Global Spectrum of Research and Humanities
ISSN: 3007-9136
Vol. 2 No. 2 (2025): March

Knowledge Management Approach to Data Mining Process in Smart Business

[1] **Abdul Jamil Sharify,** [2] **Sameulhaq Amany,** [3]**Mohammad Ekram Yawar**
https://doi.org/10.69760/gsrh.010120250041

Abstract:

The aim of this study is to examine new technologies in the field of information technology and the impact of these technologies on the field of learning, especially e-learning. Advances in information and communication technology have affected various dimensions of human life in recent years.
With the expansion of information technology and the penetration of remote communication tools, learning tools and methods have also undergone changes; As individuals can learn by using the available resources. Therefore, the development of e-learning courses has grown rapidly and expanded, and while improving the quality of education, it has become one of the most popular educational methods.
This article discusses the development and advancement of new technologies such as cloud computing, the Internet of Things, big data, responsive design, and wearable technology, and their irreplaceable role in e-learning. In addition, the challenges facing the field of e-learning are also examined.

Key words: E-Learning, Big Data, Responsive Design, Information Technology, Cloud Computing, Overlay Technology

Introduction

In the present era, known as the age of knowledge and information, organizations are forced to manage their knowledge, knowledge assets, and workforce in order to gain competitive advantage. (Manoorian et al., 2011; Drucker, 2001 and Uziene, 2010). The computer world has become a huge wave of data. Data mining tasks were used to deal with this problem to extract interesting knowledge (Chemchem and Dries, 2015).

Therefore, data mining is the process of examining and extracting from data to understand unknown relationships between data, so that the extracted relationships are valuable to the data (user). (Hand, 1998). Data mining has been recognized and established as a scientific field. (Fayyad et al., 1996; Wang, 2005; Chen and Liu, 2005)

However, most studies in this field are related to providing rule-based algorithms to explain as much data as possible, and on the other hand, the number of articles explaining how to use these discovered rules is

[1] Lec. Abdul Jamil Sharify, Head of Department of Management Information Systems, International Science and Technology University, Warsaw, Poland jamil.sharify@istu.edu.pl, https://orcid.org/0009-0001-0727-6726

[2] Sameulhaq Amany Master's student in Administration and Economics, Sabahattin Zaim University, Türkiye, sameulhaq.amany01@gmail.com, https://orcid.org/0009-0009-4681-2761

[3] Asst. Prof. Dr. Mohammad Ekram Yawar, Dean of the Faculty of Law, International Science and Technology University, Warsaw, Poland, ekram.yawar@istu.edu.pl, https://orcid.org/0000-0003-3198-5212

very limited (Wu et al., 2000). Although data mining has been recognized as a potentially very powerful tool, in fact, the application benefits of data mining for intelligent commerce have not been fully recognized. (Wang and Zu, 2007).

Commerce Intelligence is a broad category of tools and technologies for collecting, accessing, and analyzing large amounts of data in an organization, which ultimately leads to effective and accurate decision-making in the organization (Cook, & Cook, 2000; Williams and Williams, 2006). A prominent example of intelligent business technologies is business process modeling, data feature definition, data storage, and up-to-date analytical processing of data and data mining. (Loshin, 2003).

The core of intelligent business is to fully utilize the abundant volume of data so that the organization can achieve a series of competitive advantages in this way. Therefore, intelligent business is the boundary of customers (Liao et al.2010). Knowledge management is a prerequisite for e-commerce and its increasing customer focus. Companies can enter e-commerce globally through the Internet and intranet (Hajiheidari and Hashmi, 2013). There are different approaches to the concept of knowledge (Calvo-Mora et al., 2015; because it is a complex, broad and abstract term. (Alavi and Leidner, 2001).

On the other hand, Knowledge management is a set of practices for creating, developing, and applying knowledge to improve organizational performance (Wu et al., 2007; Smoliar, 2007; Lee and Chang, 2007; Feng and Chen, 2007; Buckman, 2004; Paiva and Goncalo, 2008). Like knowledge management, smart also improves the use of information and knowledge available to the organization (Sun and Chen, 2008).

However, knowledge management differs from smart business in many aspects. In general, knowledge management is related to human mental knowledge rather than to objective (real) data and information. Most models used in knowledge management are not technologically oriented.

