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Revealing Knowledge Mining Intelligence: A Paradigm Shift from Data Mining in the Foreign Cooperation Context

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Abstract

This article delves into the emerging concept of Knowledge Mining Intelligence (KMI) and its transformative impact within the realm of foreign cooperation. It examines the transition from conventional data mining practices to the advanced techniques inherent in KMI, offering a comprehensive framework for its implementation in the foreign cooperation information supply chain. The article explores the theoretical foundations of KMI, emphasizing its role as a catalyst for efficient foreign cooperation endeavours. Through a detailed analysis, it elucidates the profound shift from data-centric methodologies to knowledge-centric paradigms. This article reviews research efforts in the field of business intelligence to understand KMI by analyzing studies systematically sampled from business intelligence journals over recent decades. After examining and analyzing scholarly work on what constitutes KMI, it presents findings on the shift towards KMI, key variables for foreign cooperation, and the role of the information supply chain in KMI. The article concludes that the integration of KMI with Business Intelligence (BI) and its technology implementation marks pivotal steps in optimizing the foreign cooperation strategies of public organizations.

Keywords: knowledge mining intelligence, knowledge mining, data mining, information quality, business intelligence.

INTRODUCTION

Business Intelligence (BI) has evolved significantly from early management information systems to include descriptive data analysis and data mining (Olszak & Ziemba, 2004; Eboigbe et al., 2023). This evolution (see Figure 1) has aligned BI closely with analytics, as both disciplines leverage Big Data for making optimal business decisions (Ukhalkar, Phursule, Gadekar, & Sable, 2020).

The objective of this article is to dissect a key component of Business Intelligence (BI), known as Data

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Mining, to elucidate its characteristics and illustrate how it evolves into Knowledge Mining. The article aims to demonstrate how this transformation leads to the emergence of what can be termed "Knowledge Mining Intelligence" as a foundational element within BI.

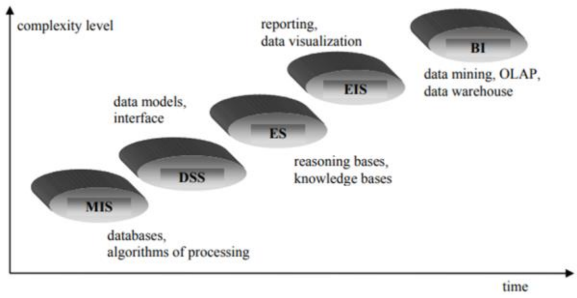

Figure 1. Development of Management Information Systems (Olszak, C. M., & Ziemba, E., 2004; Nayak, Das, Hota, & Sahu, 2022)

The following is a representation of the Business Intelligence (BI) pyramid, constructed on the foundational works of Eckerson (2010, p. 4) and Carlo (2009, p. 10). Notably, this pyramid is underpinned by a crucial element known as "Knowledge Mining Intelligence," which will be elaborated upon in a subsequent section of this academic discourse (see Figure 2).

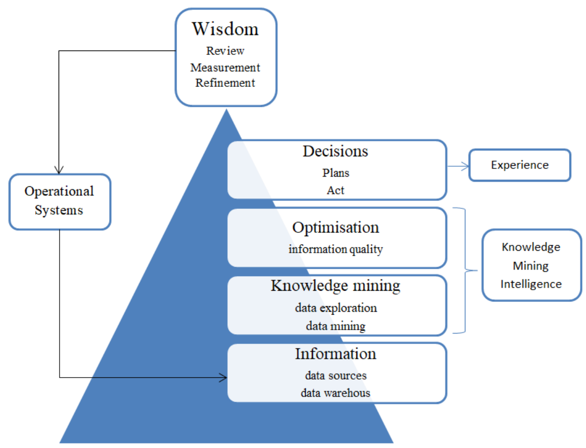

Figure 2. Knowledge Mining Intelligence within the Business Intelligence component hierarchy pyramid (developed by the author based on Eckerson (2010) and Carlo (2009)).

