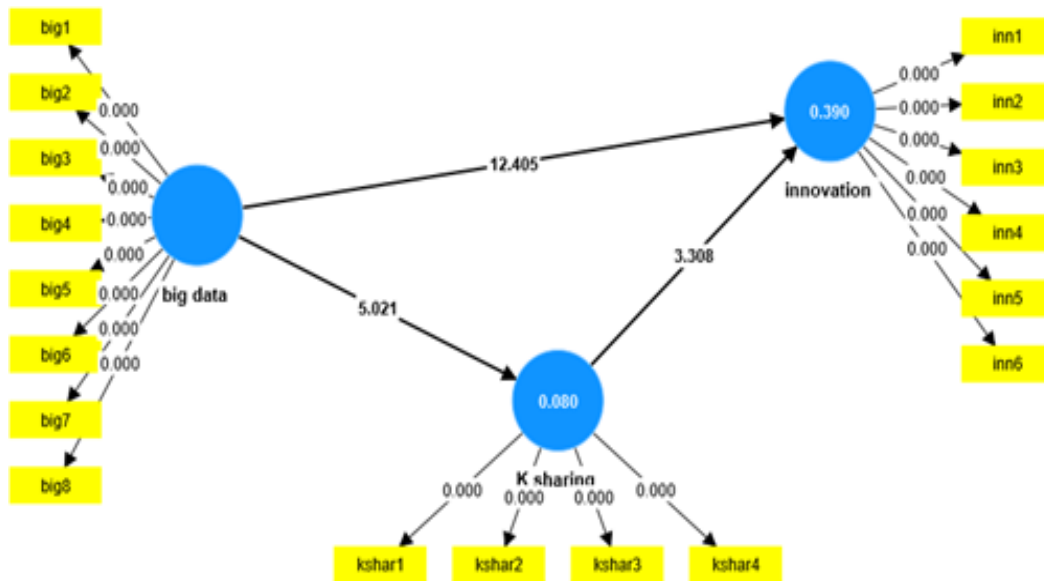


Fig. 2: The values of t

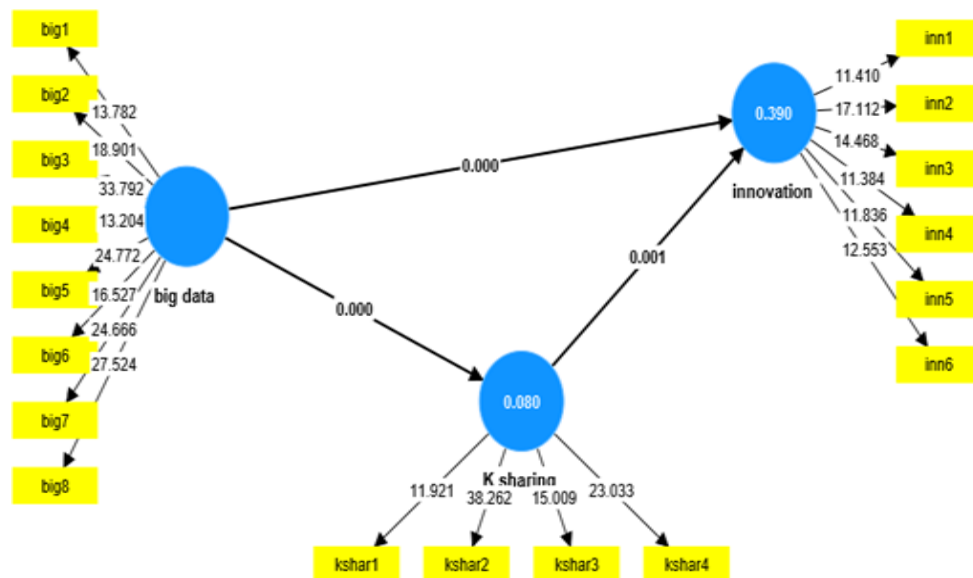


Fig. 3: The values of t sig

Table 4: Path coefficient and the indirect total effect results

| The variables path | T value | T sig |
|----------------------------------|--------------|--------------|
| K sharing -> innovation | 3.308 | 0.001 |
| big data -> K sharing | 5.021 | 0.000 |
| big data -> innovation | 12.405 | 0.000 |
| The total indirect effect | | |
| big data -> innovation | 2.594 | 0.010 |