Although Knowledge management is not a separate stylistic set of rules, but is entirely related to unstructured information and tacit knowledge, which smart business cannot apply in this field. Knowledge management is a very difficult task in the contemporary world. This is because it poses challenges to proper management and has been recognized as one of the most difficult management problems today. (Laudon and Laudon, 2002, Ogiela, 2013).

Therefore, knowledge management is an inseparable part of customer relationship management and e-commerce. (Liao et al., 2010). E-commerce strategy supports organizational strategy, as it influences and is influenced by it. (Hanafizadeh et al., 2010).

The main issue in today's competitive world is how to identify the knowledge existing in each organization and how to best utilize it. Following this issue, knowledge management has emerged as a distinctive field in modern management science with its own concepts, language, and practices. (Chen and Macredie, 2005). However, it is necessary for knowledge management to be based on changes in the organization's environment. (Afrazeh et al., 2010).

2. The Relationship of Data Mining with Smart Business and Knowledge Management

One of the mechanisms that can lead to the successful formulation of an e-business strategy is knowledge management (Khaloui et al., 2014). Most companies and thinkers emphasize the importance of knowledge as a source of competitive advantage in today's world (Rowley, 2002). Data mining, with its ability to extract knowledge, is recognized as a powerful tool (Chen and Liu, 2005).

Consequently, the data mining process is a knowledge management process because it involves human knowledge. This view of data mining naturally links intelligent business to knowledge management. There is still disagreement about whether knowledge management should be a subset of intelligent business or vice versa, but ultimately the perspectives of intelligent business and knowledge management are different.

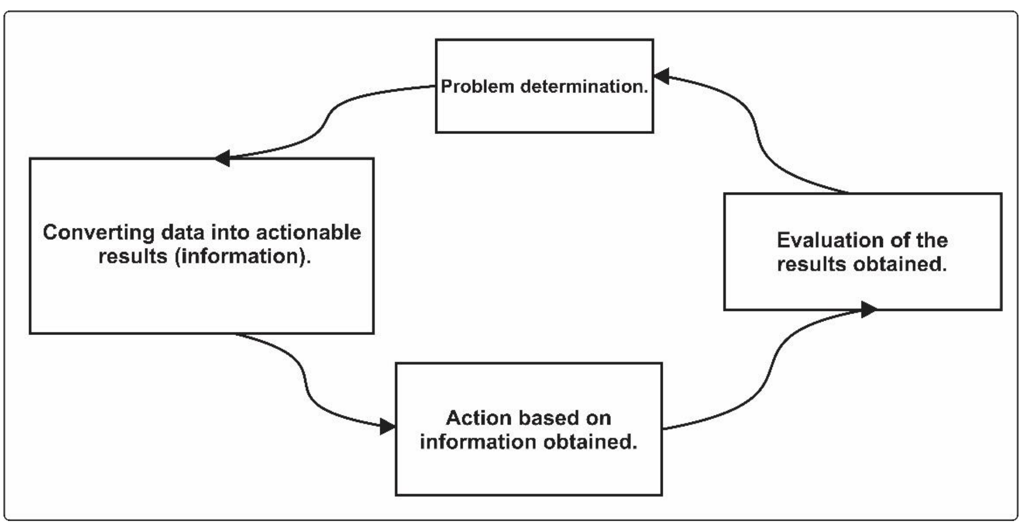
Although both debates Knowledge management and smart business are strongly influenced by research approaches and the groups involved in them, the method of creating coherence between knowledge management and smart business seems not to be unique to an individual. Several conceptual models have been presented in the field of creating coherence between smart business and knowledge management, but despite these conceptual frameworks, it is necessary to explain and explain these models in more detail for practical application. On the other hand, a few quantitative reports can be found on the implementation of the knowledge sharing process for the data mining process.

3. Data Mining Cycle Models

The data mining expert cycle model is one of the most widely developed models in the field of data mining. According to this model (Figure 1), data mining is a business process that includes 4 stages: defining the business problem, transforming data into actionable results, acting on the information, and measuring the results. The main limitation of this model is the limited applicability of this model in practice from two perspectives: First, people often assume that the knowledge gained from data mining does not always lead to the same result and action in all cases and situations, especially when Some of the knowledge acquired is hardly actionable.

