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Stevan Didijer
1911-2004

EDITOR'S NOTE **VOL 13. NO. 2 (2023)**

The Evolution of Competitive Intelligence: A Systemic Approach to Organizational Management

An integrated approach to competitive intelligence (CI) promotes a deeper understanding, and CI appears to be evolving into a systemic view with an integrated approach across all organizational management processes. Individual components of CI were previously considered mainly as specific functional responsibilities, but today they are also considered from a conceptual perspective and organizational management. Such approach must include an increasing number of elements and ensure their mutual interaction and management, resulting in an increasingly complex model.

Recent efforts are noteworthy, especially recently in Luis Madureira works, where there has been a successful attempt to anticipate organizational perspectives by integrating CI functions into the organizational framework (Madureira, L. et al., 2021, 2023).

In today's dynamic business environment, the integration of knowledge management (KM), business intelligence (BI), foresight thinking, marketing intelligence, competitive intelligence and corporate forecasting has become imperative. The authors in this volume show how important it is to use intelligence to drive innovation and efficiency in a variety of industries.

In the constant pursuit of sustainable competitive advantage, organizations are increasingly recognizing the symbiotic relationship between business intelligence (BI) and knowledge management (KM). In this context, the maturity of systemic KM practices is crucial.

The challenge for organizations is to effectively coordinate the implementation of both BI and KM, which many companies face.

Beyond the corporate sphere, the University of New Brunswick supports a noble cause: improving the economic prospects of disadvantaged regions and marginalized groups. Their methodology uses visionary and predictive systems to elevate target groups, moving them toward economic empowerment.

This initiative combines research with practical application, incorporating foresight into strategic planning. Through mentorship, strategic guidance and vision, this approach catalyzes economic growth at both the organizational and community level. It provides resilience to regions that have historically faced socio-economic challenges.

Marketing intelligence encompasses several dimensions, including market research, competitive intelligence, and consumer intelligence. A comprehensive study highlights the critical impact of market research, competitive intelligence and consumer intelligence on company efficiency. Interestingly, marketing analysis and product information have a less pronounced effect, thus acknowledging the need for further research. In addition to empirical findings, this study serves as a guide for companies, providing practical recommendations for marketing information to improve organizational strategies.

I would like to express my gratitude to all contributors to this issue.

REFERENCES

Madureira L., Popovič A., Castelli M. (2023) Competitive Intelligence Maturity Models: Systematic Review, Unified Model and Implementation Frameworks. *Journal of Intelligence Studies in Business*, 13(1), pp. 6-29.

Madureira L., Popovič A., Castelli M. (2021) Competitive Intelligence Empirical Construct Validation Using Expert In-Depth Interviews Study. *IEEE International Conference on Technology Management, Operations and Decisions, ICTMOD 2021.*

On behalf of the Editorial Board,
Sincerely Yours,

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SECI Knowledge Model and Opportunities of Engaging Business Intelligence by Maturity Level: Case Study at Selected Businesses in the Czech Republic

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ABSTRACT This study aims to examine the possibilities of engaging business intelligence (BI) with regard to the level of maturity within systemic knowledge management (KM). The individual modes of knowledge sharing and conversion are illustrated in Nonaka's SECI model that defines four conversion modes of knowledge exchange: socialisation, externalisation, combination and internalisation. The submitted case study presents the current and potential engagement of BI when applying knowledge conversion tools in three Czech organisations of various sizes. Most businesses use both tools (BI and KM) but they are often not able to coordinate their joint implementation in a suitable way. Currently, the results of the case study indicate a more optimal adaptation in the environment of larger businesses. However, the addressed businesses, regardless of their size, most often see the potential and great opportunities of the tools in the combination mode in the future.

KEYWORDS: business intelligence, case study, knowledge management, maturity model, SECI

1. INTRODUCTION

Knowledge is considered one of the most valuable assets of organisations in the current economy. The growth of modern society has moved from natural resources and physical assets to intellectual capital of organisations where it has become the source of innovation and competitive advantage (Arora 2002). Research interest in knowledge management is considerable as knowledge has become the key to success in today's global, highly competitive economy. Companies that control their organisational knowledge with a clear and well-defined vision, objectives and approaches, tend to be more successful while other companies who approach knowledge management only with focus on IT may fail as they do not concentrate on the human aspect and long-term strategy (Abubakar et al. 2019).
The main objective of the presented study is to propose potentials of engaging business intelligence tools in the process of knowledge management. The modes of knowledge sharing and conversion are illustrated on Nonaka's SECI model that defines four conversion modes of knowledge (socialisation, externalisation, combination and internalisation) (Nonaka, Toyama, and Konno 2000b). Three businesses of different sizes were selected for the case study where

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the current level of BI engagement in the processes and tools of knowledge management were ascertained. Also, the potential of future application was examined in order to determine the probable boundaries of combining business intelligence with knowledge management.
The main task of business intelligence lies in converting available data into information. The information is then used as the basis of managerial decision-making (Gaardboe and Svarre 2018). Knowledge management can be understood as a conscious implementation of strategy, based on delivering the right knowledge to the right people at the right time using the available information to improve an organisation's performance (O'Dell and Grayson 1998). The comprehensive approach to knowledge management also includes acquiring knowledge and experience so that it is available for further use. It provides an easy access to specialised knowledge and know-how, whether formally recorded or only in the minds of specific individuals (du Plessis 2007). An easier approach to knowledge and its accessibility may be supported by engaging business intelligence in selected processes within the organisation (Sabherwal and Becerra-Fernandez 2013). The integration of knowledge through knowledge management platforms, tools, methods and processes must thus facilitate accessibility and sharing of such knowledge so that it is possible to implement personal and organisational learning and the creation of innovation while using the newly acquired knowledge (Baddi & Sharif, 2003).
To meet the main intention of the submitted study, the research was divided into several stages: the first part of the literary research presents the basic characteristics of Nonaka's SECI model. This is followed with a detailed list of tools and methods used in the defined stages of knowledge conversion. The second part presents the current approaches to combining knowledge management and business intelligence, followed with a list of models of maturity of both tools, individually and together. The advantages and suitable application of case studies are briefly characterised within the methodology and the procedure of the presented study is introduced. The following part contains the outcomes that are further discussed. The conclusion contains a short summary, the limitations of the study and outlines the potential directions of future studies.

2. LITERATURE REVIEW

The first part of the detailed literary research is based on researching documents dedicated to knowledge management and Nonaka's model of knowledge management – SECI. A detailed list of tools used in the individual methods of conversion was made: socialisation, externalisation, combination and internalisation. The overview was used as a basis for creating the final list of common tools for the assessment of the engagement of BI in KM within the case study.
The second part of the research presents the fundamentals of the relation between business intelligence and knowledge management. This is followed with an overview of five approaches to the assessment of the level of implementation in an organisation – known as maturity models. Two are dedicated to BI, two to KM and the last one offers maturity levels combining both tools. This part was then used to define the levels of maturity and the levels of implementation applied in the next section of the case study.

2.1. Knowledge Management and SECI Model

Nonaka (1994) designed the SECI model to understand the dynamics of the creation of knowledge. This model is a process model and according to Nonaka et al. (2008, p. 19): "*It starts with socialisation of individuals, transfers into externalisation in groups, combination in organisations and then returns to internalisation of individuals. It is important that the individuals, groups and organisations transform in the process of creating knowledge as they are a set of processes.*" According to this model, there are two types of human knowledge: tacit and explicit. Explicit or codified knowledge relates to knowledge that can be transferred in a formal, systemic way. On the other hand, tacit knowledge has a personal quality that makes it difficult to formalise and transfer such knowledge; it is deeply rooted in the activity, engagement and involvement into the specific context of the performed activity. Tacit knowledge contains both cognitive and technical elements. Those working models contain diagrams, paradigms, beliefs and points of view that provide ‘perspectives’ that help individuals perceive and define their world. On the other hand, the technical element of tacit knowledge contains specific know-how, crafts and skills applied in specific relations. It is important to note that the cognitive element of tacit knowledge relates to the individual’s ideas about the reality and visions of the future, i.e., to what is and what should be (Nonaka, 1995).

Knowledge management is understood as the management of the processes of creating, storing, making available and spreading intellectual resources of the organisation (Antunes and Pinheiro 2020). The fundamental challenge in knowledge management is the question of how to share knowledge in the most effective and efficient way (Barbeira, Franco, and Haase 2012). Knowledge can be shared at an individual, group and organisational level, within an organisation or among organisations (Ipe 2003). Sharing knowledge is a process of transferring knowledge (especially tacit) from one person to another, at the level of individuals – knowledge exchange, or collectively – through education (Xuan 2020). To share tacit or explicit knowledge, the knowledge must be maintained within the organisation so that it is available and traceable for employees. Tacit and explicit knowledge is then created at an organisational level using conversion.

The assumption that knowledge is created by conversion between tacit and explicit knowledge makes it possible to postulate four different ‘methods’ of knowledge conversion from:

1. Tacit knowledge to tacit knowledge – socialisation mode
2. Explicit knowledge to explicit knowledge – externalisation mode
3. Tacit knowledge to explicit knowledge – combination mode
4. Explicit knowledge to tacit knowledge – internalisation mode

The individual modes of conversion are shown in Figure 1 below.

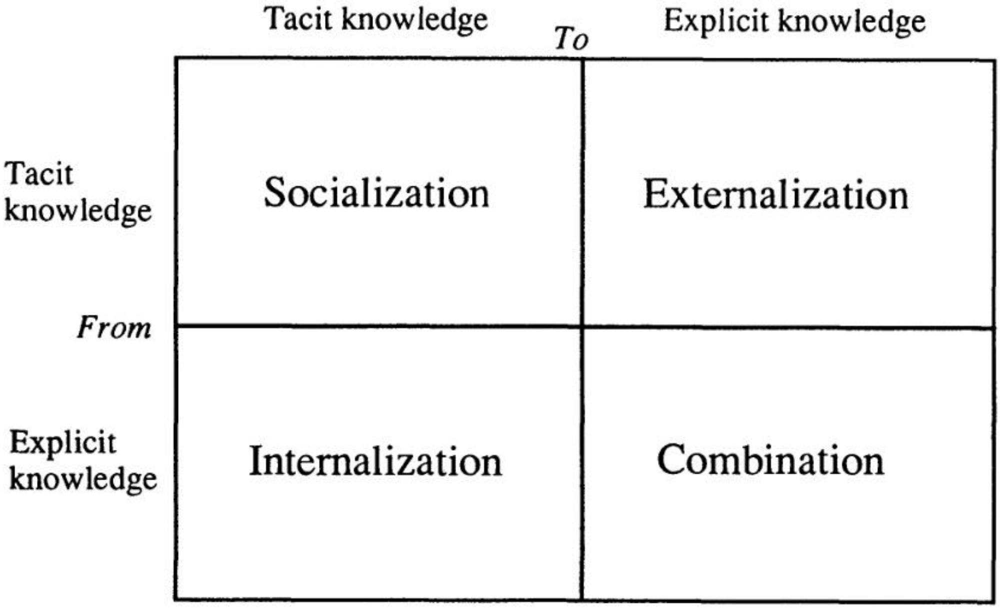


Figure 1. SECI Model. (Source: own processing according to Nonaka 1994.

The **socialisation mode** is the first method of knowledge conversion, i.e., conversion of tacit knowledge through interaction between individuals when the individual can acquire such knowledge without using speech during the transfer. The key to obtaining tacit knowledge is a shared experience; it is very difficult for people to share the line of thought with others without this form. Considering the fact that tacit knowledge is difficult to formalise and it is often specific in time and space, it is only possible to obtain tacit knowledge through a shared experience, such as spending time together or living in the same environment (Nonaka, Toyama, and Konno 2000b). When transferring tacit knowledge, emotions and nuances of contexts related to the shared experience must be applied. The socialisation process is based on the creation of tacit knowledge through a shared experience. This mode usually starts with building a 'team' or a 'field' of interaction. This field facilitates sharing experience and points of view of the members. Socialisation also takes place outside the boundary of the organisation; it can occur at informal social meetings where tacit knowledge, such as opinions about the world, mental models and mutual trust, can be created and shared (Nonaka, Toyama, and Konno 2000b).

The **second method of conversion** is the transformation of tacit knowledge to explicit knowledge, which is called externalisation and 'metaphor' plays an important role in this process. This method of knowledge transfer is very important since as soon as the tacit knowledge 'crystallises' as explicit knowledge, its transfer is easier and cheaper in terms of space and time than in case of tacit knowledge (López-Sáez et al. 2010b). In this dialogue, using 'metaphors' in a sophisticated way, team members can express their own points of view and thus uncover the hidden tacit knowledge that is difficult to formulate. A successful transformation of tacit knowledge to explicit knowledge depends on the gradual use of metaphor, analogy and model (Nonaka, Toyama, and Konno 2000b).

The third and fourth method of knowledge conversion concerns conversion containing both tacit and explicit knowledge and it expresses the idea that tacit and explicit knowledge complement one another and may expand in time through the process of mutual interaction.

The **third method of conversion** of knowledge (combination) includes the use of social processes to combine various pieces of the individuals' explicit knowledge. Explicit knowledge is collected inside or outside the organisation and then combined, modified or processed to create new knowledge. The new explicit knowledge is then spread among the members of the organisation (Nonaka, Toyama, and Konno 2000b). This process of knowledge conversion is usually facilitated with triggers such as 'coordination' between the team members and other divisions of the organisation and 'documentation' of the current knowledge. The concepts created by teams can be combined with existing data and external knowledge with such knowledge being created when explicit knowledge is combined and new ideas, or innovations, are created (Faith and Seeam 2018a). These processes of sharing information create a higher level of knowledge such as models, best practices, handbooks and information that may also spread without interpersonal relations (Farnese et al. 2019b; van den Hooff and de Ridder 2004).

The **fourth method of conversion** of knowledge (internalisation) is the transfer of explicit knowledge to tacit knowledge; this mode is known as internalisation, closely linked to 'action'. The closest manifestation of internalisation is learning through practice (López-Sáez et al. 2010b). The concepts created in the process of combination by teams are further formulated and developed through the iterative process of trials and errors until they appear in a specific form. Such 'experimenting' may create internalisation through the process of 'learning by doing'. When the knowledge is internalised and becomes a part of the tacit knowledge base of individuals in the form of shared mental models or technical know-how, it becomes a valuable asset. Such tacit knowledge collected at the level of an individual can launch a new spiral of creation of knowledge when shared with others through socialisation and expanded across organisations both horizontally and vertically. This is a dynamic process that starts at the level of an individual and expands as it moves through social interactions (Nonaka, Toyama, and Konno 2000b)

Table 1 summarises the tools and methods stated in available publications dedicated to the active use of knowledge in organisations.

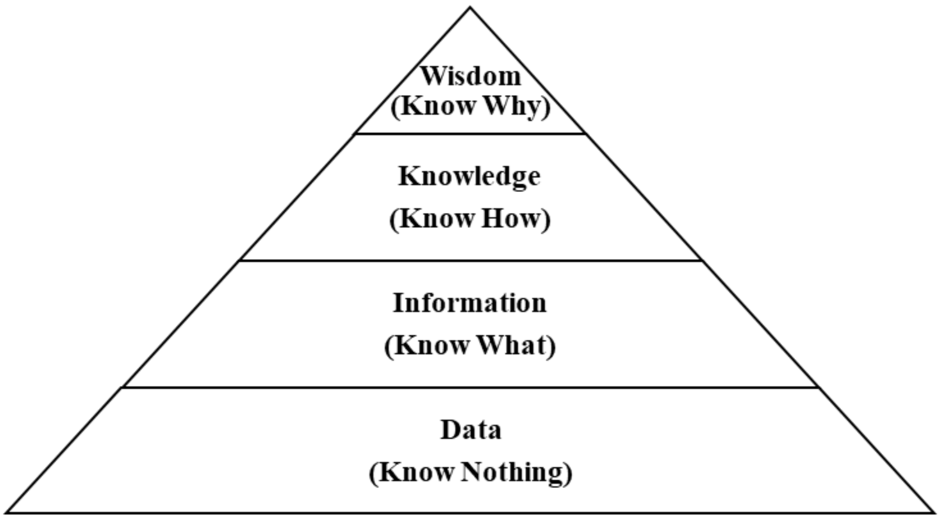
Table 1. Overview of Knowledge Conversion Tools and Methods (Source: own processing)

	SECI Model Modes			
Knowledge Conversion Tools and Methods	**Socialisation Mode**	**Externalisation Mode**	**Combination Mode**	**Internalisation Mode**
	Walking around the workplace	Concepts	Database of best practices	Simulation
	Direct interaction	Images	Intranet	Learning by doing
	Observation	Written documents	Prototypes	Encouraging workers to use explicit knowledge in organisational measures
	Listening	Seminars, informing individuals of informational and documentation methods	Computer communication networks	Designing an available bank of explicit knowledge for measures and decision-making of workers in the organisation
	Guidance (mentor x apprentice)	Handbooks	Statistical banks	Lectures
	Practice	Codified documents	Scientific works	Training programmes
	Imitation	Dialogues	Meetings	Reading documents or handbooks
	Brainstorming	Discussion platforms	Organising conferences	Trials and errors
	Brainwriting	Interviews with experts	Systematisation of terms in the knowledge system	Mentoring
	Personal contact	E-mail	Integration of concepts in the knowledge system	The organisation organises meetings where they explain the content of related messages or documents
	Group work	White pages	Overview report, trend analysis, brief summary or new database for organising content	The organisation organises meetings where they explain reports issued by customers, suppliers, competitors, partners or government

	Providing employees with opportunities to study	Minutes from meetings	Web fora	The organisation supports its employees in post-graduate studies
	Participation in formal and informal communities	Documentation of seminars, workshops, conferences and training programmes	Groupware	The organisation provides access to the results or recommends educational programmes, workshops and seminars
	Follow-up evaluation after participation in an event	Documentation of useful experience of qualified employees of the company	E-learning	
	Sharing best practices	Newsletters	Classification of information in databases, networks and reports	
	Knowledge communities	Websites	Database updates	
	Employee rotations	Patents	The organisation collects, sorts and informs its employees of reports and decisions issued by external authorities	
	Joint projects	Metaphors	Virtual communities	
	Workshops	Team confrontations	Information storage	
	Seminars		Electronic cooperation systems	
	Informal meetings outside the workplace		Net-meeting	
	Training in human resources		Podcast	
			Video-conference	
			Wiki	

2.2. Knowledge Management and Business Intelligence

The connection of key components of both strategic tools (BI and KM) in modern management can be easily organised into a value chain model of knowledge in the order of data → information → knowledge (Almarabeh et al. 2009). In this model, data are understood as descriptions of objects or events. Information represents processed data with assigned meaning and value in a specific context. When we add prior experience to information, appropriately put into context, we can transfer the information into knowledge (Martz and Shepherd 2003). The DIKW pyramid is considered an extension of this model; it expands the original diagram with the wisdom level. It is most frequently shown as follows:

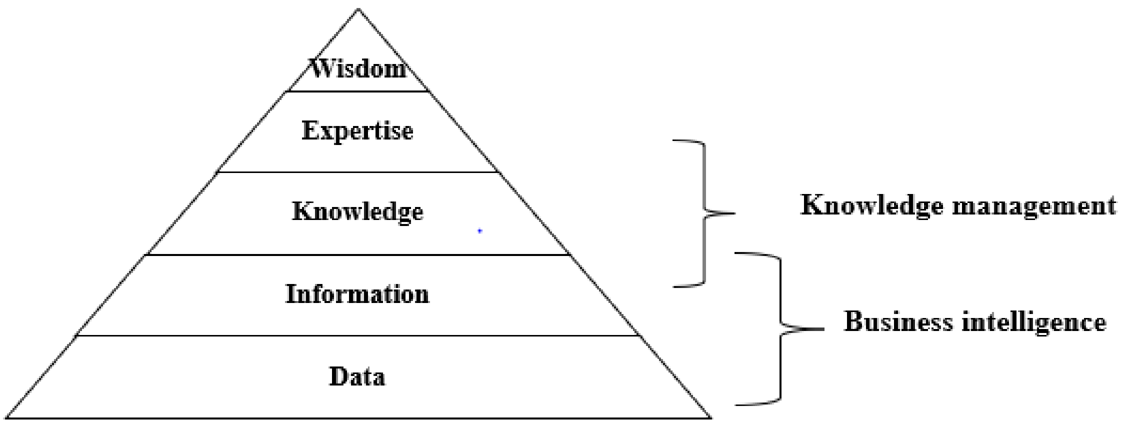


The individual levels may include idioms expressing their essence for better understanding. At the lowest level, data present symbols that only represent the properties of the environment and objects that require further observation (Know Nothing). When data are processed into information, it is possible to classify the properties of the environment and objects (Know What). The following boundary between information and knowledge can be overcome thanks to an appropriately set mutual transformation containing distribution, identification, obtaining and sharing knowledge using BI tools (Know How) (Shehabat and Berrish 2021). The last level (Know Why) can be achieved by adding value to the obtained knowledge through a strategic judgement (Mohamad, Jayakrishnan, and Mohd Yusof 2022).