In the context of the presented pyramid, we discern the progression whereby data undergoes a metamorphosis into informed decision-making, consequently culminating in an enriched experiential framework. This iterative process of refinement serves as the impetus for enhancing the entire system, setting the stage for a continuous cycle of iteration and amelioration.

We shall now embark on an academic exploration to trace the transformation from data mining to the emergence of Knowledge Mining Intelligence.

METHOD

In this paper, we will utilize data from an extensive review of existing literature on knowledge-mining intelligence, focusing on the transition from data mining to knowledge-mining intelligence in foreign cooperation within public administration. This approach aims to support effective decision-making under uncertainty by collecting, organizing, and interpreting data.

In the results and discussion sections, we will explore key aspects: the shift from data mining to Knowledge Mining Intelligence, variables for foreign cooperation, the information supply chain as a KMI technology, and the implementation of KMI based on fundamental data mining methods.

From Data Mining to Knowledge Mining Intelligence

Various terms have been used to describe the process of identifying valuable patterns in data, such as data mining, knowledge extraction, information discovery, information harvesting, data archaeology, and data pattern processing. Among these terms, "data mining" has been predominantly embraced by statisticians, data analysts, and the management information systems (MIS) communities (Fayyad et al., 1996).

As commonly acknowledged, Data Mining constitutes one of the pivotal tiers within the Business Intelligence pyramid, as elucidated by Carlo (2009). The insights derived from data mining surpass traditional knowledge derived from human experience.(Li, Huamin; Li, Xingsen; Zhu, Zhengxiang (2010).)

Within Data Mining, as a component of Business Intelligence (BI), three fundamental concepts can be distinguished: Data, Information, and Knowledge (Carlo, 2009; Jermol et al., 2003). In a generalized form, these can be envisioned as sequential links in a chain, where the initial link comprises data gathered. Subsequently, these data are transformed into information through processing filters, and, in the final stage, this information evolves into knowledge (see Figure 3). Knowledge encompasses information applied within a particular field, enriched by the wisdom and expertise of decision-makers when addressing and resolving intricate challenges (Carlo, 2009; Jermol et al., 2003).

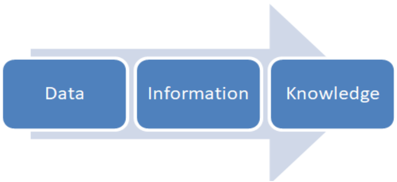

Figure 3. Data transformation chain (developed by the author)

According to Carlo and other researchers (Clark, Jones & Armstrong, 2007), Business Intelligence (BI) technologies ultimately enable the adoption of the most effective management decisions in specific situations. Consequently, knowledge represents the final stage before making such decisions.

The exponential growth in data, driven by advancements in information technologies and web-based intelligence, highlights the escalating demand for techniques to extract valuable practical knowledge from these vast data collections. This need has led to the development of a field known as Knowledge Discovery in Databases (KDD). The term was introduced by Piatetsky-Shapiro in 1991 and was initially discussed during the first KDD workshop in 1989, emphasizing that "knowledge" is the ultimate outcome of data-driven discovery. (Piatetsky-Shapiro, 1991; Fayyad et al., 1996).

During the First International Conference on Knowledge Discovery and Data Mining, there were in-depth conversations regarding the topic of Knowledge Discovery. Researchers explored various aspects of this field. Some researchers have delved into the process of knowledge discovery in databases (Brachman and Anand, 1996). Others discussed the use of graphical models for discovering knowledge (Buntine, 1996). Further discussions included topics related to Advances in Knowledge Discovery, Data Mining, and Knowledge Discovery Applications, contributed by Fayyad, Piatetsky-Shapiro, Smyth, and Uthurusamy (1996). at the same time, Silberschatz and Tuzhilin (1995) examined subjective measures of interestingness in Knowledge Discovery. The wide range of topics showcased at the conference emphasized the relevance of Knowledge Mining in contemporary BI research.