5. Conclusions and Recommendations

The study substantiates a pronounced emphasis within leading Jordanian insurance companies on leveraging big data solutions alongside knowledge management capabilities to spur organizational innovation. Nearly half the sampled personnel acknowledged concrete initiatives aimed at harnessing exponentially rising data sources through integrated collection, organizing and analytics mechanisms intended to boost new service development and process improvements. The empirical examination also validates the intermediate role of systematic knowledge transfer practices involving extensive participative interactions. Insurance firms can thus formulate customized big data strategies prioritizing areas with maximum viability for innovation as well as design appropriate technical and social platforms stimulating productive data-driven collaboration. However, more extensive investigation across hierarchical roles and institutional types can further advance understanding of appropriate balancing such technical and cultural elements within data-savvy insurance ecosystems seeking continuous innovation.

Furthermore, the implications of this study go with the assumptions and findings of [29] in terms of the association between big data and innovation and the role of information sharing in enhancing this association. Based on the results, it is recommended to continue getting the benefits of big data and to utilise the suitable tools to collect, analyse, and organise organisational data. For future research, it is recommended to conduct more studies on other sectors and to test the impact of big data on other dependent variables than organisational innovation.

References

- [1] Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. *Business horizons*, 60(3), 293-303.
- [2] Hosoya, R., & Kamioka, T. (2018, August). Understanding how the ad hoc use of big data analytics impacts agility: a sensemaking-based model. In *2018 International Conference on Advances in Big Data, Computing and Data Communication Systems (icABCD)* (pp. 1-8). IEEE.
- [3] Khan, N., Alsaqer, M., Shah, H., Badsha, G., Abbasi, A. A., & Salehian, S. (2018, March). The 10 Vs, issues and challenges of big data. In *Proceedings of the 2018 international conference on big data and education* (pp. 52-56).
- [4] McHugh, J., Cuddihy, P. E., Williams, J. W., Aggour, K. S., Kumar, V. S., & Mulwad, V. (2017, December). Integrated access to big data polystores through a knowledge-driven framework. In *2017 IEEE International Conference on Big Data (Big Data)* (pp. 1494-1503). IEEE.
- [5] Arslan, M., Roxin, A. M., Cruz, C., & Gin hac, D. (2017, December). A review on applications of big data for disaster management. In *2017 13th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)* (pp. 370-375). IEEE.
- [6] Rathnasinghe, A. P., & Kulatunga, U. (2019). Potential of using big data for disaster resilience: the case of Sri Lanka.
- [7] Akter, S., & Wamba, S. F. (2019). Big data and disaster management: a systematic review and agenda for future research. *Annals of Operations Research*, 283, 939-959.
- [8] Juneja, A., & Das, N. N. (2019, February). Big data quality framework: Pre-processing data in weather monitoring application. In *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)* (pp. 559-563). IEEE.
- [9] Cumbane, S. P., & Gidófalvi, G. (2019). Review of big data and processing frameworks for disaster response applications. *ISPRS International Journal of Geo-Information*, 8(9), 387.