Liebowitz (2019) adds an expertise level to the DIKW pyramid, placed between the levels of knowledge and wisdom. It represents corporate environment where achieving the expertise level among the maximum number of employees is a priority in a better way. Liebowitz's pyramid describes the system of organisational intelligence structure (Liebowitz 2019). The hierarchy is illustrated in Figure 3 on the left.

Figure 3. Organisational Intelligence Structure. (Source: own processing according to Liebowitz, 2019)

Figure 2. DIKW Pyramid. (Source: own processing according to Martz and Shepherd 2003)



The diagrams and models stated above clearly imply that an optimal combination of knowledge management and business intelligence represents a key instrument of a business in the effort to improve organisational intelligence and achieving the expertise level across the company. The field of activity of both tools indicates the extension of Liebowitz's pyramid in Figure 2. Their relation and overlapping in building organisational intelligence play an important role in the sequence of the individual levels.

In the past ten years, many publications discuss the successful application of knowledge management and business intelligence, separately. The studies confirm the importance of implementation of both business intelligence (e.g.: (Ain et al. 2019; Arefin, Hoque, and Bao 2015; Gaardboe and Svarre 2018; Pranjić 2018; Rouhani et al. 2016) and knowledge management (Abusweilem and Abualous 2019; Jennex and Olfman 2003; Keyes n.d.; Shehabat and Berrish 2021; Shujahat et al. 2017) in corporate processes. However, only a limited number of studies examine a suitable connection of both tools. Below, the selection of the most relevant approaches from the past ten years is presented.

Based on literary research of other studies, Rostami (2014) mentions the human factor, closely related to the setting of the corporate culture and the form of leadership, as the decisive factor of success in the mutual integration BI and KM. When the factors are set in an appropriate way, it is possible to achieve optimal organisational effectiveness, to improve the principles of learning organisation and to improve the performance of the organisation (Rostami 2014). Abusweilema and Abualoushb (2019) examined the effect of the process of knowledge management and business intelligence on the performance of the organisation. Based on the performed survey, it is possible to support the company's effectiveness by implementing activities built on generating knowledge and creating platforms for sharing knowledge. That helps organisations effectively and purposefully strengthen the capacity of knowledge management and thus achieve a higher performance (Abusweilem and Abualous 2019).

Muhammad et al. (2014) describes the role of BI and KM integration using the financial sector as an example. The financial sector is characterised by fast-changing market environment and managing huge quantities of data. He sees the main contribution of business intelligence in uncovering hidden patterns and extracting valuable information from internal and external sources of data. The knowledge management system then provides sharing and management of tacit and explicit knowledge. Within the integration of business intelligence, the tools support knowledge management for the purpose of maintaining and increasing performance of (not only) organisations operating in the financial sector (Muhammad et al. 2014).

2.3. Maturity Models

For the purpose of this study, the levels of engagement of business intelligence, knowledge management or both tools together in corporate processes were examined. Grossmann and Rinderle-ma examine only BI combined with strategic management. There are four possible scenarios of using business intelligence tools in strategic planning. The list below states the individual stages and examples from practice (Grossmann and Rinderle-Ma 2015):

1. BI and strategic management are separated: BI outputs basically represent standardised reports designed for a specific part of the organisation. They only fulfil the short-term objectives of the specific department.
2. BI as an organisation's performance control support: Monitoring is performed when checking stipulated measurable objectives. BI application is formulated within the determination of strategic objectives.
3. BI as a means of feedback when formulating the strategy: The balanced scorecard is a typical outcome of this scenario. BI tools are applied during strategy optimisation.
4. BI as a key source of strategic planning: BI outputs are used directly when defining strategies and they thus provide substantial inputs when creating the strategic plan at the top managerial level.

Gartner's model is one of the most frequently used models in the assessment of business intelligence implementation maturity. The maturity model for business intelligence recognises five levels of maturity: unconscious, tactical, concentrated, strategic and omnipresent. It is used for assessing the initial effort and the achieved maturity. The assessment includes three key areas: people, processes and metrics and technologies (Rajteri 2010). The hierarchy of the individual stages with basic characteristics is illustrated in Figure 4.

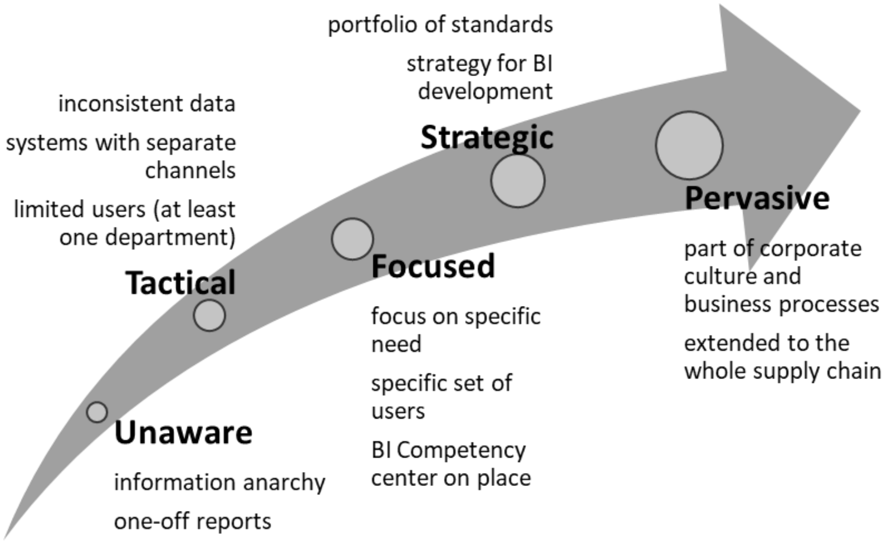


Figure 4. Business Intelligence Maturity Model. (Source: own processing according to Gartner 2006 and Rajteri 2010)

The Technology and Service Industry Association (TSIA) studies knowledge management on its own and they presented their own maturity model in 2017 (Ragsdale and Platz 2017). TSIA divides the progress of adopting knowledge management in an organisation into four stages:

- Recognition of the importance of KM
- Instantiation of the KM application strategy
- Value realization
- Strategy implementation

All four stages are then monitored from four points of view:

- Corporate culture
- People
- Processes
- Technology

The authors of a study focused on the research of fifteen models of KM maturity came up with a similar classification (Kuriakose et al. 2011). The main output of the study was a development of a new model complementing the strengths of the current approaches with flexibility, adaptability and practical application. The authors determined a total of six maturity levels after processing the existing models (Kuriakose et al. 2011):

- **Level 0, default status**: absence of any formal activity in the field of knowledge management. The organisation only acknowledges and rewards individual expert knowledge and abilities of individual workers.
- **Level 1, initial stage**: the company management shows initial interest and intention to adopt KM but there is still low awareness of the importance and advantages of knowledge management across the company.
- **Level 2, qualitative development**: the qualitative meaning of activities related to KM and their effect on the performance of individuals, divisions and the entire organisations are assessed in this stage.
- **Level 3, quantitative development**: the methods and tools of knowledge management have been implemented and objectives are achieved in a structured and coordinated way. KM activities can be connected to the organisation's effectiveness and assessed using various types of performance indicators. The organisation achieves the level of 'conscious competence'.
- **Level 4, maturity**: knowledge management becomes an integral part of work routines and is reflected not only in

everyday activities, but also in the corporate culture.

- **Level 5, extended – organisational maturity**: the last level is characterised with achieving maturity in terms of partner organisations, such as suppliers, customers, government institutions and others, as well as trouble-free integration and cooperation with such organisations.

All the levels are monitored in several segments of the organisation. The authors determined five parameters in total: once again, the parameters include people, processes and technologies, supplemented with knowledge and ROI (Return On Investments). The assessment of the adoption maturity by the individual parameters is measured using a radar chart. An example of such assessment is illustrated in Figure 5.

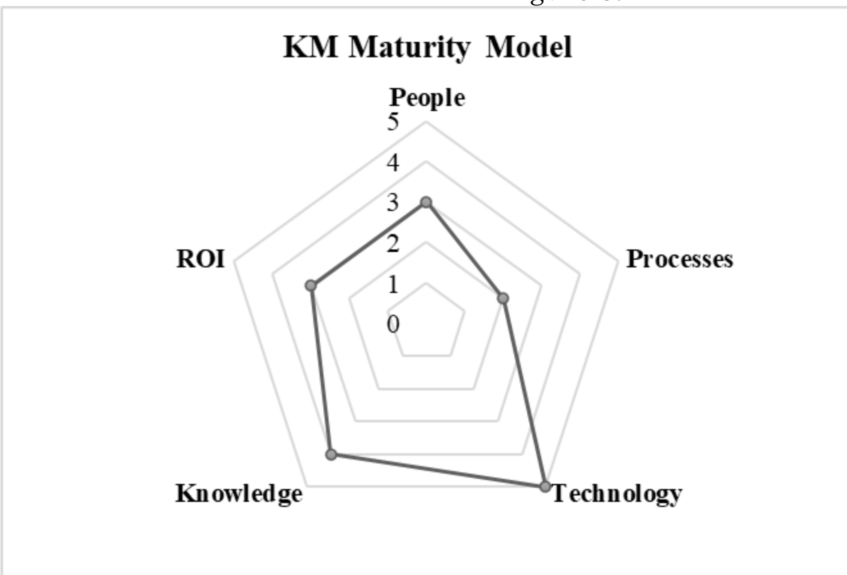


Figure 5. KM maturity model by Kuriakose et al. with completion example. (Source: own processing)

Sabherwal and Becerra-Fernandez (2013) present integration of business intelligence and knowledge management within engagement into corporate processes. They divide the process into four stages:

Both systems are separate in the first stage; therefore, it is called the **isolation stage**. There is low awareness of the possibilities of synergies and increase in effectiveness thanks to the coordination of both tools.

In the next stage, **independence**, the organisation has basic awareness of common foundations and possible positive effects obtained by cooperation between KM and BI. The management applies first trials of interaction between the systems that have been isolated so far.

In the third stage of **complementarity,** the management integrates both tools. The mutual combination is no longer based on using common principles of operation but complementary application of KM and BI is planned consciously.

The company is fully able to use the synergic effects in the last stage, **synergy**. We can register an increase in effectiveness and a positive impact on overall performance of the company (Sabherwal and Becerra-Fernandez 2013).

3. METHODOLOGY

The following chapter summarises the basic characteristics of research case studies and presents the progress and preparation of the presented research.

3.1. Case Study

The method of research case study was used to check the presented system of a potential effective connection of knowledge management and business intelligence in an organisation. Since this is pilot testing of a

newly suggested structure, the application of a research case study as a tool of qualitative research seems to be a suitable choice (Štrach 2007).
Recent publications point out that such methods have a strong position in the research methodology. The case study provides a comprehensive view of the selected unit (individual, a small group, organisation, community or even nation) within the studied topic. It also allows for the future application of principles and instructions from the pilot study in further situations (Burkholder et al. 2020). When researchers decide to include a case study, they have to make a crucial decision containing two basic elements: defining the case and limitations of the case. The first part concerns a clear and specific designation of the case, which can be any unit stated above. Limitation limits the scope – what is and what is not included in the case in terms of time, structure or other points of view (Yin 2018).

Takahashi and Araujo also refute some criticism that points out the size of the selected sample. The case study focuses on a small sample of examined units. The study examines the issue in depth (not width) and it is used to deepen the theoretical and empirical knowledge but it may also refute and question established approaches and ideas. Those are often caused by the complexity and extensiveness of the examined phenomenon, not by the internal limitations of the selected method (Takahashi and Araujo 2019).

3.2. Research design

Based on the literary review, tools used for knowledge sharing and conversion within an organisation were identified (Baldé 2015; Baldé, Ferreira, and Maynard 2018; Nonaka, Toyama, and Konno 2000a; Faith and Seeam 2018b; Farnese et al. 2019a; López-Sáez et al. 2010a; Lee and Kelkar 2013; Amidon and Mahdjoubi n.d.; Mohamad, Jayakrishnan, and Mohd Yusof 2022; Nonaka and Konno 1998). The authors assigned the acquired knowledge and tools to the individual conversion processes of the SECI model, shown in Table 1. Subsequently, with respect to the possibility to use business intelligence within the individual methods and tools, the tools were eliminated and their final selection is shown in Table 3.

Based on the literary research, approaches to maturity of the application of KM and BI were prepared. Four levels of engagement of business intelligence within the application of the individual methods of sharing knowledge were applied in the case study:

- Status 0: Zero application, no awareness of the possibility of implementing BI.
- Status 1: Sporadic use of BI for specific tasks.
- Status 2: BI as a support of monitoring performance in the context of set objectives. BI application established in the organisation.
- Status 3: BI as a key source of input information, automatic implementation in processes.

The combination of researching the available methods promoting the individual stages of knowledge conversion in Nonaka's SECI model and the four-level classification of engagement of business intelligence was used as a basis for a case study applied in three selected companies.
Three companies were nominated for the pilot study to test the designed model. Each company belonged to a different size category for the purpose of comparison. All companies asked for anonymity when presenting the study; therefore, they will be marked as A, B and C. The basic characteristics of the study participants are presented in Table 2:

Table 2. Characteristics of researched companies. (Source: own processing)

Company	Size	Line of business	Representative
A	Small, start-up (up to 50 employees)	IT	IT analyst
B	Medium (up to 250 employees)	Construction	CEO's office manager
C	Large (over 250 employees)	Logistics, shipping	System quality analyst

4. Research Results

The addressed employees were asked to determine the current engagement of BI within the application of the individual methods and to determine the potential of using data analytics that could be optimally achieved in their organisation. For the sake of clarity, the recorded results are divided into two parts and the potentially possible applications contain the letter 'p (potential)' for easier identification. Table 3. sums up obtained outputs.

Table 3. Results of qualitative research - level of engagement of BI in KM. (Source: own processing)

Methods of sharing knowledge in the individual modes / Level of engagement of business intelligence	Status 0	Status 1	Status 2	Status 3	Status 0	Status 1	Status 2	Status 3
	Current application				**Potential – optimal application**			
Socialisation mode								
Observation, monitoring of the workplace, on the job training	A, C		B		Cp		Ap	Bp
Listening	B, C	A			Bp, Cp		Ap	
Guidance (mentor x apprentice)	C	A, B			Cp	Bp	Ap	
Group work, joint projects		A, C		B			Cp	Ap, Bp
Provision of training and workshops		A, B, C				Cp		Ap, Bp
Informal meetings outside the workplace	A, B	C				Bp, Cp	Ap	
Preparation of training plans	A	B, C					Ap, Bp, Cp	
Externalisation mode								
Dialogue	B, C	A			Bp, Cp		Ap	

Discussion forum, interviews with experts	B, C	A			Bp, Cp		Ap	
Minutes from meetings, newsletters		A, B, C				Bp, Cp		Ap
Written documentation (standards, directives)		A, B	C			Bp		Ap, Cp
Seminar records		A, B, C				Bp, Cp	Ap	
Lessons learned records		A, B, C					Bp	Ap, Cp
Handbooks		A, B	C			Bp		Ap, Cp
Combination mode								
Communication networks, web fora	A		B, C				Ap, Cp	Bp
Organising conferences	A, B	C				Cp	Ap, Bp	
Intranet	A, B		C				Ap, Bp	Cp
E-learning	A, B		C				Ap, Bp	Cp
Database of best practices, information storage	B	A, C					Bp	Ap, Cp
Systematisation of terms in the knowledge system	B	A, C				Cp	Bp	Ap
Database updates	B	A	C					Ap, Bp, Cp
Internalisation mode								
Practice simulation	B	A	C			Bp	Ap	Cp
Learning by doing	B	A, C			Bp	Cp	Ap	
Trial x error	B	A, C			Bp	Cp	Ap	
Lectures	A, B	A, C			Bp	Cp	Ap	
Training programmes	A	B	C				Ap, Bp	Cp
Encouraging workers to use explicit knowledge in organisational measures	A, B	A, C			Bp		Ap, Cp	
Suggesting available banks of explicit knowledge	A, B	A, B, C					Ap, Bp, Cp	

The graphic illustration (see Figure 6) of the results could be performed after converting the verbal answers into numerical expression. The defined levels of maturity of BI implementation were assigned a score identical to the designation (0-3). Table 4 summarises the achieved results in all modes of Nonaka's model as well as for the addressed companies.

Table 4. Results in numeric expression. (Source: own processing)

Mode of knowledge sharing / Corporate setting	Current situation				Potential – possible future status			
	A	B	C	Sum	Ap	Bp	Cp	Sum
Socialisation mode	4	8	4	16	16	13	6	35
Externalisation mode	7	5	6	18	18	6	11	35
Combination mode	3	2	11	16	17	16	16	49
Internalisation mode	2	2	9	13	14	5	13	32
Sum	16	17	30		65	40	46	

Figure 6 shows the graphic illustration where the solid line indicates the level of current application and the broken line indicates the estimated potential of the application of business intelligence.

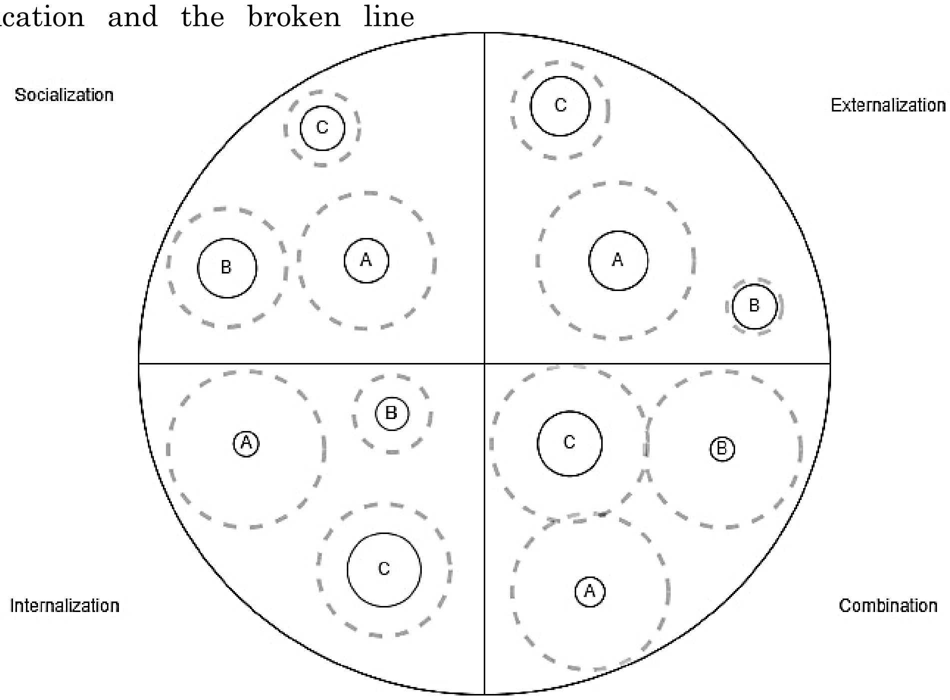


Figure 6. : Graphic illustration of current and potential application BI tools in KM. (Source: own processing)

5. Discussion

As far as the assessment of the current connection and application of business intelligence within knowledge management is concerned, organisation C, i.e., the large organisation, has made the most progress according to the results. This could be explained by a longer company history and thus a better use of the experience acquired within work with data, information or knowledge (value 30). Organisation A and organisation B achieved half the value (16 and 17) in the self-assessment of the current situation. As the results of the assessment of the business intelligence application potential imply, the organisations are aware of the possibilities and advantages that the future application offers. Especially the potential values of the small, start-up company correspond with the optimistic expectations related to the future development of the small organisation (from 16 to 65). The largest company from the presented study, organisation C, is more cautious about further expansion and estimates improvement at a lower value (from 30 to 46). The medium-sized company thinks similarly to the large company and cautiously estimates expansion of the engagement of business intelligence within knowledge management from 17 to 40.