In fact, this model emphasizes the role of data mining in the action phase, and this in turn leads to a failure to recognize the role of internal business components (the employees who perform this role) in developing relevant knowledge to coordinate actions for the business.

Second, this model combines non-sequential processes into a cyclical model, and as a result, the importance of the different roles of different people who are active in the data mining debate are not considered for smart trading.



Source from Berry and Linoff (2000)

Diagram. Traditional cyclical data mining model

4 Two-Wheel Model of Data Mining Cycle

The roles of the specialized personnel involved in data mining are usually divided into two groups: internal business components and data miners. An internal business component is a CEO or a mid-level manager who has sufficient skills and knowledge in problem-solving and decision-making methods. The person who plays this role (male or female) should understand the concept of data mining, intelligent business, and knowledge management in the organization, although this person may not be fully familiar with the details of data mining techniques and methods.

The goal of defining the role of the internal business component is to improve the performance of the organization by guiding and developing data mining. On the other hand, the person who plays the role of data miner is an expert in the field of data mining and implements data mining techniques in the organization. Fully understands.

This person should understand the concept of business and be able to explain the results of data mining in the context of the business in question, but is not directly responsible for business actions. As a result, creating collaboration between the two groups of people who play these two roles leads to a real and practical connection between data mining and intelligent business.(Lu, & Hsiao,2007)

The process of two-way communication between internal business components and data miners is actually a process of knowledge sharing. The content of the entire two-way communication process (not just the data mining results) is part of organizational knowledge and includes the following:

• Standardization of data mining terminology and concepts.

• Problem definitions.

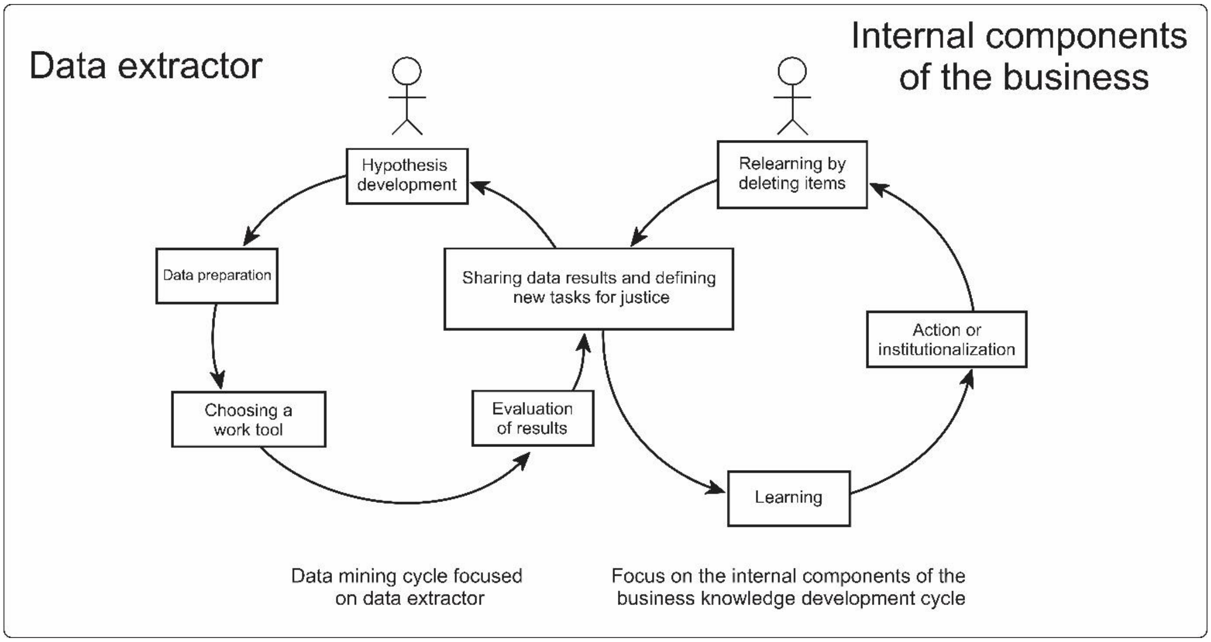
• Data mining documents.

• Data mining sources and references.

• Actions and results obtained.

To summarize the complex two-way communication between data mining personnel, the relationship between data miners and internal business components and the best aspects of data mining applications are examined using a two-cycle model.