Knowledge Discovery in Databases (KDD) is the complex process of uncovering valid, new, potentially valuable, and ultimately comprehensible patterns in data (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). The definition provided by Fayyad, Piatetsky-Shapiro, Smyth, and Uthurusamy (1996) describes data as a collection of facts, such as cases stored in a database. A pattern, in this context, represents an expression in a certain language that characterizes a specific subset of the data or a model applicable to that subset. Therefore, the act of extracting a pattern also encompasses the idea of fitting a model to the data or revealing underlying structures within the data. This process denoted as Knowledge Discovery in Databases (KDD), involves multiple steps, including data preparation, pattern search, knowledge evaluation, and refinement, which are often repeated iteratively. When referring to patterns as non-trivial, it implies that they are not the result of straightforward computations of predefined quantities, such as calculating the average of a set of numbers. Instead, they involve a degree of complexity, often requiring searches or inferences. The discovered patterns are expected to hold true for new data with a certain level of confidence (Fayyad, Piatetsky-Shapiro, & Smyth, 1996).

Considering the author's inclination towards the term "Knowledge Mining" in this context, it underscores the extraction of practical knowledge from extensive, analyzed, and filtered information, which might be a challenging task across various fields (Rui et al., 2022).

This knowledge isn't solely derived from raw data mining; it also incorporates previously acquired knowledge and metadata (Kerdprasop N., Kerdprasop K., 2008). The resulting knowledge is highly applicable in practical real-world scenarios, moving beyond theoretical value (Olszak, Zurada, & Cetindamar, 2021).

Basic Variables for Foreign Cooperation in the Public Administration Context

In previous works, the author has already described a conceptual framework for implementing foreign cooperation (see Figure 4).

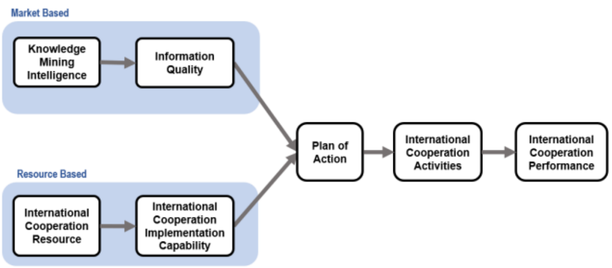

Figure 4. Conceptual Framework for Implementing Foreign Cooperation in Public Administration

The model comprises three categories of variables: resource-based (International Cooperation Activities, International Cooperation Implementation Capability), market-based (Knowledge Mining Intelligence, Information Quality) and implementation variables (Plan of Action, International Cooperation Activities, International Cooperation Performance). Below, we present the definitions of each fundamental variable within the model.

1. International Cooperation Activities: refers to the different types of cooperative activities that can be undertaken, such as language promotion, language training programs, student mobility, cultural exchange and joint exhibition, research collaboration, and technology transfer.
2. Plan of Action: pertains to the operational plan that outlines the steps to be taken in order to achieve the goals and objectives of the cooperative activity.
3. International Cooperation Implementation Capability: encompasses the leadership, vision, strategy, budget planning, contacts, and English-speaking personnel required for the successful implementation of the cooperative activity.
4. International Cooperation Resource: relates to the potential of cooperation, various institutions (universities, schools, cultural centres), human resources (students, researchers, lecturers), funding, and infrastructure (equipment, laboratories) that can be utilized as resources for cooperative activities.
5. Information Quality refers to the quality of information used in the planning, mapping, and implementation of the cooperative activities, including the optimization of accuracy, completeness, relevance, timeliness, and consistency of the information.
6. Knowledge Mining Intelligence: comprises software, programs, procedures, and algorithms of data mining, among others, that can be used to gather and analyze information for the purpose of making informed decisions in the planning and implementation of the cooperative activity.
7. International Cooperative Performance is the outcome of executing the international cooperation process.

This innovative framework is beneficial as it provides a comprehensive and systematic guide for the implementation of foreign cooperation. By addressing a series of critical questions, the framework ensures that all key components are accounted for and appropriately implemented. Additionally, the incorporation of Information Quality and Knowledge Mining Intelligence ensures that the framework is underpinned by the latest developments in data and information management.