As far as the individual modes are concerned, the differences were not large (16, 18, 16 and 13). The data analysis is most frequently used in knowledge conversion within externalisation when tacit knowledge transforms into explicit knowledge. The knowledge hidden so far is expressed. The use of databases and information and telecommunication technologies facilitates this method of knowledge conversion (López-Sáez et al. 2010b), computer systems are used for obtaining information and knowledge, and also as a database for storing such information and knowledge (Faith and Seeam 2018a). The analysis of such recorded knowledge and its assessment using business intelligence has its place in the companies. The formalisation also leads to new knowledge, accessible and available to all other co-workers in the future (Farnese et al. 2019b).

Tools applied in the combination mode excel in the assessment of the potential (value 49). In this mode, explicit knowledge is knowledge collected inside or outside the organisation and then combined, modified or processed to create new knowledge. The new explicit knowledge is then spread among the members of the organisation (Nonaka, Toyama, and Konno 2000b). These processes of sharing information create a higher level of knowledge such as models, best practices, handbooks and information that may also spread without interpersonal relations (Farnese et al. 2019b; van den Hooff and de Ridder 2004). The application of business intelligence is thus obvious and the addressed companies assess this issue the same way.

In the future, the companies see a similar application of BI in the externalisation mode (35) as well as in socialisation (also 35). The results indicate an increase in the scope of the business intelligence application in the records and analysis of the transformation of tacit knowledge to explicit knowledge, but they also see a potential in the transformation of tacit knowledge to tacit. This knowledge conversion is performed at an interpersonal level and allows defining patterns of 'how to do things' or reckon with events, beliefs, representations of objects and models of professional practices (Farnese et al. 2019b). Acquisition occurs with the use of observation, imitation and practice, which is a typical example of sharing knowledge from a mentor to the apprentice; in business, the same training principle is used, known as on-the-job training (Nonaka 1991). The addressed companies chose group work, joint projects or provision of training and workshops as other methods where BI can be used.

6. Conclusion

The objective of the presented study was to find a suitable connection between business intelligence and knowledge management. Most companies, more or less, work with both tools. However, the scientific community deals with the two methods separately, as the extensive literary research showed. However, its thorough processing indicated a suitable connection thanks to the case study using an example of specific methods and techniques. The individual modes of Nonaka's model may be very abstract for managers within operative management. Therefore, specific tools applied to a specific type of knowledge conversion were selected. The main contribution thus lies in the thorough assessment and systematisation of the methods used in knowledge management, as well as in the outline of the optimal use of data analytics in selected processes.

The study has its limitations, just like other studies. The study only refers to three companies and the presented output thus only reflects the reality using a very small sample. However, this deficiency is outweighed by the contributions that the case study offers, characterised above. The verification of the presented approach was also performed only in companies operating on the Czech market. However, this sample was found sufficient for the fulfilment of the original intention of the long-term study.

The study can be extended in several different directions in further stages. The qualitative research can focus on in-depth interviews in the individual companies in the specified area. A more extensive questionnaire survey could be performed using quantitative research to supplement the already obtained outputs based on qualitative collection of information. Also, based on the available outcomes, the future study could focus on suggesting recommendations related to the individual methods used within knowledge management so that the tools of business intelligence could be applied in the most effective way.

REFERENCES

Abubakar, Abubakar Mohammed, Hamzah Elrehail, Maher Ahmad Alatailat, and Alev Elci. 2019. 'Knowledge Management, Decision-Making Style and Organizational Performance'. *Journal of Innovation & Knowledge* 4 (2): 104–14. https://doi.org/10.1016/j.jik.2017.07.003.

Abusweilem, Mohammed A., and ShadiHabis Abualous. 2019. 'The Impact of Knowledge Management Process and Business Intelligence on Organizational Performance'. *Management Science Letters*, 2143–56. https://doi.org/10.5267/j.msl.2019.6.020.

Ain, NoorUl, Giovanni Vaia, William H. DeLone, and Mehwish Waheed. 2019. 'Two Decades of Research on Business Intelligence System Adoption, Utilization and Success – A Systematic Literature Review'. *Decision Support Systems* 125 (October): 113113. https://doi.org/10.1016/j.dss.2019.113113.

Almarabeh, Tamara, Amer Abuali, Sanaa Alsharrab, and Abed Alkareem. 2009. 'Value Chain Model in Knowledge Management', January.

Amidon, Debra, and Darius Mahdjoubi. n.d. 'Atlas of Knowledge Innovation: Beyond Business Planning'. Accessed 17 November 2020. https://www.entovation.com/whatsnew/atlas1.htm.

Antunes, Helder de Jesus Ginja, and Paulo Gonçalves Pinheiro. 2020. 'Linking Knowledge Management, Organizational Learning and Memory'. *Journal of Innovation & Knowledge* 5 (2): 140–49. https://doi.org/10.1016/j.jik.2019.04.002.

Arefin, Md, Md Hoque, and Yukun Bao. 2015. 'The Impact of Business Intelligence on Organization's Effectiveness: An Empirical Study Article Information: For Authors'. *Journal of Systems and Information Technology, ISSN: 1328-7265, Emerald Group Publishing Limited* 17 (January): 263–85.

Arora, Ravi. 2002. 'Implementing KM – a Balanced Score Card Approach'. *Journal of Knowledge Management* 6 (3): 240–49. https://doi.org/10.1108/13673270210434340.

Baldé, Mariama. 2015. 'Individual and Team-Level Predictors of SECI and Creativity: A Multilevel Approach'. MasterThesis. https://repositorio.iscte-iul.pt/handle/10071/11531.

Baldé, Mariama, Aristides I. Ferreira, and Travis Maynard. 2018. 'SECI Driven Creativity: The Role of Team Trust and Intrinsic Motivation'. *Journal of Knowledge Management* 22 (8): 1688–1711. https://doi.org/10.1108/JKM-06-2017-0241.

Barbeira, Marisa, Mário Franco, and Heiko Haase. 2012. 'Knowledge Sharing in Networks Within the Healthcare Sector: Measuring Knowledge Management Capabilities'. *European Conference on Knowledge Management*, September, 37–XX.

Burkholder, Gary J., Kimberley A. Cox, Linda M. Crawford, John H. Hitchcock, and Michael Quinn Patton. 2020. *Research Design and Methods:*

An Applied Guide for the Scholar-Practitioner / [Edited by] Gary J. Burkholder, Kimberley A. Cox, Linda M. Crawford, John H. Hitchcock ; with a Foreword by Michael Quinn Patton. Thousand Oaks, California: SAGE Publications, Inc.

Faith, Charlote, and Amar Seeam. 2018a. ‘Knowledge Sharing in Academia: A Case Study Using a SECI Model Approach’ 9 (January).

———. 2018b. ‘Knowledge Sharing in Academia: A Case Study Using a SECI Model Approach’ 9 (January).

Farnese, Maria Luisa, Barbara Barbieri, Antonio Chirumbolo, and Gerardo Patriotta. 2019a. ‘Managing Knowledge in Organizations: A Nonaka’s SECI Model Operationalization’. *Frontiers in Psychology* 10. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.02730.

———. 2019b. ‘Managing Knowledge in Organizations: A Nonaka’s SECI Model Operationalization’. *Frontiers in Psychology* 10 (December): 2730. https://doi.org/10.3389/fpsyg.2019.02730.

Gaardboe, Rikke, and Tanja Svarre. 2018. ‘BUSINESS INTELLIGENCE SUCCESS FACTORS: A LITERATURE REVIEW’. *BUSINESS INTELLIGENCE SUCCESS FACTORS*, no. 1: 15.

Grossmann, Wilfried, and Stefanie Rinderle-Ma. 2015. *Fundamentals of Business Intelligence*. Springer.

Hooff, Bart van den, and Jan A. de Ridder. 2004. ‘Knowledge Sharing in Context: The Influence of Organizational Commitment, Communication Climate and CMC Use on Knowledge Sharing’. *Journal of Knowledge Management* 8 (6): 117–30. https://doi.org/10.1108/13673270410567675.

Ipe, Minu. 2003. ‘Knowledge Sharing in Organizations: A Conceptual Framework’. *Human Resource Development Review* 2 (4): 337–59. https://doi.org/10.1177/1534484303257985.

Jennex, Murray, and Lorne Olfman. 2003. ‘A Knowledge Management Success Model: An Extension of DeLone and McLean’s IS Success Model’. *Knowledge Management*, 12.

Keyes, Jessica. n.d. ‘Knowledge Management, Business Intelligence, and Content Management: The IT Practitioner’s Guide | Jessica Keyes | Download’. Accessed 10 May 2021. https://1lib.cz/book/2383671/7a143e?id=2383671&secret=7a143e.

Kuriakose, K. K., B. Raj, S. S. Murty, and P. Swaminathan. 2011. ‘Knowledge Management Maturity Model: An Engineering Approach’. In . https://www.semanticscholar.org/paper/Knowledge-management-maturity-model%3A-an-engineering-Kuriakose-Raj/a0b243fd561ab912930f4d1a791a8faf58cdf663.

Lee, Chei Sian, and Rujuta Kelkar. 2013. ‘ICT and Knowledge Management: Perspectives from the SECI Model’. *The Electronic Library* 31 (April). https://doi.org/10.1108/02640471311312401.

Liebowitz, Jay. 2019. *Strategic Intelligence: Business Intelligence, Competitive Intelligence, and Knowledge Management*. Taylor & Francis Group.

López-Sáez, Pedro, José Emilio Navas-López, Gregorio Martín-de-Castro, and Jorge Cruz-González. 2010a. ‘External Knowledge Acquisition Processes in Knowledge-intensive Clusters’. Edited by F. Javier Carrillo, K. Metaxiotis, and T. Yigitcanlar. *Journal of Knowledge Management* 14 (5): 690–707. https://doi.org/10.1108/13673271011074845.

———. 2010b. ‘External Knowledge Acquisition Processes in Knowledge-intensive Clusters’. Edited by F. Javier Carrillo. *Journal of Knowledge Management* 14 (5): 690–707. https://doi.org/10.1108/13673271011074845.

Martz, Benjamin, and Morgan M. Shepherd. 2003. ‘Testing for the Transfer of Tacit Knowledge: Making a Case for Implicit Learning’. *Decision Sciences Journal of Innovative Education* 1 (1):

41–56. https://doi.org/10.1111/1540-5915.00004.

Mohamad, Abdul Karim, Mailasan Jayakrishnan, and Mokhtar Mohd Yusof. 2022. 'Thriving Information System through Business Intelligence Knowledge Management Excellence Framework'. *International Journal of Electrical and Computer Engineering (IJECE)* 12 (1): 506. https://doi.org/10.11591/ijece.v12i1.pp506-514.

Muhammad, Gul, Jamaludin Ibrahim, Zeeshan Bhatti, and Ahmad Waqas. 2014. 'Business Intelligence as a Knowledge Management Tool in Providing Financial Consultancy Services'. *American Journal of Information Systems*, March, 8.

Nonaka, Ikujiro. 1991. 'The Knowledge-Creating Company'. *Harvard Business Review* 85 (January): 162-+. https://doi.org/10.1016/B978-0-7506-7009-8.50016-1.

———. 1994. 'A Dynamic Theory of Organizational Knowledge Creation'. *Organization Science* 5 (1): 14–37.

Nonaka, Ikujiro, and Noboru Konno. 1998. 'The Concept of "Ba": Building a Foundation for Knowledge Creation'. *California Management Review* 40 (3): 40–54. https://doi.org/10.2307/41165942.

Nonaka, Ikujiro, Ryoko Toyama, and Noboru Konno. 2000a. 'SECI, Ba and Leadership: A Uni®ed Model of Dynamic Knowledge Creation'. *Long Range Planning* 33.

———. 2000b. 'SECI, Ba and Leadership: A Unified Model of Dynamic Knowledge Creation'. *Long Range Planning* 33 (1): 5–34. https://doi.org/10.1016/S0024-6301(99)00115-6.

O'Dell, Carla, and C. Jackson Grayson. 1998. 'If Only We Knew What We Know: Identification and Transfer of Internal Best Practices'. *California Management Review* 40 (3): 154–74. https://doi.org/10.2307/41165948.

Plessis, Marina du. 2007. 'The Role of Knowledge Management in Innovation'. *Journal of Knowledge Management* 11 (4): 20–29. https://doi.org/10.1108/13673270710762684.

Pranjić, Goran. 2018. 'DECISION MAKING PROCESS IN THE BUSINESS INTELLIGENCE 3.0 CONTEXT'. *Ekonomska Misao* 2 (July): 603–19.

Ragsdale, John, and Judith Platz. 2017. 'TSIA Knowledge Management Maturity Model'. Technology Services Industry Association. 23 October 2017. https://www.tsia.com/Resources/TSIA-Knowledge-Management-Maturity-Model.

Rajteri, Irena Hribar. 2010. 'OVERVIEW OF BUSINESS INTELLIGENCE MATURITY MODELS' 15.

Rostami, Najibeh Abbasi. 2014. 'Integration of Business Intelligence and Knowledge Management – A Literature Review | Journal of Intelligence Studies in Business', November. https://ojs.hh.se/index.php/JISIB/article/view/95.

Rouhani, Saeed, Amir Ashrafi, Ahad Zare Ravasan, and Samira Afshari. 2016. 'The Impact Model of Business Intelligence on Decision Support and Organizational Benefits'. *Journal of Enterprise Information Management* 29 (1): 19–50. https://doi.org/10.1108/JEIM-12-2014-0126.

Sabherwal, Rajiv, and Irma Becerra-Fernandez. 2013. *Business Intelligence: Practices, Technologies, and Management*. John Wiley & Sons.

Shehabat, Issa Mahmoud, and Mohammad Berrish. 2021. 'Integration Between Knowledge Management and Total Quality Management in Jordanian Universities: Empirical Study'. Chapter. Research Anthology on Preparing School Administrators to Lead Quality Education Programs. IGI Global. 2021. https://doi.org/10.4018/978-1-7998-3438-0.ch062.

Shujahat, Muhammad, Saddam Rahim, Sammar Javed, M. Malik, T. Ramayah, and Junaid Ali. 2017. 'Strategic Management Model with Lens of Knowledge Management and Competitive Intelligence: A Review

Approach'. *VINE Journal of Information and Knowledge Management Systems* 47 (February): 55–93. https://doi.org/10.1108/VJIKMS-06-2016-0035.

Štrach, Pavel. 2007. 'Tvorba Výukových a Výzkumných Případových Studií'. *Acta Oeconomica Pragensia* 2007 (June): 22–36. https://doi.org/10.18267/j.aop.62.

Takahashi, Adriana Roseli Wünsch, and Luis Araujo. 2019. 'Case Study Research: Opening up Research Opportunities'. *RAUSP Management Journal* 55 (1): 100–111. https://doi.org/10.1108/RAUSP-05-2019-0109.

Xuan, V.N. 2020. 'Factors Affecting Knowledge Sharing in Enterprises: Evidence from Small and Medium Enterprises in Vietnam'. *Management Science Letters* 10 (2): 469–78. https://doi.org/10.5267/j.msl.2019.8.023.

Yin, Robert K. 2018. *Case Study Research and Applications: Design and Methods*. Sixth edition. Los Angeles: SAGE.

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Stevan Didijer
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Putting futures literacy and anticipatory systems at the center of entrepreneurship and economic development programs – A View from the UNESCO Co-chair in Anticipatory Systems for Innovation and New Ventures

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PURPOSE The UNESCO Chair of anticipatory systems for innovation and new venture creation at the University of New Brunswick is focused on helping improve economic opportunities largely for entrepreneurs from disadvantaged regions and from marginalized groups. Research activities are conducted but, the primary objective is to use the concepts of foresight thinking and anticipatory systems to help targeted groups improve their economic opportunities. The article provides details on the chairs activities and how they have contributed to economic improvement for both organizations and communities/regions.

SUMMARY Integrating futures thinking and anticipatory thinking into programs can help improve economic opportunities The UNESCO Chair's approach has helped improve economic opportunities, for organizational and municipalities/economic regions. It is hoped that the results can be used to help others bring this approach into their programs. Perhaps those running/part of entrepreneur/small business development programs, accelerators and incubators will see the University of New Brunswick (UNB) UNESCO program and may look at ways to include futures thinking and anticipatory systems thinking in their programs. Finally, the approach has helped cities/municipalities, perhaps those involved in regional economic development will integrate the Chairs approach.

KEYWORDS: innovation, UNESCO, economic opportunities, foresight

1. INTRODUCTION

The objective and purpose of the UNESCO Chair of Anticipatory Systems for Innovation and New Ventures at the University of New Brunswick is to help improve economic opportunities largely for entrepreneurs from disadvantaged regions and from marginalized groups. The chair is a chair of impact and practice, and while research activities are conducted, the primary objective of the chair is to use the concepts of foresight thinking and anticipatory systems to help the targeted groups improve their economic opportunities. The article provides details on the chairs activities and how they have contributed to economic improvement

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both at the organization level and the community/regional level.

The chair builds on the research and experiences of the two co-chairs, Dominic Blakely and Jonathan Calof, whose past work and research has resulted in a series of programs using futures thinking and anticipatory systems integrated within a broader program to help:

1) Start-ups and other small firms build more competitive and successful businesses
2) Cities, towns, municipal areas who are encountering economic difficulties create a better more prosperous future.

The program has also helped various government agencies in formulating economic based and other policies and programs but that has been a very secondary focus

The following article provides details on the structure of these programs and how both futures thinking and anticipatory systems are at the center of them.

The core program concept

At the core of both sets of programs are two fundamental concepts related to the chair objectives:

1) Future thinking: Any idea whether a new business idea, regional economic development plan or government policy will take time to come to fruition. Between idea generation (and research), decision making, implementation and then waiting an appropriate amount of time for the results to start showing, many years can pass. Therefore, it is important to think about policy, strategy, new products/services not within the context of the environment of today but a more distant future environment: What will this future environment look like and what strategies and policies will make sense for it? In the case of economic development, it is also what do you want your future to look like and how can you shape the environment to accomplish this.

2) Anticipatory thinking: Strategy and policy can only succeed if the external environment supports it. For example, customers must want the product/service; competitors need to react in a way that does not undermine the new product/service; government regulations must be consistent with it, and so forth. In a way this does involve futures thinking but it also encompasses concepts such as competitive intelligence, market research, environmental scanning, analytics and many more that are at the center of an anticipatory system (see Calof and Bishop 2020 for more on this).

Programs aimed at Entrepreneurs, small businesses, start-ups

The J Herbert Smith Centre at the University of New Brunswick offers several entrepreneurship programs:

1) **Summer Institute:** A three-month accelerator program for early-stage entrepreneurs. This program includes several courses (for example, marketing, finance, packaging etc.), mentorship and opportunities to make pitch presentations.
2) **Energia Ventures**: A three-month program for in seed and pre-seed stage startups in energy and energy related areas (for example smart grid and clean technology). The program is similar in design to the Summer Institute program.
3) **MTME (Masters of Technology Management and Entrepreneurship)**: A 12-month Master's program which requires that participants create a startup. Similar to the other programs, mentorship is provided along with a series of courses to help the participants understand both engineering at a master's level and the requirements for creating and running a successful business.

Consistent with the objectives of the UNESCO Chair, participants are largely from marginalized groups and from regions or countries that have economic challenges. The participants for the three programs in 2023 included: Atlantic Canada, Asia (Pakistan, India, Turkey, Iran and Iraq) and Africa (mainly

Nigeria). The largest proportion of participants came from Nigeria, India and Atlantic Canada.