As shown in Figure (2), one of the cycles of this model is related to the data mining development cycle and the next cycle is the personal knowledge development cycle. The two-way communication between these two cycles is defined as planning and knowledge sharing.



Source from Wang and Wu, (2008)

Figure 2. Two-wheeled data mining model

In the data mining-centric data mining cycle, there are 5 stages: establishing relationships and planning, developing hypotheses, preparing data, selecting tools (data mining), and evaluating the results obtained (data mining). A complete explanation of these stages can be found in the literature on data mining. Here, the focus is more on the hypothesis development stage.

In the usual case, data mining is the science of using the desired patterns in data to identify hypotheses or theories for Data mining provides. A hypothesis exposes existing knowledge (or original knowledge) for data mining. A data mining algorithm is designed to identify a specific type of hypothesis. As an example of the classification of data mining algorithms, the types of hypotheses derived for data mining and examples of actual knowledge are summarized in Table (1). (Wang and and Wu,, 2008). Theories related to business processes often refer to the process Knowledge sharing depends on internal business components and data miners.

There are four stages in the centralized knowledge development cycle, excluding internal business components:

- Planning and knowledge sharing, in this stage, people playing internal business component roles understand the previous data mining results and help the data miners set new data mining tasks and objectives. The new data mining tasks and objectives become the basis for the data miners to develop specific hypotheses for the next data mining process.

- Learning; Learning is essential for people playing the role of an internal business component to effectively implement data mining results. The learning process results in how data mining results are useful for the business process. Internal business components must fully understand the precise meaning of the information packages obtained from data mining in order to implement business actions.

- Action or Institutionalization The ultimate goal of data mining is to support actions taken by internal business units. An action can be a decision-making activity or a sequential operation. In many cases, the information obtained by the data mining process is not sufficient to take a correct and fundamental action. In this case, internal business units may be able to increase their tacit knowledge through institutionalization based on the results of data mining.

- Accepting or not learning, if the data mining process results in an action, the internal business units should observe the outputs of the action after the data mining results are applied. The observations obtained confirm the learning and understanding of the data mining results. In fact, if any action is taken, the internal business units develop more and more new data mining tasks and, with the help of data miners, set new goals for the data mining cycle. Unlearning processes are also necessary in some cases. Unlearning allows the incorrect information that is obtained from the data mining process to be forgotten in some cases.

Table 1. Data mining algorithms and theories

Types of Data Mining Algorithms	**Types of Theory for Data Mining**	**Examples of Original Knowledge**
Classification*	An observation with a certain set of characteristics can be assigned to a class.	A company with certain characteristics is more likely to fail (Characteristics of Failed Companies)
Cluster analysis**	There are distinct and clear sections between the observations.	Specific consumers from the market segment
Connection rules***	There is a conditional (condition-outcome) relationship between pairs of values and attributes.	If a consumer buys product A, she is more likely to buy product B.
Regression****	There is a function that can describe the relationship between features and observations.	Product sales are declining.
Sequential analysis (time-based) *****	There is a specific pattern of time-dependent events.	An online shopper often searches for related websites.
Standard Deviation Analysis******	Among a set of observations, there is an unusual observation. A competitor takes unusual action.	

Source: Research results.

5. Weblog System for Knowledge Sharing Based on the Two-Wheel Model

Currently, weblogs have become powerful and well-known tools for the development of social networks, electronic collaborations, and learning (Liao et al., 2010). To facilitate knowledge sharing through weblogs, an appropriate overall structure of topics and concepts should be used in weblogs. Collecting the right data is the basis of data mining. (Wang et al. 2015). In this case, the following topics are presented for the structure of a knowledge sharing model for data mining.

5.1 Task

A data mining process is a task 2 to discover desired patterns from data for the data miner. The task is formally described as a hierarchical structure of subset tasks. For example, the marketing data mining task is to determine a new segmentation of consumers. This task can consist of the following two parts: - Determining the division of old consumer segments - Identifying new consumer segments.

5.2 Data

Data is the primary resource in data mining. The definitions of data characteristics and the proportion of the organizational data repository that is given to a specific data mining process are specified in this section of the design and blogs.