Below, the author presents a newly developed figure illustrating the process of Knowledge Mining within the context of this Conceptual Framework for Implementing Foreign Cooperation. It can be conceptually shown in Figure 5. (based on Fayyad et al. 1996., Kerdprasop N., Kerdprasop K., 2008).

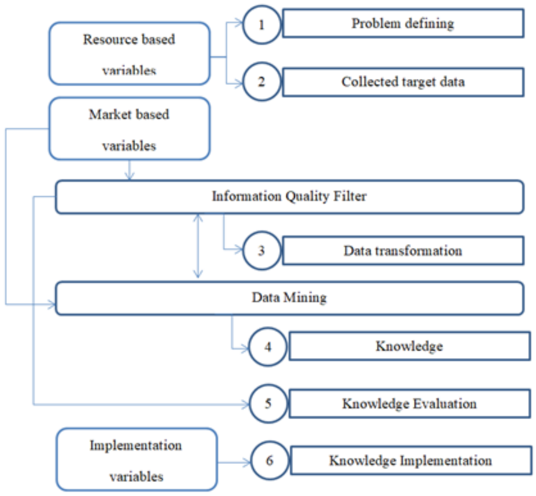

Figure 5. Process of Knowledge Mining within the context of this Conceptual Framework for Implementing Foreign Cooperation in Public Administration

The first step in knowledge mining is defining the problem, which involves establishing the objective or specifying the issue by comprehending the task goals and organizational needs. This stage is essential as it directs subsequent actions, including gathering relevant data, employing suitable algorithms for mining, and retaining only pertinent and actionable knowledge. A well-defined problem statement should outline the objectives to achieve and the anticipated outcomes. Within the model proposed by the author, variables such as "Cooperative resource availability" and "Implementation capability" are responsible for this aspect.

The second stage, data preparation, encompasses all essential tasks involved in preparing high-quality data suitable for mining. It includes collecting data from various sources, reformatting the data, and selecting representative data with the necessary attributes. Data preparation is often a time-consuming process that is likely to be carried out iteratively.

The collected target data undergoes a filtration process termed "Information Quality," which is one of the market-based variables in the model. This third step is called data transformation.

In the fourth stage, data mining involves the exploration and extraction of intriguing patterns (local generalized structures) or models (global generalized structures) from the data. These patterns and models, known as knowledge, serve as the foundation of the knowledge-mining process. While there are various techniques to choose from, their implementation may require some fine-tuning to achieve the best outcomes.

Once this stage is completed, we acquire what is known as "Knowledge."

In the fifth step of knowledge evaluation, the accuracy and interestingness of the discovered knowledge are assessed against certain threshold values. Accuracy pertains to the correctness of the model created and can be measured using a separate set of data known as test data. Users or miners must establish the desired level of model accuracy. Assessing interestingness is a more complex aspect than accuracy and relies heavily on the judgment of miners or domain experts.

In the end, the accurate and stimulating knowledge is moved to the deployment stage to provide valuable insights for an organization or serve as foundational information for future knowledge-mining projects. Variables in the model, such as "Plan of action," "International Cooperation Activities," and "International cooperation performance," aimed at enhancing the effectiveness of foreign cooperation.

As depicted in Figure 3, data mining represents only one facet of the Knowledge Mining process. In alignment with the views of fellow researchers (Fayyad et al. 1996), the concept of Knowledge Mining transcends the scope of Data Mining, signifying a more extensive domain.

KDD encompasses a multifaceted process involving critical stages such as data preparation, data selection, data cleansing, the assimilation of pertinent prior knowledge, and the precise elucidation of data mining results. When coupled with web-based intelligence and the suite of business intelligence (BI) tools, this comprehensive tool can be academically referred to as "Knowledge Mining Intelligence (KMI)". Within this nomenclature, the integration of data mining, information quality enhancement, and various BI tools converge to facilitate the knowledge extraction process.