These programs integrate futures thinking at the front end of the program. While entrepreneurs and start ups are eager to have their businesses succeed quickly, the programs direct participants to look at the temporal nature of their business. That is to realistically assess how much time it will take to develop the market ready version of their product or service, what time will they need to get regulatory approval, how much time to launch the product and how long will it take to be successful for them to justify the investment. This establishes, at the early stage of the program, a mindset which requires participants to think not of today but a future environment which in some cases will be greater than five years in the future.

Participants are then given a series of anticipatory system topics such as competitive intelligence, market research and sales. Core in these courses is the requirement to understand how the current and future industry participants will shape the future environment. To help accomplish this, program participants are introduced to several anticipatory tools, for example, timelining, back-casting, road mapping, stakeholder analysis, profiling and market assessment. There are also what would be considered non anticipatory or non futures thinking courses, such as packaging and Manufacturing outsourcing, Accounting/Finance, Human Resources, but even these are positioned in term of a view to a temporal point in the future and with an anticipatory lens. For example, in the accounting course, the entrepreneurs are tasked with developing future financial statements (forecasting) and challenged to justify them using anticipatory techniques. In stating what they expect revenues to be over the next five years, they are challenged with proving that the market will support it and that their assumptions on what the market would bear in terms of sales and product-market fit. The link between anticipatory systems and packaging is also reinforced in terms of understanding how the customers will react to the to the look and feel, the environmental impact, the viability and the professional nature as well as what competitors look like in the existing market – the message they will take away must be based on a future view.

The program includes a course looking at developing market insight using events which is anticipatory in nature and teaches them how to organize and to mine information at conferences, trade shows, and even parties. As each of the program participants deliver pitches of their company multiple times in their respective programs, this part of the program asks that they note the questions asked, who asked the question, their body language and therefore what underlies the question being asked or the comments made. They must learn to anticipate future problems based on the current comments of experts in the room, and start to build up response mechanisms to inculcate suggestions and feedback, not only into their pitches, but also their timelines, product/service features, team makeup and dynamics as well as key partners for successful product/service implementation.

Each program is subject to an internal review which includes a de-brief. Anecdotal evidence suggests that the program has been successful leading several successful businesses such as Grey Wolf Analytics, Potential Motors, Stash Energy Storage, CleanMeter and Koffee Beauty.

Why are futures thinking and anticipatory thinking so important for this kind of program? Many will read this section of the article and feel that the courses as described are similar to other entrepreneurship, startup programs: Finance/Accounting, Manufacturing, Market Research etc. So, what does the UNB Chairs approach add? The Co-chairs of the program have seen many business plans both as part of their training programs and as judges in start up competitions. These, in many cases are well researched and well written.

> Take the competitor part – many of these plans compare the product/service being developed to those of their competitors. Making a detailed assessment of the products on their competitor's website and theirs. The customer research frequently includes surveys of customers. The problem is that when their product/service is ready for market, the competitors will have launched new products or services. What is on a company's web page today will undoubtedly be different next year or the year after. Further what is on their webpages does not include the R&D they are currently working on. Similarly, what customers are saying they want today will likely change over the next few years. This is the dynamism of markets and why futures thinking and anticipatory thinking is so critical.

Programs aimed at regional economic development

Developed by Wayne Robinson (former Canadian diplomat), Roland Marcoux (facilitator) and Jonathan Calof, the regional economic development program was designed to provide community leaders with the skills needed to create an economic development plan. This program has been given to several municipalities in Canada (that are encountering economic problems) as well as to cities in other parts of the world. Conceptually, the program brings together community leaders (heads of the major employers in the region), government and political officers, association executives, academics and others in the region whose cooperation is needed to successfully develop and executive on a regional economic development plan.

The first step in this six-month program is instilling futures thinking. Under the guidance of an expert facilitator, the program asks participants to develop a shared vision of what they want their community to look like in the next 20 years. This part of the process begins with the development of a shared vision.

Here is an example from one of the programs: "By 20XX (name of the community) is a growing thriving hub of (name of province). New families are moving in and business is expanding. Quality education and business opportunities are valued and available. This regions success is used as an economic development model for the rest of Canada"

This process of building a shared visions is consistent with the definition of foresight in ForLearn, which the European Foresight Platform (EFP) developed under the auspices of the European commission:

> "Foresight is a systematic, participatory, future-intelligence-gathering and medium-to-long-term vision-building process aimed at present-day decisions and mobilising joint actions" (ForLearn 2023).

This vision statement since it was developed by the community leaders serves a focal point for the rest of the program.

The next step in this process is to go backwards – from the future vision to the present, looking at what will be required for this vision to happen. At this point, the concept of competitive advantage is introduced. Whether applied to a company or to a community for the vision to happen, you need appropriate resources and a competitive advantage that can be leveraged. Defining what the community's competitive advantage is and learning about how to assess it is key to the program success. The community leaders are asked to identify what their true competitive advantage is, or what it will need to be, for the vision to become reality. In one community it was proximity to the USA border and, equally important, that it was located on a main trucking route. Another community had difficult to find trees that form the base of quality furniture. In another community, the competitive advantage was weather related.

With knowledge of the competitive advantage (existing or to be developed) and the vision that comes from it, the discussion once again goes to futures thinking and anticipatory thinking as well. Issue analysis is used to identify the major concerns that must be addressed for the vision to be attained within the context of competitive advantage. What resources are needed? Which stakeholders will the plan need to work with?

It is at this point that the anticipatory approach is introduced. Participants are taught about competitive intelligence and then challenged in groups to develop the intelligence needed to address the issues that stand in the way of attaining the vision. In one community they recognized that one of the issues to attract people and business was that they had a dated, poorly functioning hospital - a new hospital was needed. The group that looked at this used competitive intelligence to develop a plan that it hoped would lead to approval by the province for a new hospital and subsequently it getting built. Getting a hospital is a very lengthy process which requires addressing concerns of many stakeholders. It takes many years for the decision to be made, let alone for construction to be completed. This group developed incredible intelligence on the process as they were able to call upon various community members who had knowledge of this process (once again integrated) and they got their hospital approved and built.

Finally, with the vision established and the competitive advantage identified, the issues identified and the intelligence to address those issues developed by the participants, they now develop their community action plan which is presented to the community at large.

Some of the community economic development programs had comprehensive program reviews. For one of the programs participants were asked if the process (the training itself) provided "positive gains in community capacity building knowledge and skills (including facilitation, competitive business intelligence, and networking)?" The response to this question was an overwhelming yes (95% of program participants responded yes to this question). To validate that the program had produced positive economic development results, participants were asked if the creation of the plan had contributed to the economic development of the region. 90% of program participants responded yes to this question. Given that one of the benefits of the program was to help the participants also improve their business/professional opportunities, participants were also asked if this had happened as a direct result of their involvement of the process and 60% of program participants responded yes. More, information on the evaluation of these programs is in Calof (2017).

Futures thinking and anticipatory systems single course approach.

The integrated programs mentioned above embed future thinking and anticipatory thinking within a larger program (entrepreneurship training or community economic development). The idea in the larger program is to provide more than just anticipatory and foresight training but to provide additional training/knowledge to help attain their objectives. In both programs, anticipatory systems and foresight thinking are integrated not only in single specific courses (for example competitive intelligence) but also by reinforcing the concepts in other parts of the program (for example futures thinking within the accounting course). The UNESCO co-chairs have found this approach to be very effective in creating impact. The program has also provided future think and anticipatory systems training with a single course approach. Competitive intelligence as a stand-alone course has been provided by the chairs throughout Atlantic Canada. There have been several varieties of these courses:

1. **Introduction to competitive intelligence:** This a one to two-day course that introduces participants to both anticipatory systems in general and competitive intelligence specifically.
2. **Specialized competitive intelligence:** These are generally introduction to competitive intelligence courses with a specialization added in. Two examples of this are the event intelligence course and the project intelligence course. The event intelligence course give participants an introduction to both competitive intelligence in general and how to develop intelligence at events. Several of the deliveries of this course training have been given to organizations going to the same event. The course is designed to teach the participants how to use competitive intelligence approaches to

maximize their opportunities at the event (see Calof 2023 for more on this topic). Another course is project intelligence in which participants learn about competitive intelligence and then conduct an intelligence project relevant to their organization with mentorship from the trainers.

3. "**Topic" training with competitive intelligence embedded in it**: These are one or multiple day programs helping participants make better decisions. The topic of the seminar is not intelligence but intelligence concepts are brought into various parts of the program. An example of this was a program designed to help exporters pick the correct distributors and agents. While the program was not a competitive intelligence program, in giving the training to the organizations, use was made of competitive intelligence techniques as a way to assist with distributor and agent selection. This was also the approach taken in a one-day seminar on how to chose the right export market and within an innovation program as well. In all these cases, competitive intelligence was brought into parts of the program to give participants a tool kit that can help with the seminar topic (picking the right market, the right agent/distributor, being innovative).

The Calof (2017) article also provides performance assessments of these programs which have been very positive in terms of creating economic opportunities for participants.

Other activities of the Chair

As the purpose of the chair as mentioned is impact and practice, other activities have followed this objective. First, an annual conference has been held. This conference has focused largely on futures thinking and future environments. For example, the last conference had Riel Miller (past head of Futures Literacy at UNESC) and Martin Calnan (current UNESCO Chair for Futures Literacy in Finance – Ecole des Points Business School) as speakers and panelists. Publications have also followed the chair objectives and while there has been several academic publications under the chair (for example Calof, Soilen, Klavans, Soilen , Abdulkader and El Moudni 2022 and Hakmaoui, Oubrich, Calof and El Ghazi 2022)., the focus has been on publications which will help organizations develop futures thinking and anticipatory capabilities. The "Gaining Market Insights from Events" (Calof 2021), is a good example of this. The book consistent with the chair focus is on application and practice and is available to download for free. As well, a current book is in process looking at Big Data and Analytics for international decisions. This will also be available for free to download.

Conclusions and areas for potential impact

This article has described an approach to regional economic development and helping entrepreneurs and small business develop economic opportunities. The activities of the program have benefited from the support of University of New Brunswick and several other Universities, government and corporate funding, Elements of the program have also been delivered in India, South Africa and Morocco thanks to partnerships from several Universities who supported the UNB Chair nomination. Expansion into Nigeria is also being considered with several Nigerian institutional requests to bring the program there. The internationalization of the program has taken two forms – participants physically or virtually attending the University of New Brunswick program or the local institution doing most of the program with UNB providing the futures thinking and anticipatory thinking course and concepts.

Those who read this article should see how integrating futures thinking and anticipatory thinking into programs can help improve economic opportunities. Perhaps some reading this will consider bringing this approach into their programs. As well, there are many entrepreneur programs operating around the world. As one example of this, the University of New Brunswick is part of the Global Accelerator Network (GAN), a global community linking 128 accelerators. Perhaps those running accelerators and incubators will see the UNB UNESCO program and look at ways to include futures thinking and anticipatory systems thinking in their programs. Finally, as the approach has helped cities/municipalities, perhaps those involved in regional economic development will integrate the Chairs approach.

Note: The ideas and opinions expressed in this article are those of the author and do not necessarily reflect the views or official position of UNESCO.

REFERENCES

Calof, J. (2017) 'Reflections on the Canadian government in competitive intelligence – programs and impacts', *foresight*, 19(1), pp. 31–47.

Calof, Jonathan.(2021). '*Gaining Market Insight from Events: A Lifetime Journey*.' SCIP, Virginia. Downloadable from https://www.scip.org/page/GainingMarketInsightsfromEvents

Calof, J. and Bishop, P. (2020) 'Guest editorial', *foresight*, 22(5/6), pp. 529–532.

Calof, Marcoux, Robinson (2010). 'Regional and Economic Development Planning: An exciting role for competitive intelligence. *Competitive Intelligence Magazine*, 32-39, Volume 13, Number 9.

Calof, J. *Soilen, K, Klavans R, Abdulkader B and El Moudni, I.* (2022) 'Understanding the structure, characteristics, and future of collective intelligence using local and global bibliometric analyses', *Technological Forecasting and Social Change*, 178

European Foresight Platform (no date) '*What is foresight?*,' *European Foresight Platform*. Available at: http://foresight-platform.eu/community/forlearn/what-is-foresight/ (Accessed: 11 May 2023).

Hakmaoui, A. *et al.* (2022) 'Towards an anticipatory system incorporating corporate foresight and competitive intelligence in creating knowledge: A longitudinal Moroccan bank case study', *Technological Forecasting and Social Change*, 174, p. 121-139.

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The Role of Marketing Intelligence in Improving the Efficiency of the Organization: An Empirical Study on Jordanian Hypermarkets

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ABSTRACT In today's competitive business environment, marketing intelligence plays a crucial role in improving the efficiency of organizations in hypermarkets in Jordan. The purpose of this study is to explore the role of marketing intelligence in improving the efficiency of hypermarkets in Jordan. The paper discussed the concept of marketing intelligence, the importance of marketing intelligence in hypermarkets, the benefits of marketing intelligence, and the challenges that hypermarkets may face while using marketing intelligence. The study conducted on a convenience sample consisting of 256 respondents showed that there is an impact of market research, competition intelligence, and consumer intelligence as the main dimensions of marketing intelligence on the efficiency of hypermarkets in Jordan. While there was no effect of the dimensions of marketing analytics and product intelligence on the efficiency of hypermarkets in Jordan. The study also provided a set of important recommendations for the companies surveyed.

KEYWORDS: marketing intelligence, market research, competition intelligence, consumer intelligence, marketing analytics, product intelligence, organizational efficiency, Hypermarkets, Jordan.

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1. INTRODUCTION

Marketing intelligence gathers, analyses, and interprets data about the market, customers, competitors, and environment to make informed decisions. Identifying market opportunities, understanding consumer behaviour, and developing effective marketing strategies are all crucial marketing functions (Gottfried, Hartmann, & Yates, 2021). Due to the growing number of players in the Jordanian market, hypermarkets face intense competition (Al-Hawary & Obiadat, 2021). Marketing intelligence is therefore essential for hypermarkets to gain a competitive edge and improve their efficiency (Mulekye, 2018). The dimensions of marketing intelligence which be involved in this study: Market Research which addresses gathering and analyzing data on customers, competitors, and market trends. and competitive intelligence that illustrates monitoring and analyzing the actions and strategies of competitors (Lies, 2019). In addition, consumer Intelligence discusses understanding the needs, preferences, and behaviour of customers (Mogaji, Soetan, & Kieu, 2021). And product Intelligence that analyzes product and service features, benefits, and limitations. Moreover, marketing analytics uses statistical methods and models to analyze data and make informed decisions (Birjali, Kasri, & Beni-Hssane, 2021). On the other hand, the dependent variables include; Operational Efficiency, financial Efficiency, human Resource Efficiency, customer Efficiency, and Innovation Efficiency, which will be measured collectively (Madanat & Khasawneh, 2018). The researcher's selection of hypermarkets in Jordan came because of its wide range of products, which in turn tend to attract a larger segment of consumers. Thus, the controversy remains related to the reality of the efficiency of these markets in terms of their human resources and operational efficiency, in addition to innovation efficiency (Shao, Hu, Cao, Yang, & Guan, 2020). This opens the way for the current study to research the main issue, for which the study questions were developed as follows:

what is the role of Market Research in improving the efficiency of Hypermarkets in Jordan?
what is the role of Competitive Intelligence in improving the efficiency of Hypermarkets in Jordan?
what is the role of Consumer Intelligence in improving the efficiency of Hypermarkets in Jordan?
what is the role of Product Intelligence in improving the efficiency of Hypermarkets in Jordan?
what is the role of Marketing Analytics in improving the efficiency of Hypermarkets in Jordan?

2. LITERATURE REVIEW

2.1 Importance of Marketing Intelligence in Hypermarkets

The importance of marketing intelligence for hypermarkets in Jordan lies in the fact that it helps them to understand the market and how consumers behave (Al-Adamat, et al., 2023). To develop products and services that meet the needs of their customers, hypermarkets can use marketing intelligence to identify their needs and preferences (Mandal, 2017). In addition, marketing intelligence can help hypermarkets identify their competitors' strengths and weaknesses, allowing them to develop strategies to gain a competitive advantage (Keiningham, et al., 2020). By using marketing intelligence, hypermarkets can make informed decisions about pricing, promotion, and distribution, which can help them to improve their efficiency (Yoseph, 2023).

2.2 Benefits of Marketing Intelligence

Marketing intelligence provides several benefits to hypermarkets in Jordan. Firstly, it helps hypermarkets to identify market opportunities and develop effective marketing strategies (Bader, Al-Alwan, & Twaissi, 2023). Secondly, marketing intelligence helps hypermarkets to understand the needs and preferences of their customers, which can help them to improve customer satisfaction and loyalty

(Ismaeel & Alzubi, 2020). Thirdly, marketing intelligence helps hypermarkets to identify the strengths and weaknesses of their competitors and develop strategies to gain a competitive advantage (Mandal, 2022). Finally, marketing intelligence helps hypermarkets to make informed decisions about pricing, promotion, and distribution, which can help them to improve their efficiency (Kumar, Leone, Aaker, & Day, 2018).

2.3 Challenges of Marketing Intelligence in Hypermarkets

Although marketing intelligence provides several benefits, hypermarkets in Jordan may face several challenges while using marketing intelligence (Maria, Pusriadi, & Darma, 2020). Firstly, hypermarkets may face challenges in gathering accurate and reliable data due to the complex nature of the market and the diverse needs of customers (Dash, McMurtrey, Rebman, & Kar, 2019). Secondly, hypermarkets may face challenges in analyzing and interpreting data due to the lack of skilled professionals in marketing intelligence (Rojas-Mendez, Parasuraman, & Papadopoulos, 2017). Finally, hypermarkets may face challenges in implementing marketing intelligence in their decision-making process due to the resistance to change and lack of awareness about the benefits of marketing intelligence (Johnstone & Tan, 2015).

2.4 Hypermarkets in Jordan

A hypermarket is a large retail store combining a supermarket and a department store (Ferreira & Ferreira, 2018). Many countries have hypermarkets, especially in developing markets where the middle class and urbanization are growing. Jordan's hypermarkets face some challenges, including competition from traditional retailers, high operating costs, cultural preferences, and regulations (Elasrag, 2016). As well as increasing consumer demand, modernizing the retail sector, diversifying products and services, and expanding to new locations, hypermarkets also present some opportunities (Stanciu, Vîrlănuță, Vochin, Ionescu, & Antohi, 2019). We examined the following Jordanian hypermarkets: **Carrefour**: A French multinational retailer operating 11 hypermarkets in Jordan offering food, household goods, electronics, clothing, and more (Du & Salameh, 2019). In 2019, Carrefour held a 28% market share in Jordan, making it one of the country's leading hypermarkets (Yousef, L. S., 2021). Jordanian retailer **Safeway** operates nine hypermarkets in Jordan, offering food, household goods, electronics, clothing, and more. The Safeway hypermarket was founded in 1998 and is one of the oldest in Jordan (Al-Shaikh, 2020). Jordanian retailer **Cozmo** operates 7 hypermarkets in Jordan that sell food, household goods, electronics, clothing, and more. Cozmo is one of the most innovative hypermarkets in Jordan, introducing online shopping, loyalty programs and home delivery services (Migdadi & Abdel-Rahman, 2020).

2.5 Hypotheses Development

H1: Marketing intelligence (Market Research, Competitive Intelligence, Consumer Intelligence, Product Intelligence, and Marketing Analytics) play a significant and positive role in improving the efficiency of Hypermarkets in Jordan. From this hypothesis, the following sub-hypotheses were developed:

H1-1: Market Research plays a significant and positive role in improving the efficiency of Hypermarkets in Jordan

H1-2: Competitive Intelligence plays a significant and positive role in improving the efficiency of Hypermarkets in Jordan

H1-3: Consumer Intelligence plays a significant and positive role in improving the efficiency of Hypermarkets in Jordan

H1-4: Product Intelligence plays a significant and positive role in improving the efficiency of Hypermarkets in Jordan

H1-5: Marketing Analytics play a significant and positive role in improving the efficiency of Hypermarkets in Jordan

The conceptual research model shown in Fig. 1 was developed with the support of research hypotheses. The aim of this study is to offer a more thorough knowledge of how marketing intelligence affects organizational efficiency for hypermarkets in Jordan.