5.3 Data Mining Tools

A tool that can be used by a data mining to retrieve data, test theories, and extract results is called a data mining tool. A data mining tool can be a statistical method, a data mining algorithm, an artificial intelligence model (e.g. neural networks), or an undefined model (e.g. search engine and logical reasoning). A complex data mining tool can be a set of constructed methods that are formulated by defining a sequence of data operations.

5.4 Hypothesis

Hypotheses or theories are powerful tools for conceptualizing real-world knowledge. is derived for data mining. The goal of a data mining task is to specify the theories that are held in the mind of the data miner. For example, a general assumption of a dependency rule such as; If a customer buys product A, then he will also buy product B is a theory. Deep data mining is considered to require intelligent theories to perform a data mining task.

5.5 Data Mining Output

A data mining output is the output of the process Data mining that tests a hypothesis based on the data provided. [A data mining output therefore summarizes the hypotheses, data, and tools used in the process, the results obtained from the process, and the key points of the data mining.

5.6 Action

An action is a business decision and the implementation of that decision in response to a data mining result. An action has a leader who is responsible for the action and includes a team of participants and a specific timeframe.

5.7 Action Output

An action must have an associated output. Action output is the evaluation of a business decision and its implementation based on observable and unobservable costs and benefits. The criteria and tools for measuring costs and benefits should be defined at the same organizational level.

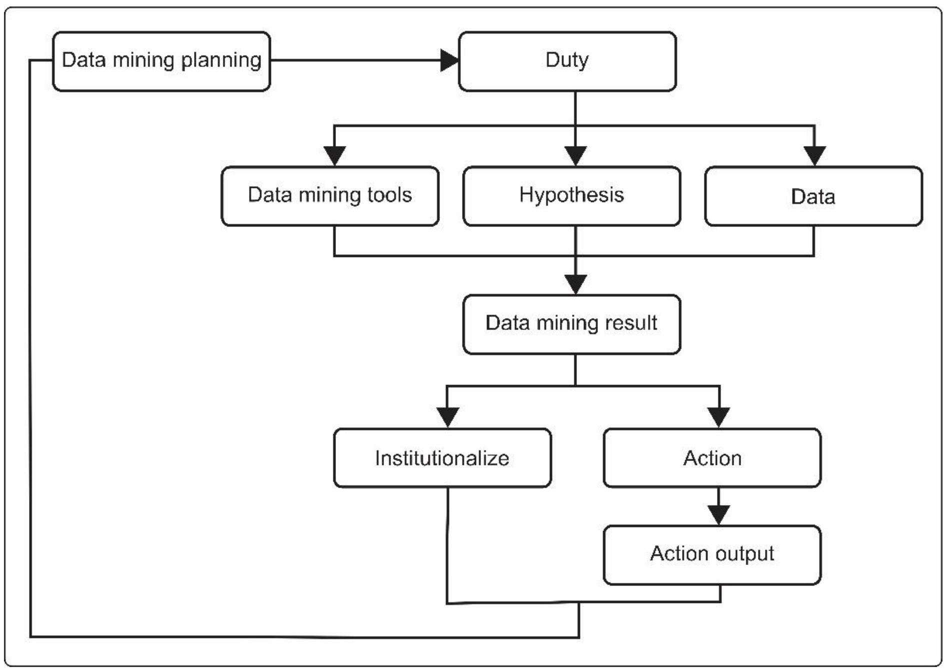
5.8 Institutionalization

The result of data mining may not result in an action, but it can be learned by people (playing roles within the business) or it can lead to an increase in tacit knowledge about the desired data pattern. Institutionalization is the process of converting the result of data mining into tacit knowledge. Open, unformatted discussions on blogs that are relevant to a specific data mining task result from the process of institutionalization. Institutionalization may not be directly applicable to a specific data mining task, but it can be useful for sharing knowledge within the organization.

5.9 Data Mining Planning

Data mining planning is a collaborative process for developing new data mining tasks. Using this section and blogs, internal business units and data miners organize a series of new tasks. The goals of a new data mining task are to serve as a foundation for data miners so that Can develop specific theories for the subsequent data mining process.

In practice, when weblogs are organized to share knowledge for data mining, each weblog has a title named after the data mining task. There is also a temporary data mining task template that may be considered by the weblog system administrator so that data mining planning weblogs can be linked to the subsequent data mining task. The relationship structure between the 9-fold classification of topics and blogs of knowledge sharing systems for data mining is shown in Figure (3).