Indeed, Business Intelligence (BI) manifests itself as a comprehensive system where Knowledge Mining Intelligence represents the foundational ensemble of essential BI tools. Within this schema, Knowledge Mining assumes the role of a fundamental process intrinsic to Knowledge Mining Intelligence, and it is imperative to note that Data Mining is distinctly confined to a singular stage within the broader continuum of the Knowledge Mining process.

Information Supply Chain as a Knowledge Mining Intelligence Technology

Acquiring the pertinent information in a timely manner is essential for the success of any public organization. With the accelerated globalization of industries, foreign cooperation has become increasingly vital in achieving organizational goals. To optimize their endeavours within limited time constraints and scarce resources, organizations are exploring innovative "knowledge mining" techniques (see Figure 5, table 1). This paper explores a selection of emerging technologies and related research methodologies through the lens of an information supply chain approach to facilitate and enhance foreign cooperation in public organizations. A "high-velocity" framework for knowledge extraction and a series of guidelines are suggested, drawing on critical success factors, key performance indicators, and mining strategies to tap into both explicit and implicit sources of knowledge. This approach enables public organizations to leverage Internet resources and other innovative techniques to achieve more creative and efficient foreign cooperation. The experience gained from the implementation of this approach can also help address initial issues and problems encountered in the foreign cooperation environment.

According to Fellows and Liu (2021), knowledge acquisition is not a completely closed system. In order to make informed decisions, public organizations and international cooperations must engage in purposeful and rigorous knowledge mining that is based on testable, repeatable, objective, and generalizable information that reflects the true state of affairs. This knowledge mining process involves gathering information from a variety of sources, including documented information sources, as well as gathering experiential knowledge by conducting interviews with subject matter experts and experienced practitioners who may have limited time to spare.

In this context, the effectiveness of the "information supply chain" in public organizations and international collaborations is contingent on key performance indicators, including (1) collector parameters such as skills, attitude, commitment, comprehensibility, and time, as well as (2) provider parameters such as skills, understanding, and time constraints of those providing the information). Additionally, (3) accessibility parameters such as speed and flexibility, as well as (4) manageability of information load and (5) data quality, including accuracy, relevance, and timeliness, are crucial for informed decision making Fellows and Liu (2021).

A typical knowledge mining framework for public organizations and international cooperations includes the searching for information from various sources, extracting raw data/knowledge from these sources, storing the extracted information in suitable formats, the filtering and comprehension of extractions, the segregation and sorting of distillations, the establishment of knowledge bases, and the updating and enhancement of knowledge to fill any gaps.

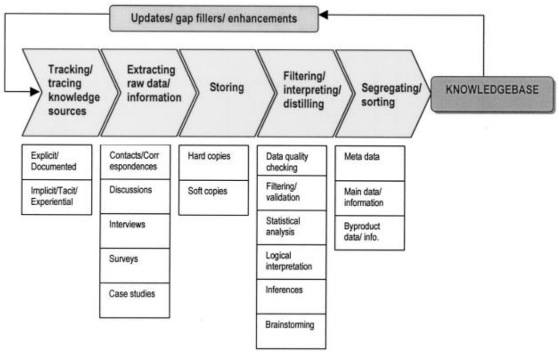

Figure 6. Typical knowledge mining framework for public organizations and international cooperations (Ekambaram et al., 2003)

Tracking and tracing knowledge sources is an essential task for extracting explicit and implicit knowledge in knowledge mining. The former is widely available and documented, while the latter is often hidden and buried beneath experiential sources. The conventional sources of knowledge mining for foreign cooperation in public organizations include a range of documented information such as official reports, policy documents, and newspapers. Direct and telephone interviews with experts and experienced practitioners, along with face-to-face meetings and discussions, also constitute important sources of knowledge. However, it should be noted that tacit and implicit knowledge is frequently hidden within experiential sources and requires further probing and exploration. While traditional knowledge mining sources are available, they may not always be flexible or fast enough to provide the necessary information for decision-making in a timely manner.