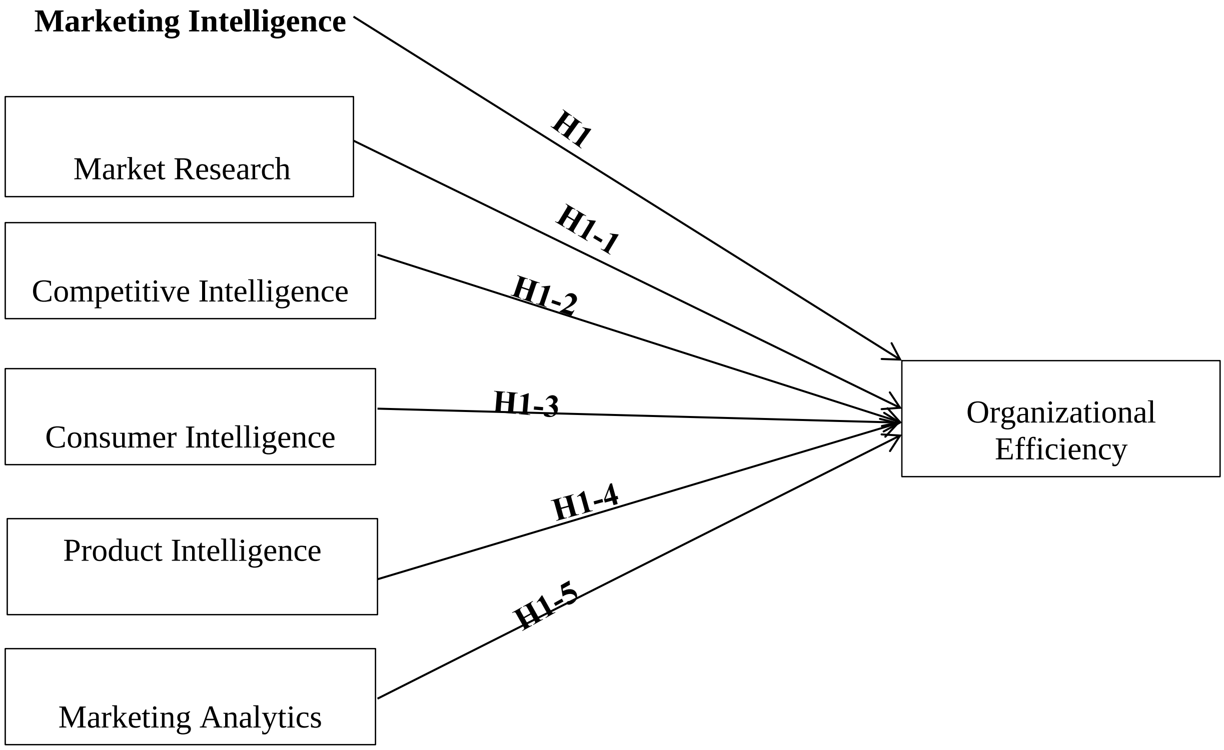

Figure 1. Research Model

3. RESEARCH METHODOLOGY

3.1 Research strategy

In this study, the organizational efficiency of Jordan's hypermarkets was quantitatively analyzed using a questionnaire. The results are more accurate as they are reflective of the population as a whole because a sizable sample size was gathered using a survey methodology. Using a convenience sample method, respondents are selected from each of the 27 hypermarkets in Jordan that are being studied. According to (Pace, 2021), a non-probability sampling technique called convenience sampling involves choosing participants based on their availability and openness to participate in the study. A sample size calculator was used to determine the sample size, and it was determined that 256 participants were required for sufficient statistical power (a 95% confidence level and a 5% margin of error).

3.2 Data gathering technique

The data were collected via an online survey that was self-administered. For the research of hypermarkets, survey questions were created to gauge organizational effectiveness and marketing intelligence. To create the survey questions, existing scales and validated measures from the literature were consulted. To ensure that the questions were clear and understandable, the survey was pretested on a small sample of customers.

3.3 Data analysis

The primary data gathered for the study through the questionnaire was analyzed using the Statistical Package for Social Sciences (SPSS), where percentages, frequencies, arithmetic averages, and standard deviations were calculated for the various questionnaire items to display, tabulate, and read the most crucial features and characteristics of the study population in accordance with the statistical tests utilized for this study's nature and goals were: Cronbach alpha test (Reliability): to make sure that the research tool is stable (Amirrudin, Nasution, & Supahar, 2021). Simple regression test: To test hypotheses by building an F-test and utilizing it to quantify the relationship between the independent and dependent factor variables. Multiple regression analysis: To determine the role of marketing intelligence that effect organizational efficiency levels (Saputra, F., 2022).

3.4 Ethical Considerations

The conduct of this study has been conducted under stringent ethical guidelines. Each participant will voluntarily give their consent after being advised of their right to withdraw at any time. The participant-provided data will be kept confidential and used only for the purpose of the study.

4. FINDINGS

4.1 Tool's stability

The internal consistency coefficient, which was determined using the Cronbach alpha equation, was calculated to ensure the tool's stability. Its values for marketing intelligence as a whole were (0.79), organizational efficiency as a whole was (0.83), and the tool as a whole was (0.84). as shown in table 1.

Table 1. Cronbach Alpha Coefficients for study variables

Variables	Cronbach Alpha
Marketing intelligence	0.794
Organizational Efficiency	0.822
Measurement as a whole	0.838

4.2 Hypothesis Testing

H1: Marketing intelligence (Market Research, Competitive Intelligence, Consumer Intelligence, Product Intelligence, and Marketing Analytics) play a significant and positive role in improving the efficiency of Hypermarkets in Jordan.

Table 2. represents the regression model summary, Table 3 shows the ANOVA test, and Table 4 shows all dependent variables were statistically significant (α = 0.01). In the current study, multiple regression analyses have been conducted for examining the impact of marketing intelligence on the organizational efficiency.

Table 2. Regression Model Summary.

Model	R	R^2	Adjusted R^2	Std. Error of the Est.	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.902[a]	.813	.810	.221	.813	163.462	13	243	.000

a Predictors: (Constant), competitive intelligence, product intelligence, market research, marketing analytics, consumer intelligence

Table 3. ANOVA[b].

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	91.813	13	7.063	163.462	.000[a]
	Residual	13.843	243	.057		
	Total	105.656	256			

a Predictors: (Constant), competitive intelligence, product intelligence, market research, marketing analytics, consumer intelligence
b Dependent variable: organizational efficiency

Table 4. Coefficients[a].

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.467	.086		5.490	.000		
OE	Operational efficiency	.051	.024	.060	2.302	.032	.46	2.19
FE	financial Efficiency	.007	.030	.010	.301	.802	.23	4.41
HRE	human Resource Efficiency	-.012	.032	-.015	-.348	.811	.23	4.45
CE	customer Efficiency	.081	.024	.131	3.362	.002	.310	3.22
IE	Innovation Efficiency	-.032	.020	-.061	-1.502	.141	.30	3.3
MR	market research	.113	.028	.121	2.77	.006	.250	3.97
CI	competitive intelligence	.178	.029	.228	6.741	.000	.39	2.57
PI	product intelligence	-.013	.033	-.018	-.405	.69	.24	4.22
CsI	consumer intelligence	.209	.038	.240	5.681	.000	.25	3.90
MA	marketing analytics	-.016	.021	-.026	-.902	.37	.54	1.85

a Dependent variable: organizational efficiency

$Reg.Model$

$$Y = 0.467 + 0.051OE + 0.007FE - 0.012HRE + 0.081CE - 0.032IE + 0.113MR + 0.178CI - 0.013PI + 0.209CsI - 0.016MA$$

Partial Hypothesis

H1-1: Market Research plays a significant and positive role in improving the efficiency of Hypermarkets in Jordan

Market research's impact on the efficiency of Jordan's hypermarkets was tested with a simple regression analysis. Table (5) shows this.

Table 5. Impact of market research on the organizational efficiency for Hypermarkets in Jordan

	R	R^2	Beta	F	Sig.
Organizational Efficiency	.570	.325	.570	41.862	.000

According to Table (5), there is a positive relationship between market research and the efficiency of the organization. The statistical analysis showed that market research explained 0.325 of the variation in the organization's efficiency, with an "F" value of 41.862 and a statistical significance of 0.000, which is significant at the 0.05 level of significance. Thus, the partial hypothesis is accepted.

H1-2: Competitive Intelligence plays a significant and positive role in improving the efficiency of Hypermarkets in Jordan.

A simple regression analysis was used to test the impact of competitive intelligence on Jordan's hypermarkets' efficiency. Table 6 shows this.

Table 6. Impact of competitive intelligence on the organizational efficiency for Hypermarkets in Jordan

	R	R^2	Beta	F	Sig.
Organizational Efficiency	.484	.235	.484	26.655	.000

According to Table 6, there is a positive relationship between competitive intelligence and the efficiency of the organization. The statistical analysis revealed that competitive intelligence explained 0.235 of the variation in the organization's efficiency, with an "F" value of 26.655 and a statistical significance of 0.000, which is significant at the 0.05 level of significance. Therefore, the partial hypothesis is accepted.

H1-3: Consumer Intelligence plays a significant and positive role in improving the efficiency of Hypermarkets in Jordan

In order to evaluate the impact of Consumer Intelligence on Jordan's hypermarkets' efficiency, a simple regression analysis was used. This is shown in Table 7.

Table 7. Impact of consumer intelligence on the organizational efficiency for Hypermarkets in Jordan

	R	R^2	Beta	F	Sig.
Organizational Efficiency	.422	.178	.422	18.879	.000

According to Table 7, there is a positive correlation between the efficiency of the organization and consumer intelligence, as evidenced by the statistically significant value of "F" of 18.879 and a significance level of 0.000, which supports the partial hypothesis. Additionally, Consumer intelligence was found to account for 0.178 of the variation in the organization's efficiency.

H1-4: Product Intelligence plays a significant and positive role in improving the efficiency of Hypermarkets in Jordan

The impact of product intelligence on Jordan's hypermarkets' efficiency was assessed using a simple regression analysis. According to Table 8, this is the case.

Table 8. Impact of product intelligence on the organizational efficiency for Hypermarkets in Jordan

	R	R^2	Beta	F	Sig.
Organizational Efficiency	.022	.000	.022	.041	.840

Table 8 indicates that there is no significant positive relationship between the intelligence of the product and the efficiency of the organization. The statistical analysis revealed that the intelligence of the product explained 0.000 of the variation in the organization's efficiency, with an "F" value of 0.041 and a statistical significance of 0.840, which is not significant at the 0.05 level of significance. Therefore, the partial hypothesis is rejected.

H1-5: Marketing Analytics play a significant and positive role in improving the efficiency of Hypermarkets in Jordan.

A simple regression analysis was implemented for assessing the effect of marketing analytics on the efficiency of

Jordan's hypermarkets. This appears to be the scenario, as shown in Table 9.

Table 9. Impact of marketing analytics on the organizational efficiency for Hypermarkets in Jordan

	R	R^2	Beta	F	Sig.
Organizational Efficiency	.163	.027	.163	2.389	.126

Based on Table 9, it can be concluded that there is no positive correlation between the efficiency of the organization and marketing analytics. This is supported by the statistically insignificant value of "F" of 2.389, and a significance level of 0.126, which fails to meet the level of significance ($\alpha \leq 0.05$). This suggests that the hypothesis partial is rejected and Marketing analytics only accounts for 0.027 of the variance in the efficiency of the organization.

5. DISCUSSION

This research looked into how marketing intelligence affects hypermarket efficiency in Jordan. consumer intelligence, competitive intelligence and market research were shown to have the greatest impact on the organization to improve hypermarket's efficiency based on the study's findings, and this result agrees with (Alasiri & Salameh, 2020). The results show there is no impact of marketing analytics and product intelligence on the hypermarket's efficiency in Jordan. this may be due to the limited use of analytics; Thus, this outcome is consistent with the study by Bader, Al-Alwan, and Twaissi (2023). The researcher found that hypermarkets in Jordan are not fully utilizing marketing analytics and product intelligence tools to the extent that they could be. Without proper implementation and analysis of these tools, their potential benefits may not be fully realized. In addition, cultural and societal factors; there may be cultural and societal factors unique to Jordan that impact the effectiveness of marketing analytics and product intelligence, which was covered in the study by Di Vaio, et, al., (2020) as a literature review. For example, consumer preferences and behaviours may be different, making it more challenging to accurately predict demand and consumer behaviour through data analysis. Moreover, Hypermarkets in Jordan may be facing intense competition, making it challenging to differentiate themselves through data-driven insights alone. Other factors such as pricing, product selection, and customer service may be more critical to success in the Jordanian market. Finally, hypermarkets in Jordan may not have the necessary resources, such as skilled personnel or advanced technology, to fully leverage marketing analytics and product intelligence tools. As a result, the potential benefits of these tools may not be fully realized, and this is what agrees upon Alawamleh, et, al., (2022).

In conclusion, marketing intelligence plays a crucial role in improving the efficiency of hypermarkets in Jordan. Hypermarkets can use marketing intelligence to identify market opportunities, understand consumer behavior, and develop effective marketing strategies according to Jordao, et, al., (2017). Marketing intelligence provides several benefits to hypermarkets, including improved customer satisfaction, increased loyalty, and competitive advantage, in light of what was stated in the study of Chitty, Ward, & Chua (2007). However, hypermarkets may face several challenges while using marketing intelligence, including the lack of reliable data, lack of skilled professionals, and resistance to change, according to Najm & Manasrah, (2017). Therefore, hypermarkets need to invest in marketing intelligence to gain a competitive advantage and improve their efficiency, from the perspective of the researcher.

By implementing the following recommendations, hypermarkets in Jordan can effectively use marketing intelligence to improve their efficiency, better understand their customers and competitors, and

ultimately increase their competitiveness in the market.
- Hypermarkets in Jordan should invest in marketing intelligence tools to better understand their customers, competitors, and market trends. These tools could include data analytics software, social media monitoring tools, or market research firms.
- Analyzing competitor activity can help hypermarkets in Jordan stay competitive by identifying potential threats and opportunities. This could include monitoring competitor pricing strategies, product offerings, and marketing campaigns.
- Hypermarkets in Jordan should collect and analyze customer feedback, both online and in-store, to better understand customer needs and preferences. This information can be used to improve product offerings, customer service, and overall shopping experience.
- develop targeted marketing campaigns that resonate with their target audience. This could include targeted social media ads, email marketing campaigns, or in-store promotions.

REFERENCES

Al-Adamat, A. M., Alkhawaldeh, M. I., Mansour, S. S., Eldahamsheh, M. M., Mohammad, A. A., Alshura, M. S., & Al Kurdi, D. B. (2023). The Effect of Electronic Marketing on Customer Satisfaction of the Insurance Companies in Jordan. In *The Effect of Information Technology on Business and Marketing Intelligence Systems. Studies in Computational Intelligence, vol 1056* (pp. 2249–2264). Cham: Springer International Publishing.

Alasiri, M. M., & Salameh, A. A. (2020). The impact of business intelligence (BI) and decision support systems (DSS): exploratory study. *International Journal of Management, 11(5)*, 1001-1016.

Alawamleh, M., Al-Hussaini, M., & Bani Ismail, L. (2022). Open innovation in the food industry: trends and barriers—a case of the Jordanian food industry. *Journal of Global Entrepreneurship Research*, 1-12.

Al-Hawary, S. I., & Obiadat, A. A. (2021). Does mobile marketing affect customer loyalty in Jordan?. *International Journal of Business Excellence, 23(2)*, 226-250.

Al-Shaikh, M. S. (2020). The effect of shopping centers on consumer buying decision for consumer goods-afield study on safeway Amman-Jordan. *International Journal of Scientific & Technology Research, 9(1)*, 2292-2299.

Amirrudin, M., Nasution, K., & Supahar, S. (2021). Effect of variability on Cronbach alpha reliability in research practice. *Jurnal Matematika, Statistika dan Komputasi, 17(2)*, 223-230.

Bader, D., Al-Alwan, M., & Twaissi, N. (2023). Big data and sustainable supply chain management of hypermarkets in Jordan: An experimental study using structural equation modeling approach. *Uncertain Supply Chain Management, 11(3)*, 1111-1120.

Birjali, M., Kasri, M., & Beni-Hssane, A. (2021). A comprehensive survey on sentiment analysis: Approaches, challenges and trends. *Knowledge-Based Systems, 226*, 107134.

Chitty, B., Ward, S., & Chua, C. (2007). An application of the ECSI model as a predictor of satisfaction and loyalty for backpacker hostels. *Marketing Intelligence & Planning, 25(6)*, 563-580.

Dash, R., McMurtrey, M., Rebman, C., & Kar, U. K. (2019). Application of artificial intelligence in automation of supply chain management. *Journal of Strategic Innovation and Sustainability, 14(3)*, 43-53.

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research, 121*, 283-314.

Du, Y., & Salameh, E. (2019). MAF Carrefour Jordan: management control systems at an early-stage retail company. *Emerald Emerging Markets Case Studies, 9(3)*, 1-19.

Elasrag, H. (2016). *Halal industry: Key challenges and opportunities*. Egypt: ISBN: 153002997X, 9781530029976.

Ferreira, J., & Ferreira, C. (2018). Challenges and opportunities of new retail horizons in emerging markets: The case of a rising coffee culture in China. *Business Horizons, 61(5)*, 783-796.

Gottfried, A., Hartmann, C., & Yates, D. (2021). Mining open government data for business intelligence using data visualization: a two-industry case study. *Journal of Theoretical and Applied Electronic Commerce Research, 16(4)*, 1042-1065.

Ismaeel, B., & Alzubi, M. M. (2020). The impact of marketing intelligence on the market share of the Jordanian Commercial Banks. *Suntext Review Of Economics And Business, 1(3)*, 1-8.

Johnstone, M. L., & Tan, L. P. (2015). An exploration of environmentally-conscious consumers and the reasons why they do not buy green products. *Marketing Intelligence & Planning*, 804-825.

Jordão, I. L., Souza, M. T., Oliveira, J. H., & Giraldi, J. D. (2017). Neuromarketing applied to consumer behaviour: an integrative literature review between 2010 and 2015. *International Journal of Business Forecasting and Marketing Intelligence, 3(3)*, 270-288.

Keiningham, T., Aksoy, L., Bruce, H. L., Cadet, F., Clennell, N., Hodgkinson, I. R., & Kearney, T. (2020). Customer experience driven business model innovation. *Journal of Business Research, 116*, 431-440.

Kumar, V., Leone, R. P., Aaker, D. A., & Day, G. S. (2018). *Marketing research*. John Wiley & Sons.

Lies, J. (2019). Marketing intelligence and big data: Digital marketing techniques on their way to becoming social engineering techniques in marketing. *International Journal of Interactive Multimedia and Artificial Intelligence, 5(5)*, 134-144.

Madanat, H. G., & Khasawneh, A. S. (2018). Level of Effectiveness of Human Resource Management Practices and Its Impact on Employees' Satisfaction in The Banking Sector of Jordan. *Journal of Organizational Culture, Communications and Conflict, 22(1)*, 1-19.

Mandal, P. C. (2017). Customer databases and database marketing: roles in relationship marketing. *International Journal of Business Forecasting and Marketing Intelligence, 3(3)*, 327-336.

Mandal, P. C. (2022). Marketing information and marketing intelligence for customer insights. *International Journal of Business Excellence, 28(1)*, 18-31.

Maria, S., Pusriadi, T., & Darma, D. C. (2020). Marketing intelligence: Benefits and implementation of its business. *Problems of Management in the 21st Century, 15(2)*, 92-99.

Migdadi, Y. K., & Abdel-Rahman, E. H. (2020). The impact of grocery retail superstores location on the customer's perceived quality of servicescape in Jordan. *Quality Management Journal, 27(2)*, 120-132.

Mogaji, E., Soetan, T. O., & Kieu, T. A. (2021). The implications of artificial intelligence on the digital marketing of financial services to vulnerable customers. *Australasian Marketing Journal, 29(3)*, 235–242.

Mulekye, M. M. (2018). *Sources of Supply Market Intelligence in Strategic Sourcing Among Supermarkets in Kenya: a Case Study of Tuskys Supermarket.* Doctoral dissertation, university of nairobi.