Source: Wang and Wu, 2008.

Figure 3. Topics and structure of blogs from the knowledge sharing system for data minin

6. A case study example

The knowledge sharing model has been presented as a model of the relationship between smart commerce and knowledge management, which complements the smart commerce curriculum. MBA students in the Smart Business course used blogs (Google Blogger, 2008).

To experiment with knowledge sharing for data mining. In this study, the instructor acts as a data miner and communicates with students, who act as internal business components, through blogs. This data mining case is based on a well-known supermarket data mining scenario, in which customers who buy barley water are likely to at the same time, the old ones are also buying.

This topic seems interesting because it seems that there is no such buying pattern. It seems that these potential customers are not a representative sample of the customer community. This topic is used as an example in this study to show how data mining can help businesses to seize new opportunities through knowledge sharing, although unimaginable realities can be permanent or fleeting. In the case of the example given, centralized data mining is almost explicitly shown in the stages of the data mining cycle. The teacher has shared blogs on the following topics related to a data mining construction process:

• The task of this data mining process is to find an unusual buying pattern of consumers.

• The data used in this case study is related to the recorded data of customers' purchases in the past 6 months.

• The hypothesis of this study is a case of a dependency rule hypothesis. More specifically, a customer who buys product A is more likely to buy product B, if products A and B are not normally related to each other.

• The data mining tool used in this study is reports from the SQL database.

• The data mining results show that 36 percent of customers also buy old-fashioned baby food when buying milk and 95 percent of these customers use multi-purpose credit cards from large supermarkets.

• As a result, this scenario basically aims to show the importance of powerful data mining, and the issue of how valuable knowledge can be extracted from data to business associations.

In this scenario, the role of internal business components in a supermarket is not discussed much. In this case study, students were tasked with evaluating the centralized development cycle of internal business execution to the extent possible and publishing blogs to share knowledge. Students learned new things about data mining through the professor’s blog and presented several actionable steps that internal departments of the store can take:

• Placing barley and old-fashioned wheat next to each other so that customers can easily access these products.

• Separating barley and old-fashioned wheat from each other with a large distance so that customers can see more products while shopping.

• Determining and replenishing the availability of Ma’al-Sha’ir and old baby milk simultaneously.

• Printing and sending Ma’al-Sha’ir and old baby milk bills together to customers.

• New pricing of Ma’al-Sha’ir and old baby milk by briefly reducing the price of one of these two goods and increasing the price of the other to achieve greater profit.

Most of the internal components of the business (students) decided to increase the price of barley water and reduce the price of old baby food, expecting to make more profit. After two weeks of testing, a data mining result was sent that the sales of barley water were decreasing and the sales of old baby food were increasing, but the total profit from the sale of these two goods was significantly lower than before.(ALhawamdeh,2007)

The internal components of the business after studying the textbook They presented a new solution to data mining tasks. They found that the programming part of data mining, although problematic, was very attractive to them. The web system includes general knowledge of data mining, data mining objectives, data, data mining tools, and various types of assumptions.

In this system, internal business components are allowed to communicate with the web system to introduce new actions, share the output of the actions with everyone, and gain tacit knowledge. Develop the results within the organization. Our experience in this area has been that built-in systems and blogs for sharing knowledge to make sense of data mining for smart business are very useful.

7 Conclusion

Most data mining research has focused on data mining techniques and algorithms, and there is limited research on how to use data mining to make it more relevant to business. For data mining to be a real tool for knowledge extraction in smart business, it needs to be integrated with the knowledge management discourse in the organization to develop and improve knowledge.

Knowledge management processes are not only used for knowledge collection methods, but also for its processing and use for the purpose of improving organizational operational processes (Ogiela, 2015). In this article, a model of knowledge development through data mining is presented. This model adds a focused, deterministic cycle of knowledge development of internal business components to the traditional accepted cycles of data mining.

Developing collaboration between knowledge management personnel can make data mining more and More realistically related to smart commerce. This paper also presents a knowledge sharing web system that facilitates collaboration between knowledge miners and internal business components. This paper also illustrates the usefulness of this system for data mining in a dynamic mode of tacit and explicit knowledge transfer for knowledge management using a case study example.