Compared to traditional methods, modern electronic means such as online databases, email communication, surveys conducted online, online discussion forums, and FTPs offer faster and more cost-effective "high velocity" knowledge mining opportunities. With structured and indexed formats of verified data, electronic databases provide advanced data mining tools to mining agents. Online communication through web resources, on the other hand, offers nonlinear search facilities, making it easier and faster to acquire knowledge. These contemporary mining tools offer flexibility, enhancing the potential for efficient and swift knowledge acquisition at a lower cost. As a result, mining agents should transition to real-time and multitasking environments when utilizing internet resources like web-based search engines, online databases, FTPs, emails, and discussion forums.

Both conventional and contemporary high-speed sources provide mined data/information that can be saved in either hard copies or electronic formats for additional processing. However, mining agents should check the quality of the data, examining aspects such as accuracy, comprehensiveness, and legitimacy, utilizing appropriate frameworks such as the one proposed by Loshin (2003) to eliminate any erroneous data. Appropriate tools for analysis, inference, and interpretation, such as statistical analysis and brainstorming, can be employed to understand the data and extract knowledge. Additionally, metadata, including data source origins, provider background information, contact details, data types, and categories, should be stored appropriately for updating, filling gaps, and enriching the knowledge base.

Simultaneously, the utilization of knowledge mining to inform decision-making must consider scenario constructions within the context of international collaboration, encompassing areas such as education and politics. Initially, the knowledge base should incorporate a range of scenarios, including an optimistic scenario that highlights factors positive to cooperation, a pessimistic scenario that underscores the abundance of limiting factors hindering the initiation of cooperation, and a realistic scenario that balances these factors while outlining potential strategies to overcome the problems and find solutions. From the perspective of implementing the process, the incorporation of this knowledge system may necessitate integration with other systems and projects. Without this integration, it would be impossible to address the issues encountered during the logical evaluation and scenario forecasting stage.

As an illustration, within the context of international relations, one can designate a national education development strategy as an entity that warrants the application of knowledge exploration. However, in order to achieve the desired model of cooperation, it becomes necessary to incorporate external unpredictable factors. As an illustration, the education strategy of country A may seek to restrict foreign exchange to give priority to local students, whereas country B's strategy may strive to enhance the volume of student exchange with country A. Therefore, during the model-building phase, it may not be possible to consider or be aware of contradictions in the strategies and regulating documents of the two countries, which will only be revealed during the implementation phase.

This introduces an additional vital component in the system for constructing the knowledge base, specifically an open and transparent avenue for exchanging official information with partners. This can be incorporated into the knowledge base, aligning with our ultimate goal of achieving an ideal collaboration model through the knowledge base recommendations.

Therefore, applying the international framework to this kind of planning on the basis of qualitative and selected data, we should, first of all, pay attention to geopolitical, economic, socio-cultural and so-called bureaucratic factors, which should be the primary object of collecting the necessary information and its subsequent qualitative selection, including through brainstorming, expert evaluation, and short-term and long-term forecasting.

Among the pessimistic or negative factors which can sometimes hinder the original concept, one should consider the following knowledge presented as a product of original analysis and data mining.

1. Geopolitical contradictions: political disagreements between countries can hinder the establishment of strategic cooperation and the exchange of educational resources.
2. Political instability or transformations: changes in the political situation can affect long-term cooperation strategies and require constant monitoring and adaptation.
3. Economic aspects and financial constraints: insufficient funding can limit the implementation of educational programs and projects involving both countries.
4. Differences in economic development: variations in economic capabilities can impact the equality of partnerships and resource distribution.
5. Bureaucratic aspects: disparities in educational systems and legislation may require additional efforts to coordinate and comply with the requirements of both countries.
6. Cross-cultural interaction: differences in cultural values and traditions can affect mutual understanding and successful interaction between partners.
7. Language barriers: differences in languages can make it difficult to exchange information and ideas, which is effective work in knowledge mining.
8. Social norms and stereotypes: biases and social stereotypes can have a negative impact on collaboration and knowledge sharing.
9. Intercultural communication: effective communication and understanding of differences in social customs can contribute to successful collaboration in knowledge mining.
10. Technology gap: differences in technological equipment, training and competencies can create problems in interaction and collaboration, especially when working with global partners.