Najm, A., & Manasrah, A. K. (2017). The effect of talent management on organizational performance: applied study in Jordanian banks. *Review of Applied Socio-Economic Research, 13(1)*, 36-51.

Pace, D. S. (2021). Probability and non-probability sampling-an entry point for undergraduate researchers. *International Journal of Quantitative and Qualitative Research Methods, 9(2)*, 1-15.

Rojas-Mendez, J. I., Parasuraman, A., & Papadopoulos, N. (2017). Demographics, attitudes, and technology readiness: A cross-cultural analysis and model validation.

Marketing Intelligence & Planning, 35(1), 18-39.

Saputra, F. (2022). Analysis Effect Return on Assets (ROA), Return on Equity (ROE) and Price Earning Ratio (PER) on Stock Prices of Coal Companies in the Indonesia Stock Exchange (IDX) Period 2018-2021. *Dinasti International Journal of Economics, Finance & Accounting, 3(1)*, 82-94.

Shao, S., Hu, Z., Cao, J., Yang, L., & Guan, D. (2020). Environmental regulation and enterprise innovation: a review. *Business Strategy and the Environment, 29(3)*, 1465-1478.

Stanciu, S., Vîrlănuță, F. O., Vochin, O. A., Ionescu, R. V., & Antohi, V. M. (2019). Fast Moving Consumer Goods (FMCG) Market in Romania Features and Trends. *Amfiteatru Economic, 21(13)*, 778-794.

Yoseph, F. (2023). *New Approach for Market Intelligence Using Artificial and Computational Intelligence.* Abo Akademi: Abo Akademi University.

Yousef, L. S. (2021). Majid Al Futtaim Retail–Carrefour's Successful Big Transition to Online Presence. In Corporate Success Stories in the UAE: The Key Drivers Behind Their Growth. *Emerald Publishing Limited*, 109-119.

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1911-2004

The Use of Theories in Competitive Intelligence: a Systematic Literature Review

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ABSTRACT The field of competitive intelligence is growing as organisations are looking to increase their competitive advantage in a global society. As this field grows, so does the research and academic literature on this practice. While theory that specifically focuses on competitive intelligence may be limited, theories from other popular and related fields such as management and psychology have been used to explain or guide some the popular competitive intelligence processes with the competitive intelligence cycle. This paper attempts to lay a foundation of relevant theory from previously published literature on competitive intelligence by mapping these theories against the six identified competitive intelligences processes.
The qualitative approach used to achieve this was a literature analysis, involving thematic analysis through a process of coding. The resulting consolidation and processing of these theories led to the development of a useful framework from which other current and future theories can be added, paving the way for further theory development in the field of competitive intelligence.).

KEYWORDS: competitive intelligence, competitive intelligence cycle, theories

1. INTRODUCTION

In highly competitive and uncertain business environments, competitive intelligence is a critical function that promotes informed decision-making and improves corporate information analysis (van den Berg et al., 2020, 2; Wu et al., 2023, 1104). Literature has presented a wide array of varying competitive intelligence definitions (Ranjan & Foropon 2021, 2; Cloutier 2013, 5; Hughes 2007, 5). The various definitions of competitive intelligence given in the literature involve various meanings and applications depending on the audience, according to Du Toit (2015,7). Fleisher and Wright (2009) came to the conclusion that most definitions that have developed over time only differ in terms of semantics and emphasis, and those new emerging definitions are simply tweaks of previous definitions, leaving out one word, adding another, but rarely anything more substantial. Examples of competitive intelligence definitions includes those definition by McGonagle (2016), who views competitive intelligence as the gathering and use of publicly available information, which is analysed and transformed to reveal important findings about rival companies, and the overall market business environment. Cloutier (2013,5), mentions

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that, other definitions are broader and include the environment as a whole such as the definition by Hughes et al., (2013,5), who defines competitive intelligence as the conversion of unprocessed data about the external environment into actionable intelligence that supports business decisions. Similarly, Nasri (2011,63), defined competitive intelligence as a continuous process of gathering data, information and knowledge about actors (competitors, customers, suppliers, government etc) which interact with organisation in the business external environment in order to support decision making process for enhancing competitiveness of organisation.

Theoretically it is postulated that the competitive intelligence process is presented in a cycle of phases (Wright & Calof 2006; Bose 2008; Madureira et al., 2021; Cavallo & Sanasi, 2021). Since the process of competitive intelligence never stops and is always ongoing, it makes sense to express it in a cyclic manner. Additionally, the cycle is utilised to show how the phases are connected and how the output of one phase becomes the input for the following phase (Murphy 2016; Ranjan & Foropon 2020). This paper notes that similarly, to competitive intelligence definitions, there exists corpus amounts of competitive intelligence cycles in literature. The most common phases of the competitive intelligence cycle which are mostly cited in literature are; planning and direction, data collection, analysis and dissemination of the intelligence, which were proposed by Kahaner (1996). Despite the complexity, and availability of various competitive intelligence cycles, this article further notes that common elements are present in each cycle however the naming convention, and the number of phases diverge (Nenzhelele 2013; Du Toit 2015; Author 1 & Fourie 2018). Furthermore, some scholars outline more phases in the competitive intelligence process, whilst others identify fewer phases, and influential factors. Despite these variations, the premises still follows the same notion.

From the consulted literature, it is evident that the competitive intelligence literature has exhaustively discussed both the competitive intelligence cycles and definitions (Bose 2008; Gundersen 2019; Rangone 2021; Ranjan & Foropon 2021; Wu and Umair 2023). Theory usage, which is still somewhat in its infancy and is steadily rising, is one area of competitive intelligence that has not been well investigated. A few authors that have incorporated theories into their research are; Naeini (2019), who used the Bourdieu capital theory to study competitive advantage in Iranian food industry, Nemutanshela and Iyamu (2011) applied the diffusion of innovation theory for enhancing competitive intelligence system, Opait et al., (2016) used the information energy theory to explain the influences of competitive intelligence budgets on informational energy dynamics, furthermore Gatibu and Kilika (2017), used strategic balancing theory, theory of network organisation, Ansoff's growth matrix and Porter's generic strategy to explain the orientation of a firm in aspect that strategically related to competitive intelligence. Jin and Bouthiliier (2006), employed activity theory to understand information transformation process in the context of competitive intelligence specifically to the central phases of competitive intelligence; information analysis. While theory adoption in competitive intelligence is not as popular as compared to related disciplines such business management and business intelligence, this article notes that most competitive intelligence authors "borrow" or use theories that were developed in other disciplines and then apply them to competitive intelligence, similar development is however noted in other fields such as management, industrial marking and industrial engineering (Sidorchuk 2015; Hasen et al., 2016; Fox 2021). Given that competitive intelligence involves concepts such as information needs identification, decision-making, communication, data collection, information analysis. Such concepts suggest the importance of learning from disciplines that directly study these behaviours. This research paper thus explores the following research question: *How can one map theories from other disciplines to the competitive intelligence process, to extend our understanding of the competitive intelligence cycle?* In pursuing this research question, this paper makes several contributions to the competitive intelligence literature. First, we extend our understanding of competitive intelligence by acknowledging the existence of multiple competitive intelligence cycles that are characterised by varying phases, which are analysed and categorised to form a unified understanding of the competitive intelligence process. Secondly, we identify theory utilisation and citation within competitive intelligence. Thirdly we map the identified theories against the unified competitive intelligence process, by doing so this paper helps to determine theoretical gaps and better understanding of the competitive intelligence process. The paper begins by providing a detailed discussion of the methodology followed.

2. METHODS

2.1. Design

Following Lacey et al., (2011) and Papaioannou et al., (2016) this paper developed a systematic review of literature to analyse the main academic contribution to the related topic of competitive intelligence and its related theories. Guillaume (2019,1) claims that systematic literature reviews are a method for synthesising scientific data to address a specific research issue in a transparent and replicable manner, while attempting to incorporate all available data on the subject and evaluating the quality of this data. Furthermore, Mengist et al., (2020, 2) note that systematic literature reviews aid in mapping out existing knowledge and identifying knowledge gaps on particular issues, which will help to expand the body of knowledge. In this case, the systematic literature review aims to identify commonalities and differences in the emerging competitive intelligence processes and associated theories that can help describe the competitive intelligence process. To further confirm a guided process of conducting a systematic literature review, the paper considered the work of Tawik et al., (2019) on "A step by step guide for conducting a systematic review". To ensure unbiased research activity during document selection and analysis while conducting the systematic literature review, specific elements of the criteria are discussed below.

2.2. Literature search

For the completion of this paper, two literature searches were conducted. The first literature search was aimed at tracing publications that discuss the competitive intelligence process. Due to the number of results retrieved, it was deemed relevant to limit the search publication date restriction to (2000 - 2023). This restriction was however only applied to the first literature search and practice. The second literature search was directed at identifying publications that discuss theory use in competitive intelligence. From the literature search, it was evident that theory adoption and usage in competitive intelligence is relatively low, therefore there was no date restriction on the search key terms of the competitive intelligence theories. Table 1 provides a detailed scope of the literature search.

Table 1. detailed explanation of the literature search

Literature search component	Competitive intelligence processes	Competitive intelligence theories
Consulted key databases	Academic Search Premier, Business Premium Collection, Econlit Scopus, Emerald insight, Library and Information Science Abstracts, Web of Science, Library Information Science & Technology Abstracts	Academic Search Premier, ERIC, IEEE Xplore, Scopus, Emerald insight, Library and Information Science Abstracts, Web of Science, Library Information Science & Technology Abstracts, Ebscohost, Googlescholar
Key search terms	competitive intelligence cycle, competitive intelligence practice, competitive intelligence constructs, competitive intelligence phases, competitive intelligence process	competitive intelligence AND theory, competitive intelligence AND theories
Manual searches (citation tracking)	NONE	The reference list of all the retrieved relevant material was screened for more references that mentioned theories in competitive intelligence (citation tracking). Most of the citations in the reference list had hyperlinks, which made it easier to access
Search indexes	Subject heading, abstract, document tittle	Subject heading, abstract, document tittle

Selection criteria	Type of publication: Full text, scholarly and peer reviewed research articles; opinion pieces by experts, books Language: English	Type of publication: Full text, scholarly and peer reviewed research articles; opinion pieces by experts, book chapters. Language: English
Retrieved sources	31 journal articles 12 key expert books	49 journal articles 3 book chapters

2.3. Analysis of selected literature

The method of literature analysis was based on thematic analysis. According to Braun and Clarke (2015, 225), "thematic analysis is the process of identifying patterns or themes within qualitative data". For data on the competitive intelligence processes, the analysis commenced with first becoming familiar with the data, this meant reading the abstracts of all the articles and scanning the content of the article with particular focus on the competitive intelligence cycle and its related phases. This step allows you to take notes and scribble down thoughts, according to Charmaz (2015, 10).

Once the researchers were familiar with the data, the next step was inductive coding. Inductive coding is the process of identifying meaning units or codes that serve as labels or tags for evaluating the meaning of the descriptive or inferential data gathered during a study (Thornberg & Charmaz, 2014). The method used for inductive coding was line-by-line coding, which according to Thornberg and Charmaz (2014,153), entails naming each line of the written data. Line-by-line coding prevents personal opinions from being imposed on the data, which made it easier to begin developing ideas inductively. Each code was assessed to identify a particular competitive intelligence phase (Phase1 – Phase 6), to determine how closely various competitive intelligence phases activities are connected to particular categories, and eventually to assess the codes and categories in accordance with the unified competitive intelligence processes. The coding process for the theories used in competitive intelligence followed a similar procedure, however while familiarising ourselves with the theory used in each article, it was important to make note of the discipline that the theory emerged from and confirm if the theory is compatible with any of the competitive intelligence phases identified in the unified competitive intelligence cycle. This, provided insights into resemblances and differences between competitive intelligence and discipline origin of the identified theory (see Table 3).

3. RESULTS AND DISCUSSION

3.1. Variations of the competitive intelligence phases

The literature search on competitive intelligence processes published between (2000 – 2023) yielded 43 publications. It was noted that certain publications (12) just mentioned the competitive intelligence process without providing a thorough explanation of the phases or an example of the process; as a result, these publications were not taken into consideration during analysis. Furthermore, 17 articles made reference to the "*traditional competitive intelligence cycle*" which according to Rouach and Santi (2001, 554-555), Yap et al., (2013, 465) and Fernándes et al (2017,115) includes 4 phases; planning and direction, information collection, analysing and dissemination. Therefore, to avoid duplication, only 1 of these competitive intelligence cycles was included for analysis, which is the competitive intelligence cycle by Bose (2008). The remaining 14 publications that were analysed either provided an illustration of the competitive intelligence process or an illustration followed by a description of the phases. Some authors however mention central competitive intelligence influential factors, which are; skills development, process and structure, organisational awareness and organisational culture, these were however omitted from Table 2, as according to Wright and Calof (2002, 460) and Pellissier and Nenshelele (2015, 688), as these do not form part of the phases needed to complete the competitive intelligence process. The competitive

Table 2. Variation of the competitive intelligence phases

Competitive intelligence phases (varying naming convention)[1]	**Muller (2002)**	**Wright and Calof (2006)**	**Bose (2008)**	**Sawka and Hohhof (2008)**	**Botha and Boon (2008)**	**Cucui (2009)**	**Haddadi et al., (2010)**	**Bartes (2013)**	**Cloutier (2013)**	**Pellissier and Nenzhelele (2013)**	**Du Toit (2015)**	**Maungwa and Fourie (2018)**	**Koseoglu and Okumus (2021)**	**Ali (2021)**
PHASE 1														
-Planning and direction			■		■		■			■	■		■	
-Planning and focus	■	■						■	■					
-Obtaining the competitive intelligence request				■										
-Task definition														
-Articulating key intelligence needs			■		■									■
-Identifying competitors							■							
-Defining the competitive intelligence demand						■								
-Determining key intelligence needs				■	■							■		
PHASE 2														
-Information collection	■	■	■		■				■					
-Gathering information								■		■	■			
-Research and gathering	■												■	■
PHASE 3														
-Processing				■	■		■							
-Information sorting	■							■	■	■				
-Information processing		■	■		■	■								■
-Evaluation												■		
-Filtering													■	
PHASE 4														
Information analysis	■	■	■		■				■					
Intelligence analysis								■		■	■		■	
PHASE 5														
-Dissemination			■		■		■				■			
-Communicating the intelligence	■	■								■				■
-Intelligence dissemination			■	■	■	■		■	■			■		
-Providing the final service													■	
PHASE 6														
-Feedback			■				■							
-Decision-making	■			■	■	■								■

intelligence processes that presented varying competitive intelligence phases were then analysed. Each phase was then labelled with a number from 1-6, in an attempt to group together similar phases (these are represented by different colours in Table 2). The explanation of each grouped phase was analysed to see if the varying naming refers to the same activity under the phase. Both and Boon (2008), however had subphases for phase 1, these were grouped and treated as a single phase. Table 2 therefore shows different phases of the competitive intelligence cycle.

From the competitive intelligence processes depicted in Table 2, one can observe that there is no agreement on the naming convention and specific content of the phases comprising the competitive intelligence cycle. However, when analysing the above phases, one can find in literature some common trends from different authors as well as factors that differentiate them The authors concluded that the various competitive intelligence phases are characterised by the same or similar descriptions after analysing the descriptions of the 14 competitive intelligence processes and each of their different phases. This article suggests a unified naming convention that includes these competitive intelligence processes. This proposal is shown in figures (1-6), and it is followed by a discussion of the phase.

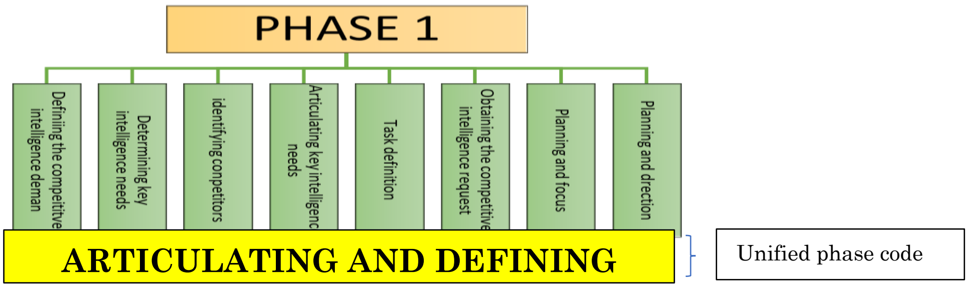

Figure 1. Articulating and defining

Key intelligence needs and topics are mentioned in the various competitive intelligence cycles, according to the literature that was consulted, but they are typically part of the first phase rather than being represented as a separate phase, as in the competitive intelligence cycles by Bose (2008) and van den Berg et al (2019). This phase's primary goal is to identify, articulate, and focus on critical intelligence themes the managers key intelligence needs (Botha & Boon, 2008:3). Adapted from the definition of Du Toit (2007) with elements from Muller (2002), Sewlal (2003) and Johnson (2006): Key intelligence needs represent all key organisational areas that influences strategic decision-making (e.g., business issues, strategic and tactical matters, early warning signs, market segmentation and other priorities) related to the internal and external business environment on which information must be collected to produce intelligence on the threats and opportunities that can affect the organisation. While key intelligence topics are questions that might be specific or discrete directly addressing the key intelligence needs of decision makers and other senior personal in a company or organisation or smaller enterprise (Bose, 2008:513). The goals of this phase are to specify the decision-makers' needs and to identify the resources needed to gather the pertinent data in order to satisfy those needs (Pellissier & Nenshelele 2013, 5; De Pelsmacker et al., 2006, 606-607).

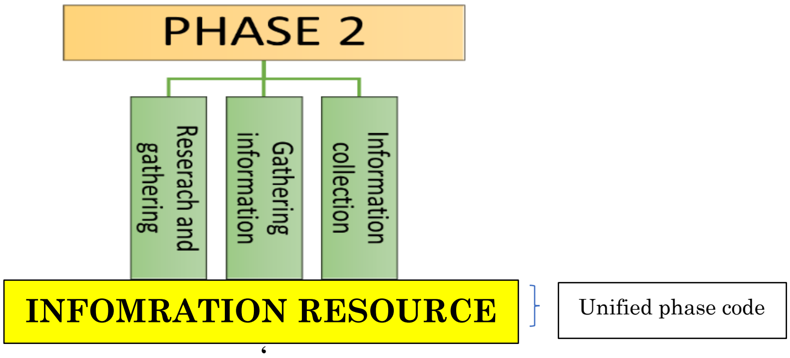

Figure 2. Information resource gathering

Once the key intelligence needs and topics have been defined, the collection resource gathering phase begins (Blenkhorn & Fleisher 2015, 105). A variety of sources, including primary and secondary sources of information, are used to obtain and compile data (Prescott & Miller, 2002:98). Primary sources of information, according to Du Toit (2014, 4), are those that acquire information directly from the targeted information source. These consist of interviews, polls, company websites, and speeches (Sandman 2000, 12; Bose 2008, 515). Analyst reports, financial reports on the company, and online sources are a few examples of secondary information sources that are acquired second-hand through the transfer of a mediator to the source (Du Toit 2014, 4).

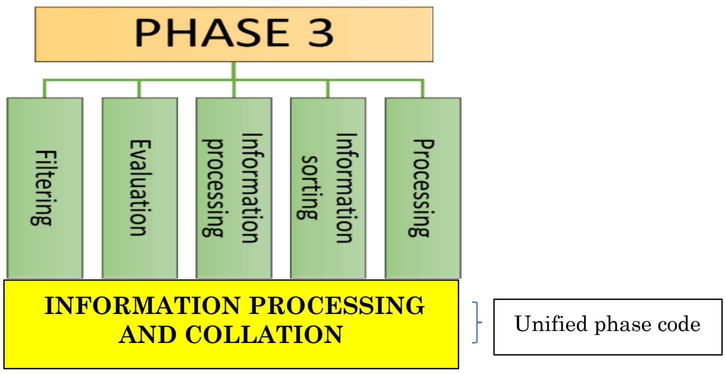

Figure 3. information processing and collation

This phase comes shortly after data has been gathered and collected, the phases entail the electronic storage of data (Blenkhorn & Fleisher 2015, 105). The information processing and collation phase involves; systematising, organising information, and providing sorting, and -storage methods. (Pellissier & Nenzhelele 2013). Although it was observed in many cases in the literature study that the processing phase of the competitive intelligence cycle had been included as part of the information gathering phase, it essentially involves separate activities than mere collection of data, and should therefore be regarded as a phase on its own.