References

Afrazeh, Abbas; Mohammad Nabi, Saviz and Sina Mohammad Nabi (2010)., "A Model for Measuring and Improving the Degree of Organizational Sustainability with a Knowledge Management Approach", Publisher. Journal of Improvement and Development Management Studies, No. 61, pp. 63-73. For access: https://tinyurl.com/2cbsphfk

Alavi, M.,& D.E. Leidner, (2001), "Review: knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues," MIS Q, Vol. 25, No. 1,PP. 107–136.

ALhawamdeh, M. A. (2007), The Role of Knowledge Management in Building EBusiness Strategy, Proceedings of the World Congress on Engineering and Computer Science WCECS, San Francisco, USA.

Amany, S. (2025). The Strategic Role of E-Commerce in Supply Chain Management. *Luminis Applied Science and Engineering*, *2*(1), 93-104. https://doi.org/10.69760/lumin.20250001015

Buckman, R. H. (2004), Building a Knowledge-Driven Organizations, McGraw Hill, New York, NY.

Calvo-Mora, A. (2015)," Project to Improve Knowledge Management and Key Business Results through the EFQM Excellence Model", International Journal of Project Management, JPMA-01730 , PP. 1-14.

Chemchem , A.& H. Drias, (2015)," From Data Mining to Knowledge Mining: Application to Intelligent," Expert Systems with Applications, Vol. 42, PP. 1436–1445.

Chen, S. Y. & R. D. Macredie (2005), The Assessment of usability of Electronic Shopping: A Heuristic Evaluation, International Journal of Information Management, Vol. 25, No. 6, PP. 516–532.

Chen, S.Y. & X. Liu, (2005), "Data Mining from 1994 to 2004: an Application- Oriented Review", International Journal of Business Intelligence and Data Mining, Vol. 1, No. 1, PP. 4-11.

Cook, C. & M. Cook (2000), the Convergence of Knowledge Management and Business Intelligence, Auerbach Publications, New York, NY.

Drucker, P. F. (2001), "The Next Society-A Survey of the Near Future," The Economist, Vol. 361 No. 8246, PP. 1-5.

Ekram Yawar, M., & Amani, A. (2025). Review of the World Trade Organization General Agreement on Trade in Services and International Trade in Legal Services. *Acta Globalis Humanitatis Et Linguarum*, *2*(1), 297-307. https://doi.org/10.69760/aghel.02500138

Ekram Yawar, M., & Qurban Hakimi, M. (2025). Explaining the Digital Health Marketing Model in Gaining Health Welfare Support from Nonprofits. *Acta Globalis Humanitatis Et Linguarum*, *2*(2), 4-28. https://doi.org/10.69760/aghel.02500201

Ekram Yawar, M. (2025). Examining the Importance of Education Management with the Approach of Building a Culture of Commerce and E-Economy in Afghan Society. *Luminis Applied Science and Engineering*, *2*(1), 77-92. https://doi.org/10.69760/lumin.20250001014

Fayyad, U., Piatetsky-Shapiro, G. & P. Smyth (1996), "The KDD Process for Extracting useful Knowledge from Volumes of Data", Communications of the ACM, Vol. 39, No. 11, PP. 7-34.

Feng, D. & E.T. Chen (2007), Firm Performance Effects in Relations to the Implementation and use of knowledge Management Systems .International Journal of Innovation and Learning, Vol. 4, No. 2, PP. 172-185.

Hajiheidari, Naser and Naveen Hashemi (2013), "Customer Knowledge Management and E-Purchase Intentions: A Comparative Study in Two Societies", Publisher: Iranian Journal of Management Sciences, Vol. 7, No. 82, Winter 2012, pp. 27-44. For access: https://tinyurl.com/mtku69d4

Hanafizadeh, Payam; Alizadeh, Alireza and Mehrdad Rezai (2010), Book, Electronic Commerce: Definitions, Obstacles and Strategies, Publisher. Terme Publications. For access: https://tinyurl.com/45v5utxp

Hand, D.J. (1998), "Data mining: Statistics and More?", The American Statistician, Vol. 52, No. 2, PP. 112-118.