Accordingly, when using knowledge mining technologies, we face the problem of creating a consistent, reliable, but at the same time flexible algorithm of actions based on the results obtained.

The reliability of cooperation and predictability of interaction with partners depend on strategy stability, while flexibility is also important for preserving resources in the face of negative influences.

Accordingly, one come to the need to introduce standardization as an important element in systematizing international cooperation based on knowledge mining.

The standardization of programs facilitates the unification of core curricula and teaching principles, enabling flexibility in adapting and modifying programs to accommodate specific needs and changes for collaborative purposes.

The unity of standards and principles of education contributes to the establishment of stable relations between educational institutions of different countries. This ensures stability of interaction and long-term cooperation, allowing both parties to feel reliability and continuity in the process of working together.

An actor in the educational sphere can get the maximum effectiveness from participation in multilateral international formats, within which standardization will affect not only two actors (as in bilateral cooperation) but many at once, leading them to a coordinated and transparent system of educational interaction.

However, the party relying on knowledge mining is also able to act as a kind of conductor of educational agency, influence the normative and conceptual content of international educational cooperation, and introduce the best practices of national experience, including promoting them as the final product of knowledge and education. The result of data and knowledge mining may be the creation of an international ranking, advanced analytics and systems of educational change, including export-oriented products.

While creating opportunities to employ knowledge bases for a public organization, the issue of system operation and management arises, as a repository alone lacks human interpretation. Additionally, it is important to consider the various formats that can facilitate the most effective management of this system.

To foster international educational cooperation, a public organization can effectively utilize a knowledge base built on best practices. To accomplish this, one option is to establish a centre of expertise for international educational collaboration that is responsible for coordinating and fostering partnerships in this field.

It is crucial to distinguish the roles of expert centres or councils from those of regular government departments in this area. The main goal for experts is to maximize the utilization of their knowledge base in order to create strategies and forecasts.

It is also possible for these expert centres to organize training and workshops for partners, as well as produce public reports and studies to disseminate experience and knowledge about effective practices. Supporting projects and programs for the development of education, as well as participating in international conferences and forums, will also help strengthen the position of the public organization in the field of international educational cooperation.

However, the introduction of an expert level, although helpful in terms of creative, social and academic tools, may increase the risk of biased assessment of the data provided during knowledge mining. Here, artificial intelligence (AI) can be an additional help factor for experts and officials.

AI has the potential to significantly enhance the development and operation of knowledge bases in the field of international educational cooperation. It is capable of automating the processes of information collection, analysis, and classification, thereby reducing the time spent on working with the database and increasing its accuracy. Additionally, AI can analyze user preferences and deliver personalized content for specific needs, making information access more convenient. Data analysis using AI enables the identification of hidden patterns and the prediction of future trends, facilitating informed decision-making.

The creation of intelligent decision support systems based on AI will help professionals optimize activities in the realm of international educational cooperation. AI also possesses the ability to continuously learn from new data and user feedback, enhancing the quality and relevance of the knowledge base in this domain.

However, government tasks also require the independence of such AI software from external developers. Part of such an ecosystem in the form of AI, a knowledge base and the results of transparent experts' assessment can even be available to external partners, while other levels contain purely classified information.

DISCUSSION

Implementation of Knowledge Mining Intelligence Based on Basic Data Mining Methods

Knowledge mining intelligence has emerged as an important approach to support international cooperation in public organizations. One study argues that knowledge mining can be used to identify key issues and trends in the international arena and help policymakers make informed decisions (Shan, W., & Zhang, Q., 2007, Prasath, R., Vuppala, A. K., & Kathirvalavakumar, T., 2015). Another article suggests that knowledge mining can be used to support the identification of potential partners and collaborators for international cooperation initiatives, as well as to identify successful practices and models that can be scaled up in other contexts (Mori, J., Kajikawa, Y., Kashima, H., & Sakata, I., 2012).