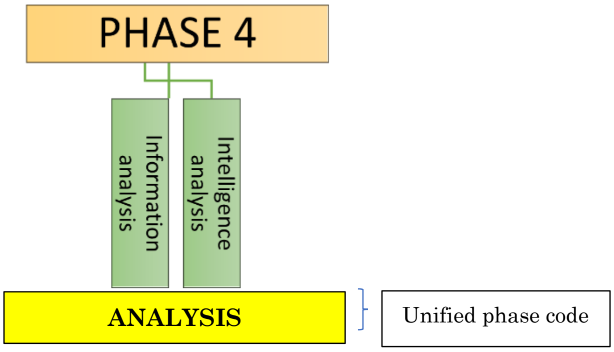

Figure 4. Analysis

Most competitive intelligence authors call this phases "analysis" which is the only phase that is not characterised by various naming conventions. According to Muller (2002:4) and Nasri and Sarai (2013:241), the analysis phase of the competitive intelligence process is referred to as "the central nervous system," where true intelligence is produced through the conversion and manipulation of data using both scientific and non-scientific methods to interpret data. The analysis phase is directed at providing answers to the key intelligence needs and topics that were identified in the first phase (Diyaolu 2019, 5). These findings have to be communicated to the decision-makers. Competitive intelligence specialists or analysts who are taught to demonstrate particular analysis skills are primarily responsible for performing the analysis. These include knowledge of research techniques, analytical skills, the capacity to use both qualitative and quantitative approaches, knowledge of the best techniques, and the capacity to communicate findings (Tej Adidam et al., 2012; Du Toit 2015). Additionally, the capabilities of a competitive intelligence analyst include familiarity with and proficiency with a variety of tools and methods of analysis that are industry-specific and benefit the firm (Freyn & Hoffman 2022, 6). The skilled analyst has to be able to use a range of analytical methods such as competitor profiling, alternative scenarios, SWOT analysis, industry analysis, critical success factor analysis as well as Porter's five forces (Nasri 2011; Tej Adidam et al., 2012; Wright & Calof, 2006).

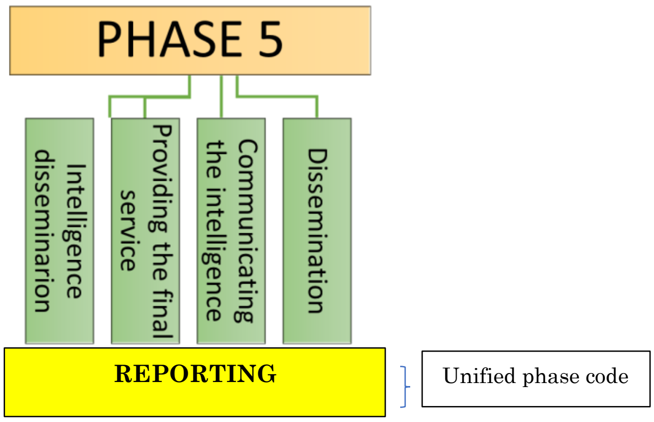

Figure 5. Reporting

The competitive intelligence reporting phase entails sharing the findings with the appropriate parties (Muller 2002, 39-40; Bose 2008, 515). Identifying the preferred format for delivering intelligence to decision-makers is crucial (Heppes 2006, 40). The intelligence should always be presented in a style that is appropriate for the audience, focusing primarily on the most important components of the findings (Muller 2000, 7).

Muller (2002, 39) claims that there are numerous ways to convey intelligence results, including alerts, newsletters, and intelligence reports. The final stage of the competitive intelligence cycle is input from decision-makers, who offer feedback after reviewing the intelligence reports and chances for evaluating and revising the original intelligence sought.

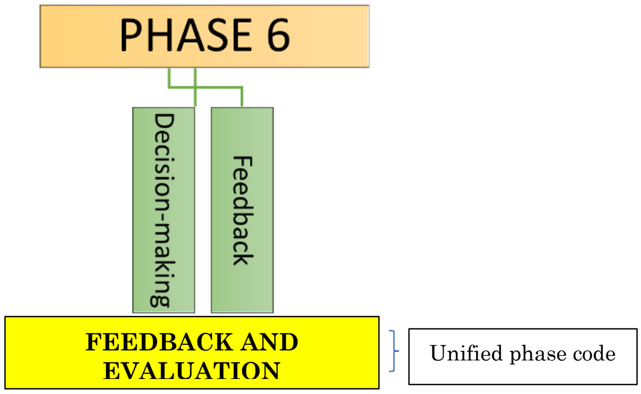

Figure 6. Feedback and evaluation

Feedback and evaluations enable course corrections and the discovery of new problems (Rapp et al., 2015, 360). The feedback allows for changes of the initial intelligence request as well as constructive criticism of the deliverable of earlier requests, promoting an environment of continual progress (Nasri 2011, 64).
The proceeding section has thus presented a unified competitive intelligence process by showing that the various named phases have similar descriptions and therefore producing the same end result. The following section attempts to map different multidisciplinary theories to the unified competitive intelligence process.

3.2. Theories identified in the competitive intelligence literature

In an attempt to map the theories against the CI phases, the researchers needed to study the 49 publications identified in the literature analysis to understand how these theories were used in the context of CI. From scrutinising and familiarising ourself with the publications, it was noted that 16 articles only mentioned the theory without providing any context or detail on how the theory is applied to the competitive intelligence context, nor did the authors provide a discussion of the theory; as a result, these publications were excluded from the analysis. The remaining 33 publications were then analysed and summarised in Table 3. It was identified that some of the publications used multiple theories, while some publications referred to the same theory using different terms (e.g., Porter's five forces theory and competitive forces theory), such theories were standardised to a single theory. After this consolidation the next approach taken was to identify the number of unique theories in our dataset and standardise the way a theory was coded for each article. The final preparatory step was to identify the referent disciplines for each theory. In order to achieve this a search for the foundational publications for each theory was conducted to determine the referent disciplines for these theories. Table 3 also goes into detail to explained how each theory was connected by the authors to competitive intelligence.

Table 3. Multidisciplinary theories identified in competitive intelligence

Theory	Discipline	Number of CI studies cited (count)	Authors who used theory in a competitive intelligence context	How author(s) applied the theory to competitive intelligence
Activity theory	Management	1	Jin and Bouthillier (2006)	Activity theory is used to explain the information behavior of the competitive intelligence analyst in the setting of competitive

Theory	Discipline	Number of CI studies cited (count)	Authors who used theory in a competitive intelligence context	How author(s) applied the theory to competitive intelligence
				intelligence. This is done to determine how the analysts characterize their main daily tasks and activities, which ones are the most time-consuming, difficult, significant, and frequent, and what tools and resources do competitive intelligence professionals utilize in their analysis processes.
Archive theory	Library science	1	Nitse and Parker (2003)	The competitive intelligence systems' information gathering procedures were explained using the archive theory. According to the notion, competitive intelligence systems can put structure in place for the archiving of public documents in both printed and electronic media.
Bordieu capital theory	Sociology	2	Naeini and Mosayebi (2019); Ali and Anwar (2021)	According to Bourdieu's capital theory, people do not exist in a vacuum but rather in a variety of fields made up of elements such as economic, cultural, social, and symbolic capitals. Therefore, from the perspective of competitive intelligence, someone who is in line with such factors can get an advantage.
Contingency theory	Psychology	1	Johannesson and Palona (2010);	The contingency theory was used to propose that; In order to achieve maximum performance, managers of the various global business divisions can be urged to align their functional plans to the level of turbulence in their firms' global business environments.
Competitive intelligence theory	Management	1	Kun (2014); Mogbolu (2022)	According to the hypothesis, competitive intelligence improves business performance, creating a competitive edge. Businesses must develop an understanding of the interactions between variables in order to obtain information and direct actions toward a desired outcome.
Information theory	Mathematics	1	Fellman and Post (2008)	Competitive intelligence's information theory is used to explain why data analysis is flawed. Disinformation, which is described as incomplete or erroneous information intended to deceive the organization's competitive intelligence operations, could lead to inaccurate data being generated.
Interaction theory	Sociology	1	Prilop and Maicher (2013)	Competitive intelligence is the process of continuously and cooperatively making sense of the competitive environment by actively involving all pertinent stakeholders. The interactive theory was used to propose the use of interactive competitive intelligence systems which aims to complete competitive intelligence activities in a collaborative, non-linear manner.
Innovation theory	Management	1	Calof and Sewdass (2020)	The competitive intelligence and subjects connected to competitive intelligence were examined using the innovation theory to explore how they may be used to enhance organizational innovation.
Knowledge based view	Management	1	Hanif et al., (2022)	Data collection is defined as knowledge in the competitive intelligence perspective of a product, which is why management accumulates and safeguards it for strategic management activities. The success of strategic management within an organization is significantly influenced by the knowledge that has been gained.
Management theory	Management	1	Hoffman and Freynn (2019)	Unrealistic manager expectations are a problem that was explained using management theory. When managers want to make changes but do not want to accept the repercussions, they frequently hire consultants.
Managerial cognition theory	Management	1	Hanif et al., (2022)	The main focus of managerial cognition theory is how managers observe and analyze the corporate environment to choose their course of action. Strategic activities are influenced by managerial cognition, among other things. Therefore, managerial cognition can be defined as the process through which managers observe and evaluate changes in their organizational environments. This process has a significant impact on the strategic decisions and actions of a corporation. The managerial cognition theory has been positioned to support this viewpoint.
Organisational learning theory	Management	1	Maune (2014)	The theory of organizational learning has been used to argue that in order to succeed, managers must foster a culture of competition and knowledge and idea sharing among employees and departments inside their organizations. Businesses must have the right procedures, rules, and infrastructure in place for their employees to properly contribute to the competitive intelligence system.
Open system theory	Biology	5	Moneme et al., (2017); Obonyo and Kilika (2020); Omede et al., (2020); Muritala et al., (2019); Mogbolu (2022)	Open system theory describes how organisations interact with their external environment to gather competitive intelligence data, information, and knowledge about environment actors (competitors, customers, suppliers, government, etc.) in order to create or improve goods and services that meet or even exceed the needs of customers.
Porters five forces theory	Management	1	Ahmadinia and Karim (2016) Ezenwa et al., (2018); Nte et al., (2020); Ahmadinia, and Karim (2016)	Porter's five forces theory assessed the degree of industry competition in terms of buying power, supplier power, threat of new entry, industry rivalry, and threat of substitution. According to Porter's five forces theory, attractiveness refers to overall profitability, and an unattractive industry is one in which the interaction of these five forces lowers overall profit.
Reasoned action theory	Psychology	1	Qui (2008)	As our behavioral category of interest, we are scanning for competitive intelligence. Competitive intelligence's reasoned action theory is

				utilized to support the idea that an individual's attitude and normative views may be traced back to the origins of scanning behavior.
Resource based view theory	Management	5	Grant (1991); Voola et al., (2004); Taib et al., (2008); Olszak (2014); Hanif et al., (2022)	The resource-based views shows how resources and competitive advantage are related. The goal of competitive intelligence as a whole is to gather data for strategic management, the outcome of which will have a significant impact on the firms' resources. Accordingly, in accordance with this notion, businesses obtain a competitive edge by amassing significant resources and talents.
Social cognition theory	Psychology	1	Rapp, et al (2015)	Employee motivation and efforts to gather competitive information will be further increased if they feel that the work they are doing is adequately acknowledged and that the boss appreciates their contributions, according to the social cognition theory.
Theory	**Discipline**	**Number of CI studies cited (count)**	**Authors who used theory in a competitive intelligence context**	**How author(s) applied the theory to competitive intelligence**
Stewardship theory	Management	1	Jarfar (2020)	According to stewardship theory, management is dependable to act in the interests of the general public and its shareholders in particular. In theory, actions related to corporate management and competitive intelligence demonstrate how significantly competitive intelligence affects the competitiveness and performance of the organization. Corporate management focuses on operational management, executive controls, and decision-making.
Strategic balance theory	Psychology	1	Sande and Ragui (2018)	Strategic balance theory, holds that firms that are neither very conforming nor highly differentiated perform better than those that are moderately different, which explains why businesses seeking a competitive edge should be as unique as is legitimately possible, being unique reduces competition and boosts competitive advantage, but being too unique raises questions about legitimacy, which has a detrimental effect.
Theory of performance	Management	1	Nte, et al (2019); Calof and Sewdass (2020)	For organizations that practice competitive intelligence, which raises organizational performance, the theory of performance has considerable value. High quality performance results in deserving accomplishments. A manager who increases his level of accomplishments can be examined very well using the theory of performance. A manager's ability to organize people and resources more effectively and produce higher-quality outputs faster increases as his level of performance rises. According to performance theory, organizations that achieve higher levels of performance provide outcomes including higher quality goods and services, lower costs, and gains in competence, knowledge, skill, identity, and motivation.

The theories discussed above (see Table 3) indicate that competitive intelligence is increasingly adopting theories from a number of different fields and backgrounds, with the majority of publications coming between 2014 to 2022. At first glance, it was found that the majority of referenced theories originated in the management and psychology fields. However, this was expected, given that competitive intelligence has its roots in and functions within the dimensions of strategic and corporate management, according to Calof and Viviers (2001, 62) and Du Toit (2015, 16). For McKenna (2000), psychology is a critical component within the workplace, which assists managers at all levels support, motivate, and train employees, an example that aligns with McKenna (2000), can be observed in the theory of social cognition used by Rapp et al (2015). Authors like Sewdass and Calof (2020) and Hannif et al., (2022), for example, have occasionally cited multiple theories in the same publication. In these situations, the authors had a literature review where they talk about how various theories connect to the topic under investigation. Furthermore, the open system theory, resource-based theory and Porter's five forces theory were found to be the most prevalent theories in the literature consulted. Although competitive intelligence involves extensive communication between the intelligence requesters and competitive intelligence professionals, and among the competitive intelligence team itself, it was however noted that apart from the interaction theory, there was no theories stemming from the communication discipline.

Following the identified and analysis of these theories, the next step was to develop a framework which maps the different theories to phases of the competitive intelligence cycle was developed as depicted in Figure 7. The use of theories to describe the phases of competitive intelligence gives scholars and practitioners of competitive intelligence a shared vocabulary and understanding. The objective and function of each competitive intelligence phase are further categorised by identified CI theories. The development of this framework was guided by the description of each theory from its grounding discipline, and how authors writing from a competitive intelligence perspective have explained the use and implementation of these theories. It was however noted that many theories can be used to explain activities under multiple phases, e.g., interaction theory, which can be mapped against the defining and articulation phase, the information resource gathering phase, analysis phase and the feedback and evaluation phase. The authors therefore mapped each theory to a phase that would best fit its description and activities.

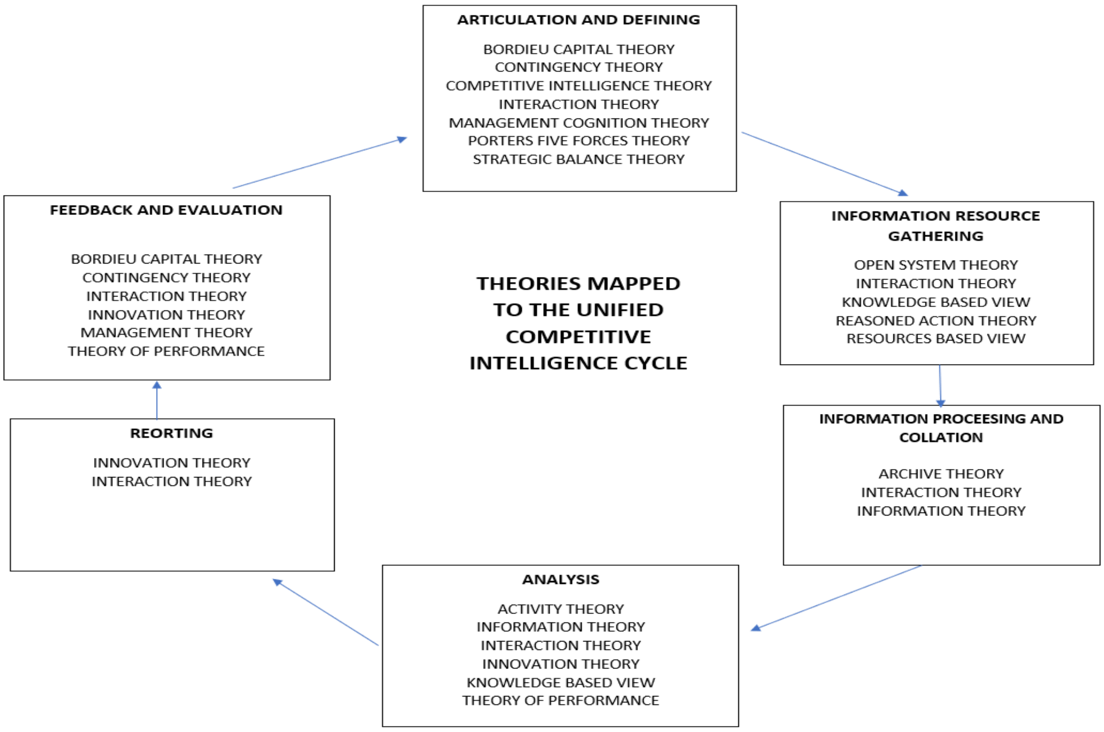

Figure 7. Mapping theories to the competitive intelligence process (Author 1 and Author 2 2023)

Theories like interaction theory, management theory, and strategic balance theory can be used to describe the articulation and defining phase (see Figure 7). These theories highlight the internal and external possibilities and threats of an organisation as well as its strengths and weaknesses (Sande & Ragui 2018; Hoffman & Freynn 2019). They make it possible for businesses to identify their competitive advantages and weaknesses, assisting in the creation of successful strategies (Jin & Bouthillier 2006; Hoffman & Freynn 2019). The information resource gathering phase can be regarded as a response to the external environment, trying to successfully obtain and use information to gain a competitive edge (Bergeron & Hiller, 2002, 20). Open system theory, the resource-based view, and the knowledge-based view are a few theories that can be used to explain the information resource gathering phase (Moneme et al., 2017; Mogbolu 2022). Additionally, these theories contend that in order to acquire and utilise special assets and capabilities, competitive intelligence engages with the outside world through a variety of channels, including suppliers, consumers, and rivals (Muritala et al., 2019; Omede et al.,2020).

When considering the information processing and collation phase, the archival theory describes how data like financial reports, market research findings, consumer surveys, product specifications, and more are processed and stored (Nitse & Parker 2003). Access to competitor data is ensured via well-organised data sources. Competitive intelligence teams may quickly access historical data and detect and analyse historical patterns, rival strategies, and market dynamics, assisting them in making informed judgments by putting into practice appropriate processing, storing, and archiving processes (Blenkhorn and Fleisher 2005, 56). In the analysis phase, the data that has been gathered and processed and stored are examined and turned into useful intelligence. Several theories, such as information theory, innovation theory, knowledge-based view, and theory of performance, can be applied at this phase. These theories aid in comprehending market dynamics, identifying threats, and forecasting upcoming developments (Nte et al., 2019; Calof & Sewdass 2020). The knowledge-based perspective can help an organisation further in utilising internal knowledge by interpreting and analysing information from diverse departments and people, which can lead to a deeper understanding of the significance of the data that has been analysed (Hanif et al., 2022). A culture that supports open communication, cooperation, and the sharing of information insights should be promoted by organisations, according to the knowledge-based view. Part of the reporting process is disseminating the intelligence to decision-makers and relevant stakeholders (Bose 2008; Murphy, 2016). This phase can be explained by theories relating to communication and knowledge management, hence the interaction theory, which provides a helpful framework for comprehending the role for communication in competitive intelligence, along with the influence of socialisation and contact on the formation of knowledge and meaning (Prilop & Maicher 2003). Finally, the feedback and assessment phase can be explained using management theory, Bourdieu capital theory, and performance theory. These theories emphasise the necessity of performance evaluation to gauge both individual and organisational effectiveness (Naeini & Mosayebi 2019; Calof & Swedass 2020; Ali & Anwar 2021). Feedback enables firms to assess the effectiveness of their intelligence collection procedures and the effects of intelligence on overall business performance in the context of competitive intelligence (Du Toit 2015; Murphy, 2016). This assessment aids in locating areas in need of development and efficiently allocating resources.