Khaloui, Ali; Pourezat, Ali Asghar and Mehdi Shami Zanjani (2014), "Investigating the Role of Knowledge Management in Developing Electronic Acquisition and Career Strategies", Publisher. Journal of Information Technology Management, No. 3, pp. 375-394. For access: https://tinyurl.com/yy2v723v

Laudon, K. C., & J. P. Laudon (2002), Management Information Systems Managing the Digital Firm, (7th ed.), New Jersey: Prentice-Hall International: Inc.

Lee, M.C. & T. Change (2007), "Linking knowledge Management and Innovation Management in E-Business", International Journal of Innovation and Learning, Vol. 4, No. 2, PP. 145-159.

Liao, S., Chen, Y. & M. Deng, (2010), "Mining Customer Knowledge for Tourism new Product Development and Customer Relationship Management, Expert Systems with Applications,Vol. 37, PP.4212–4223.

Loshin, D. (2003), Business Intelligence: the Savvy Manager's Guide, Morgan Kaufmann, San Francisco, C. A.

Lu, H. & K. Hsiao (2007), Understanding Intention to Continuously share Information on Weblogs, Internet Research, Vol. 17, No. 4, PP. 345-354.

Manoorian, Abbas; Khairandish, Mehdi and Nasser Asgari (2011), "Expanding the Structural Dimensions of the Organization in Accordance with the Knowledge Management Approach", Publisher. Information Technology Management, No. 7, Summer – pp. 150-133. For access: https://tinyurl.com/42p32bue

Ogiela , L. (2015)," Advanced Techniques for Knowledge Management and Access To strategic Information", International Journal of Information Management," Vol. 35,PP. 154–159.

Ogiela, L. (2013), Data Management in Cognitive Financial Systems, International Journal of Information Management, Vol. 33, PP. 263–270.

Orucova , G. (2025). Bridging Borders: Social Work in the International Arena. *Acta Globalis Humanitatis Et Linguarum*, *2*(1), 150-156. https://doi.org/10.69760/aghel.02500118

Paiva, E.L. & C.R. Goncalo (2008), "Organizational Knowledge and Industry Dynamism: an Empirical Analysis", International Journal of Innovation and Learning, Vol. 5, No. 1, PP. 66-80.

Rowley, J. (2002), Reflections on Customer Knowledge Management in E-Business.Qualitative Market Research: An International Journal, Vol. 5, No. 4, PP. 268-280.

Smoliar, S.W. (2007), "The Poetics of knowledge Sharing: Putting Aristotle to Work in the Enterprise", International Journal of Innovation and Learning, Vol. 4, No. 1, PP. 26-39.

Sun, S.Y. & Y.Y. Chen (2008), "Consolidating the Strategic Alignment Model in Knowledge Management", International Journal of Innovation and Learning, Vol. 5, No. 1, PP. 51-65.

Uziene, L. (2010), Model of organizational Intellectual Capital Measurement,Engineering Economics, Vol. 21, No. 2, PP. 151-159.

Wang, J. (Ed.) (2005), Encyclopedia of Data Warehousing and Mining, Idea Group Inc., Hershey, PA.

Wang, J.; Hu, X. & D. Zu (2007), "Diminishing Downsides of Data Mining",International Journal of Business Intelligence and Data Mining, Vol. 2, No. 2,pp. 177-96.

Wang, S-L. and Wu, P.-Y. (2008) The Role of Feedback and Self Efficacy on Web-Based Lerning: The Social Cognitive Perspective. Computers and Education, 51, 1589-1598.https://doi.org/10.1016/j.compedu.2008.03.004

Wanga, J., Lin , Y & Sh. Ho (2015), "A data Mining Approach for Training Evaluation in Simulation-Based Training", Computers & Industrial Engineering,.Vol. 80, PP. 171-180.

Williams, S. & N. Williams (2006), The Profit Impact of Business Intelligence, Morgan Kaufmann, San Francisco, CA.

Wu, J. H.; Chen, Y.C.; Chang, J. & B. Lin (2007), "Closing off the Knowledge Gaps in IS Education", International Journal of Innovation and Learning, Vol. 4, No. 4, PP. 357-75.

Wu, X.; Yu, P. & G. Piatesky-Shapiro (2000), "Data Mining: How Research Meets Practical Development?", Knowledge and Information Systems, Vol. 5, No. 2,PP. 248-61.

Received: 06.03.2025
Revised: 08.03.2025
Accepted: 12.03.2025
Published: 18.03.2025