In addition, knowledge-mining intelligence can be used to support the development of evidence-based policies and programs. By analyzing large volumes of data it can help identify gaps in knowledge, evaluate the effectiveness of existing policies and programs, and inform the development of new interventions (Van Kammen, J., de Savigny, D., & Sewankambo, N., 2006, Sharma et al., 2021). Moreover, it can help to support the monitoring and evaluation of international cooperation initiatives by tracking progress towards goals and objectives, identifying areas for improvement, and evaluating the impact of cooperation initiatives over time (Mazumdar, S., 1990).

Let's thoroughly examine the data mining methods utilized in KMI and their practical applications (see Table 1). In real-world scenarios, the selection of the appropriate method must be tailored to the database's specific characteristics (Fang, F. 2023, Abu et al., 2019).

Table 1. Data Mining Methods and Their Applications in the Ministry of Education, Culture, Research, and Technology of Indonesia (developed by the author based on Fayyad et al. 1996, Ahmad Baig et al., 2024, Kulkarni, Shilpa. (2023)

Data Mining Method	Description	Application in the Ministry of Education, Culture, Research, and Technology of Indonesia
Classification	Classification involves categorizing data items into predefined classes based on certain attributes. In education, this can be used to categorize students by their academic performance, learning styles, or specific needs.	Designing personalized educational programs and support systems tailored to individual student profiles. Identifying students at risk of underperformance for targeted interventions.
Regression	Regression analysis aims to predict numerical outcomes or relationships between variables. In education, it can be applied to predict exam scores, dropout rates, or the impact of policy changes on educational outcomes.	Forecasting student performance, understanding the impact of educational policies, and identifying factors influencing academic achievement.
Clustering	Clustering groups data into clusters based on similarities. Within the Ministry of Education, this can be used to group schools or students with similar characteristics for resource allocation and tailored strategies.	Optimizing resource allocation, identifying areas that require specific attention, and designing educational strategies based on student or school profiles.
Association Rule Mining	Association Rule Mining identifies patterns and relationships within data. In education, it can reveal which teaching methods are most effective or factors influencing student performance.	Identifying effective teaching practices, improving curriculum design, and enhancing student outcomes by leveraging insights from associations in educational data.
Text Mining	Text Mining analyzes unstructured text data to extract insights. In education, it can be applied to analyze student feedback, research papers, and sentiment analysis to assess the quality of education and policies.	Monitoring student feedback to improve the quality of education, conducting sentiment analysis to gauge public sentiment on educational policies, and guiding policy decisions with research analysis.
Pattern Recognition	Pattern Recognition detects patterns or anomalies within data. In education, it can be used to identify irregularities in student attendance, such as absenteeism or truancy.	Enhancing student attendance and addressing dropout issues by recognizing patterns of absenteeism, allowing timely interventions and support for at-risk students.
Change and Deviation Detection	This method is employed to identify significant changes or deviations in data, such as shifts in student performance or unexpected resource utilization.	Monitoring changes in student performance, identifying unusual trends, and optimizing resource allocation by detecting unexpected deviations in educational data.

The table provides a structured overview of various data mining methods and how they can be practically applied within the Ministry of Education, Culture, Research, and Technology of Indonesia. Each method is described, and its specific applications in the educational context are detailed, highlighting their potential for improving educational outcomes and decision-making processes within the ministry that guide the way in which to cooperate with foreign partner institutions.

CONCLUSION

This article has explored the paradigm shift represented by Knowledge Mining Intelligence (KMI) in the context of foreign cooperation. It has elucidated the transition from traditional Data Mining to KMI, emphasizing its role as a catalyst for efficient foreign cooperation by enhancing information quality and decision-making. KMI, underpinned by advanced techniques, empowers stakeholders with valuable insights, reshaping the foreign cooperation landscape in public organizations.

The integration of KMI with business intelligence (BI) and its implementation of technology marks pivotal steps in optimizing public organizations' foreign cooperation strategies. This evolution in data analysis holds the potential to revolutionize approaches to foreign cooperation, fostering more informed decision-making and enhanced collaboration, aligning with the contemporary importance of data-driven strategies and their critical role in achieving impactful outcomes.

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