- [10] Ferraris, A., Mazzoleni, A., Devalle, A., & Couturier, J. (2019). Big data analytics capabilities and knowledge management: impact on firm performance. *Management Decision*, 57(8), 1923-1936.
- [11] Shabbir, M. Q., & Gardezi, S. B. W. (2020). Application of big data analytics and organizational performance: the mediating role of knowledge management practices. *Journal of Big Data*, 7(1), 1-17.
- [12] Obitade, P. O. (2019). Big data analytics: a link between knowledge management capabilities and superior cyber protection. *Journal of Big Data*, 6(1), 1-28.
- [13] Munawar, H. S., Qayyum, S., Ullah, F., & Sepasgozar, S. (2020). Big data and its applications in smart real estate and the disaster management life cycle: A systematic analysis. *Big Data and Cognitive Computing*, 4(2), 4.
- [14] Wang, Y., Ali, Z., Mehreen, A., & Hussain, K. (2023). The trickle-down effect of big data use to predict organization innovation: the roles of business strategy alignment and information sharing. *Journal of Enterprise Information Management*, 36(1), 323-346.
- [15] Shah, S. A., Seker, D. Z., Hameed, S., & Draheim, D. (2019). The rising role of big data analytics and IoT in disaster management: recent advances, taxonomy and prospects. *IEEE Access*, 7, 54595-54614.
- [16] Ghasemaghahi, M., & Calic, G. (2020). Assessing the impact of big data on firm innovation performance: Big data is not always better data. *Journal of Business Research*, 108, 147-162.
- [17] Del Vecchio, P., Di Minin, A., Petruzzelli, A. M., Panniello, U., & Pirri, S. (2018). Big data for open innovation in SMEs and large corporations: Trends, opportunities, and challenges. *Creativity and Innovation Management*, 27(1), 6-22.
- [18] Zheng, L. J., Zhang, J. Z., Wang, H., & Hong, J. F. (2022). Exploring the impact of Big Data Analytics Capabilities on the dual nature of innovative activities in MSMEs: A Data-Agility-Innovation Perspective. *Annals of Operations Research*, 1-29.
- [19] Taleb, I., & Serhani, M. A. (2017, June). Big data pre-processing: closing the data quality enforcement loop. In *2017 IEEE International Congress on Big Data (BigData Congress)* (pp. 498-501). IEEE.
- [20] Gurusamy, V., Kannan, S., & Nandhini, K. (2017). The real time big data processing framework: Advantages and limitations. *International Journal of Computer Sciences and Engineering*, 5(12), 305-312.
- [21] Xu, Y., Liu, X., Cao, X., Huang, C., Liu, E., Qian, S., ... & Zhang, J. (2021). Artificial intelligence: A powerful paradigm for scientific research. *The Innovation*, 2(4).
- [22] Chauhan, S., Agarwal, N., & Kar, A. K. (2016). Addressing big data challenges in smart cities: a systematic literature review. *info*, 18(4), 73-90.
- [23] Sung, W., & Kim, C. (2021). A study on the effect of change management on organizational Innovation: Focusing on the mediating effect of members' innovative behavior. *Sustainability*, 13(4), 2079.
- [24] Birkinshaw, J. M., & Mol, M. J. (2006). How management innovation happens. *MIT Sloan management review*, 47(4), 81-88.
- [25] ÖZBEBEK, A., & TOPLU, E. K. (2011). EMPOWERED EMPLOYEES' KNOWLEDGE SHARING BEHAVIOR. *International Journal of Business and Management Studies*, 3(2), 69-76.

- [26] Amayah, A. T., & Nelson, F. F. (2010, September). Knowledge sharing–Types of knowledge shared and rewards. In *29th Annual Midwest Research-to-Practice Conference In Adult, Continuing, Community and Extension Education* (p. 275).
- [27] Rahman, S., Di, L., & Esraz-Ul-Zannat, M. (2017, September). The role of big data in disaster management. In *International Conference on Disaster Risk Mitigation* (pp. 1-5).
- [28] Kimmerle, J., Moskaliuk, J., Oeberst, A., & Cress, U. (2015). Learning and collective knowledge construction with social media: A process-oriented perspective. *Educational Psychologist*, 50(2), 120-137.
- [29] Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, 1(2), 107-123.