4. CONCLUSION

The results of the competitive intelligence process' thematic analysis has shown that, despite the literature's increasing divergences, the various competitive intelligence cycles are predicated on the same premises and yield the same outcomes. One of the prominent findings was the infancy of theory usage in competitive intelligence and how it is steadily growing. The proposed competitive intelligence process was mapped against theories used in academic competitive intelligence literature, laying a foundation for future research and expansion of competitive intelligence theory. The use of theories in explaining the competitive intelligence process, while enhancing the overall effectiveness of information gathering, processing, storing, analysis, disseminating and decision making. The compilation of these theories also offers an organised approach for comprehending the competitive intelligence landscape, spotting possibilities and risks, and creating plans for swaying the competition. Another notable findings from this work is the realisation that there is a lot of textbooks and academic writing from various disciplines that can help scholars learn more and generate understanding on how these theories can utilised to explain the stages and activities of competitive intelligence. Furthermore, this paper can be extended by exploring more theories especially from the management and psychology discipline, that might deepen our understanding of the competitive intelligence process.

REFERENCES

Abedin, B. 2022. Managing the tension between opposing effects of explainability of artificial intelligence: a contingency theory perspective. *Internet Research* 32(2): 425-453.

Ahmadinia, H. and Karim, M. 2016. Competitive intelligence: A case study on Qoros automotive manufacturing. *Journal of Intelligence Studies in Business* 6(2): 52-65.

Ali, B. J. and Anwar, G. 2021. Measuring competitive intelligence Network its role on Business Performance. *International Journal of English Literature Social Sciences*, *6*(2).

Bergeron, P. and Hiller,C. A. 2002. Competitive intelligence. *Annual Review of Information Science Technology* 36(1): 353-390.

Blenkhorn, D. L., and Fleisher, C. S. (Eds.). 2005. *Competitive intelligence global business*. Greenwood Publishing Group.

Bose, R. 2008. Competitive intelligence process tools for intelligence analysis. *Industrial management and data systems* 108(4): 510-528.

Botha, D.F. and Boon, J.A. 2008. Competitive intelligence in support of strategic training learning. South African Journal of Information Management 10(3): 1-6.

Calof, J. and Sewdass, N. 2020. On the relationship between competitive intelligence innovation. *Journal of Intelligence Studies in Business*, 10(2): 32-43.

Cavallo, A. Sanasi, S. Ghezzi, A. and Rangone, A. 2021. Competitive intelligence strategy formulation: connecting the dots. *Competitiveness Review: An International Business Journal* 31(2): 250-275.

Charmaz, K. 2015. Teaching theory construction with initial grounded theory tools: A reflection on lessons learning. *Qualitative health research* 25(12): 1610-1622.

Clarke, V. Braun, V. and Hayfield, N. 2015. Thematic analysis. *Qualitative psychology: A practical guide to research methods* 3(1): 222-248.

Cloutier, A. 2013. Competitive intelligence process integrative model based on a scoping review of the literature. *International Journal of Strategic Management* 13(1): 57-72.

De Pelsmacker, P. Muller, M.L. Viviers, W. Saayman, A. Cuyvers, L. and Jegers, M. 2005. Competitive intelligence practices of South African Belgian exporters. *Marketing Intelligence and Planning* 23(6): 606-620.

Dishman, P.L. and Calof, J.L. 2008. Competitive intelligence: a multiphasic precedent to marketing strategy. European Journal of Marketing 42(7/8): 766-785

Diyaolu, A. M. 2019. The role of competitive intelligence in provision of quality information services. *Library Philosophy Practice*, (1)1: 1-9.

Du Toit, A.S.A. 2015. Competitive intelligence research: an investigation of trends in the literature. *Journal of Intelligence Studies in Business* 5(2): 14-21.

Ezenwa, O. Stella, A. and Agu, A. O. 2018. Effect of competitive intelligence on competitive advantage in Innoson technical industry limited, Enugu state, Nigeria. *International Journal of Business, Economics and Management* 1(1): 28-39.

Fellman, P. V. and Post, J. V. 2008. Complexity, competitive intelligence the “first mover” advantage. In *Unifying Themes in Complex Systems: Proceedings of the Sixth International Conference on Complex Systems* (pp. 114-121). Springer Berlin Heidelberg.

Fernández Arias, M. Quevedo Cano, P. and Hidalgo Nuchera, A. 2017. Relevance of the competitive intelligence process on the Spanish pharmaceutical companies. *Brazilian journal of operations and production management* 14(1): 112-117.

Fleisher, C.S. and Wright, S. 2009. Causes of competitive analysis failure: understanding responding to problems at the individual Level. In *Third European Competitive Intelligence Symposium*. Stockholm. [Online]. Available from: https://www.dora.dmu.ac.uk/bitstream/handle/2086/4518/2009%20-%20ECIS%20Conference%20Paper%20-%20Analyst%20Failure%20FINAL.pdf?sequence=1 [11 July 2023].

Fox, S. 2021. Active inference: Applicability to different types of social organization explained through reference to industrial engineering quality management. *Entropy* 23(2): 198.

Freyn, S. and Hoffman, F. 2022. Competitive intelligence in an AI world: Practitioners’ thoughts on technological advances the educational needs of their successors. *Journal of Intelligence Studies in Business* 12(3): 6-17.

Gatibu, J. and Kilika, J. 2017. Competitive intelligence practices performance of Equity Bank in Kenya. *International Academic Journal of Human Resource Business Administration* 2(4): 219-239.

Grant R.M. 1991. The resource based theory of competitive advantage: implications for strategy formulation. California Management Review 33(3): 114–135.

Hanif, N. Arshed, N. and Farid, H. 2022. Competitive intelligence process strategic performance of banking sector in Pakistan. *International Journal of Business Information Systems* 39(1): 52-75.

Hazen, B. T. Skipper, J. B. Ezell, J. D. and Boone, C. A. 2016. Big data predictive analytics for supply chain sustainability: A theory-driven research agenda. *Computers and Industrial Engineering* 101(1): 592-598.

Heppes, D. and Du Toit, A. 2009. Level of maturity of the competitive intelligence function: case study of a retail bank in South Africa. *Association for information Management Proceedings: New Information Perspectives* 61(1): 48-66.

Heppes, D.W. 2006. An assessment of the level of maturity of the competitive intelligence function within a South African retail ankb. Master's dissertation, University of Johannesburg. [Online]. Available from: https://ujcontent.uj.ac.za/vital/access/manager/Repository/uj:8447 [22 May 2017]

Hoffman, F. P. and Freyn, S. L. 2019. The future of competitive intelligence in an AI-enabled world. *International Journal of Value Chain Management* 10(4): 275-289.

Hristovski, R. and Balagué, N. 2020. Theory of cooperative-competitive intelligence: principles, research directions, applications. *Frontiers in Psychology* 11(1): 2220.

Hughes, S. F. 2017. A new model for identifying emerging technologies. *Journal of Intelligence Studies in Business* 7(1): 20-35.

Jafar, M. (2020). The impact of competitive intelligence (CI) management on the competitiveness performance of retail companies in Indonesia. *Journal of Social Science Advanced Research* 1(2):138-159.

Jin, T. 2008. *An exploratory study on information work activities of competitive intelligence professionals*. Quebec: McGill University.

Jin, T. and Bouthillier, F. 2006. Understanding information transformation process in the context of competitive intelligence. *Proceedings of the American Society for Information Science Technology* 43(1): 1-14.

Johannesson, J. and Palona I. 2010. Environmental turbulence the success of a firm's intelligence strategy: Development of research instruments. *International Journal of Management* 27(3): 448.

Johannesson, J. and Palona, I. 2010. Environmental turbulence and the success of a firm's intelligence strategy: Development of research instruments. *International Journal of Management* 27(3): 448.

Johnson, A.R. 2004. The top 12 priorities for competitive intelligence [Online]. Available from: http://www-sop.inria.fr/acacia/WORKSHOPS/ECAI2002-OM/soumissions/ECAI2002-johnson-1.htm [28 June 2023].

Kahaner, L. 1996. *Competitive Intelligence: From Black Ops to Boardrooms – How Businesses Gather, Analyse, Use Information To Succeed in The Global Marketplace*. New York: Simon Schuster

Kun, S. 2014. Enterprise competitive intelligence system research based on data mining technology. *Applied Mechanics Materials* 654(1): 1562-1565.

Lacey, F. M. Matheson, L. and Jesson, J. 2011. Doing your literature review: Traditional systematic techniques. *Doing Your Literature Review* 1(1): 1-192.

Madureira, L. Popovič, A. and Castelli, M. 2021. Competitive intelligence: A unified view modular definition. *Technological Forecasting Social Change* 173(1): 121086.

Maune, A. 2014. Competitive intelligence as an enabler for firm competitiveness: An overview. *Journal of Governance Regulation* 3(2): 29-42.

Author 1 and Fourie, I. 2018. Competitive intelligence failures: An information behaviour lens to key intelligence information needs. *Aslib Journal of Information Management*, 70(4): 367-389.

McGonagle, J. J. and Vella, C. M. 2002. *Bottom line competitive intelligence*. Greenwood Publishing Group.

McGonagle, J. J.2016. Competitive intelligence. *Journal of US Intelligence Studies Volume* 22(2): 55-56.

McKenna, E. F. (2000). *Business psychology organisational behaviour: a student's handbook*. Psychology Press.

Mengist, W. Soromessa, T. and Legese, G. 2020. Method for conducting systematic literature review meta-analysis for environmental science research. *MethodsX* 7(1): 100777.

Miller, J. 2000. Millennium intelligence: understanding conducting competitive intelligence in the digital age. Menford, N.J: CyberAge Books.

Mogbolu, N. 2022. Advancing competitive advantage in manufacturing firms through competitive intelligence. *Journal of Global Economics Business 3*(11): 61-80.

Moneme, C. P., Nzewi, H. N., and Mgbemena, I. C. (2017). Competitive intelligence product development in selected pharmaceutical firms in Anambra state of Nigeria. *International Journal of Scientific Research Publications 7*(4): 288-299.

Muller, M.L. 2002. *Managing Competitive Intelligence*. Johannesburg: Knowres Publishing.

Muritala, A. S. Asikhia, O. U. Makinde, O. G. and Akinlabi, H. B. 2019. Competitive Intelligence Employee Productivity Of Selected Insurance Companies In Nigeria. *International Journal of Innovative Research Advanced Studies* 6(6): 128-134.

Murphy, C. 2006. Competitive intelligence: what corporate documents can tell you. *Business information review* 23(1): 35-42.

Murphy, C. 2016. *Competitive intelligence: Gathering, analysing putting it to work*. Routledge

Naeini, A. B., Mosayebi, A., and Mohajerani, N. (2019). A hybrid model of competitive advantage based on Bourdieu capital theory competitive intelligence using fuzzy Delphi ism-gray Dematel (study of Iranian food industry). *International Review*, (1-2): 21-35.

Nasri, W. 2011. Competitive intelligence in Tunisian companies. *Journal of Enterprise Information Management* 24(1): 53-67.

Nasri, W. and Zarai, M. 2013. Key success factors for developing competitive intelligence in organisation. *American Journal of Business Management* 2(3): 239-244.

Nemutanzhela, P. and Iyamu, T. 2011. The impact of competitive intelligence on products services innovation in organizations. *International Journal of Advanced Computer Science Applications* 2(11): 9-157.

Nikolaos, T. and Evangelia, F. 2012. Competitive intelligence: concept, context a case of its application. *Science Journal of Business Management* (2)15: 1-15

Nitse, P. S., and Parker, K. R. (2003). Library Science, Knowledge Management, Competitive Intelligence: Archive Theory—The Common Link. *The Reference Librarian* 38(79-80): 395-407.

Nte, N. D. Omede, K. N. Enokie, B. K. and Bienose, O. 2020. Competitive Intelligence Competitive Advantage in Pharmaceutical Firms in Developing Economies: A Review of Lagos State, Nigeria. *Journal of Management, economics, Industrial Organization* 4(1): 76-99.

Obonyo, M. O. and Kilika, J. M. 2020. Competitive Intelligence Corresponding Outcome in a Strategic Management Process: A Review of Literature. *Journal of Economics Business*, *3*(4): 1689-1707.

Olszak, C. M. 2014. Towards an understanding business intelligence. A dynamic capability-based framework for Business Intelligence. In *2014 Federated conference on computer science information systems*, (2)1: 1103-1110.

Omede, N. K., Egwuenu, A. S., and Ibekwe, E. M. (2020). Competitive Intelligence Product Development/Innovations in Pharmaceutical Firms in Lagos State, Nigeria. *Jurnal Ekonomi Akuntansi dan Manajeme* 19(2): 92-110.

Opait, G. Bleoju, G. Nistor, R. and Capatina, A. 2016. The influences of competitive intelligence budgets on informational energy dynamics. *Journal of business research* 69(5): 1682-1689.

Pellissier, R. and Nenzhelele, T. E. 2013. Towards a universal competitive intelligence process model. *South African Journal of Information Management* 15(2): 1-7.

Prescott, J.E. and Miller, S.H. 2002. Proven strategies in competitive intelligence: lessons from the trenches. NY: John Wiley and Sons.

Ranjan, J. and Foropon, C. 2021. Big data analytics in building the competitive intelligence of organizations. *International Journal of Information Management* 56(1): 102231.

Rouach, D. and Santi, P. 2001. Competitive intelligence adds value:: Five intelligence attitudes. *European management journal* 19(5): 552-559.

Sande, G. and Ragui, M. 2018. Competitive intelligence practices performance of Equity Bank Limited. *International Academic Journal of Human Resource Business Administration* 3(1): 282-302.

Sassi, D. B. Frini, A. Karaa, W. B. A. and Kraiem, N. 2016. A competitive intelligence solution to predict competitor action using K-modes algorithm rough set theory. *Procedia Computer Science* 96(1): 597-606.

Seng Yap, C. Zabid Abdul Rashid, M. and Amat Sapuan, D. 2013. Perceived environmental uncertainty competitive intelligence practices. *The journal of information knowledge management systems* 43(4): 462-481.

Sewlal, R. 2004. Effectiveness of the Web as a competitive intelligence tool. *South African Journal of Information Management* 6(1): 1-16.

Sidorchuk, R. 2015. The Concept of" Value" in the Theory of Marketing. *Asian Social Science* 11(9): 320.

Søilen, K. S. 2017. Why care about competitive intelligence market intelligence? The case of Ericsson the Swedish Cellulose Company. *Journal of Intelligence Studies in Business* 7(2): 28-38.

Taib, K. M. Yatin, S. F. M. Ahmad, A. R. and Mansor, A. N. 2008. Knowledge management competitive intelligence: A synergy for organizational competitiveness in the K-Economy. *Communications of the IBIMA* 6(1): 25-34.

Tawfik, G. M. Dila, K. A. S. Mohamed, M. Y. F. Tam, D. N. H. Kien, N. D. Ahmed, A. M. and Huy, N. T. 2019. A step by step guide for conducting a systematic review meta-analysis with simulation data. *Tropical medicine health* 47(1): 1-9.

Tej Adidam, P. Gajre, S. and Kejriwal, S. 2009. Cross-cultural competitive intelligence strategies. *Marketing Intelligence and Planning* 27(5): 666-680.

Thornberg, R. and Charmaz, K. 2014. Grounded theory theoretical coding. *The SAGE handbook of qualitative data analysis* 5(1): 153-69.

van den Berg, L. Coetzee, B. and Mearns, M. 2020. Establishing competitive intelligence process elements in sport performance analysis coaching: A comparative systematic literature review. *International Journal of Information Management* 52 (1): 102071.

Voola, R. Carlson, J. and West, A. 2004. Emotional intelligence competitive advantage: examining the relationship from a resource-based view. *Strategic Change* 13(2): 83-93.

Weiss, A. 2002. A brief guide to competitive intelligence: how to gather use information on competitors. *Business Information Review* 19(2): 39-47.

Wright, S. and Calof, J.L. 2006. The quest for competitive, business marketing intelligence: a country comparison of current practices'. *European Journal of Marketing* 40(5/6): 453–465.

Wu, Q. Yan, D. and Umair, M. 2023. Assessing the role of competitive intelligence practices of dynamic capabilities in business accommodation of SMEs. *Economic Analysis Policy* 77(1):1103-1114. Author, author and author (YEAR) *Name of article in italics*. (pp. X-Y) Publication.

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A comparative analysis with machine learning of public data governance and AI policies in the European Union, United States, and China

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ABSTRACT This paper explores the public data governance and AI policies in the world's three main technological regions which are the United States, China, and European Union based on scientific literature analysis with machine learning. We used the RapidMiner text mining algorithm to classify texts and define the recuring themes in each region through Terms Frequency-Inverse Document Frequency, supervised machine learning techniques with KNN, and Naïve Bayes. Therein, our results reveal the most influential items for each region that emphasize three different approaches in China, the United States and the EU.

KEYWORDS: public data governance, artificial intelligence policy, text mining.

1. INTRODUCTION

Data has been construed as a key resource for companies and states pushing to be competitive (Kshetri, 2014). Furthermore, Mazurek and Malagocka (2019, 344) argue that "data may be seen as a currency in the digital world, and even compared to oil, gold or nowadays to labor." However, unlike other resources such as oil, data can be reused endlessly for different purposes and with unrestricted cross-border flows (Aaronson, 2019). Yet, data is often closely related to the notions of privacy and ethics, as it deals with human activities (Bisson, 2013).

The rise of the digital age was initially accompanied by the ambition to break down frontiers and create a "global village" (McLuhan, 1967). However, the digital transformation of many societies and the digitalization of human activities are challenging the concept of sovereignty. Yet, the conflict in Ukraine has further divided the world and ended the "fruitful" globalization that increased the importance of international public data governance policies. Therein, data storage and data infrastructures now crystallize the new spots of international geopolitical tensions and rivalries.

Various international regulations regarding data governance are also becoming weapons of economic warfare, as shown by

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the China-U.S. rivalry (Zeng, 2020). Nowadays, to ensure the security and sovereignty of their data, states are adapting their laws to the digital sphere with technical and legal arsenals. Thus, data, AI technologies, and infrastructure networks today represent "a stake of sovereignty and power for states, international firms and other non-state actors" (Seurre, 2020, 3). Hence, digital technology is reshuffling the cards of the international power game and "data governance is becoming a political issue of crucial importance" (Matthews, 2019, 1) that can generate geopolitical conflicts. Furthermore, according to Zheng (2021, 1), policymakers must consider the concept of trilemma, i.e., "personal data protection, free transborder flow of information and the expansion of national jurisdiction" to build up new data transfer regulations.

In addition, the amount of data that companies have is essential for their development and contributes to sustaining their competitive advantages. Indeed, data that feeds their AI algorithms enables them to improve the efficiency and quality of their products and services, but it also helps them to create, or take part in the creation of, new ones.

According to the Data Governance Institute (2017), data governance is "a system of decision rights and accountabilities for information-related processes, executed according to agreed-upon models which describe who can take what actions with what information, and when, under what circumstances, using what methods." Thus, data governance must be thought of as an ecosystem that encompasses privacy, security, ownership, use, and reuse of data, but also as the values and interests it contains (Winter and Davidson, 2017).

However, we cannot apply the same model of data governance in the private sector and in the public sector, as doing so requires political discussions (Okuyucu and Yavuz, 2020). As data governance involves various and numerous stakeholders, it is also closely linked to the concepts of sovereignty and data politics (Mureddu, Schmeling, and Kanellou, 2020). Woods (2018, 360) defines data sovereignty as the combination of "supreme control, over a territory, independent from other sovereigns." Yet, Liu (2021, 46) highlights the strategic role that data policies play in the "interactions between sovereign states or between the state and non-state actors over the collection, processing, transfer, sale, or use of data." Moreover, data policy is part of a much broader set of strategic digital policies, including the development of new technologies such as AI and its algorithms, and the security of their networks.

Data governance is closely related to privacy, as "data collection, analysis and processing are mainly perceived as a threat to privacy" (Mazurek and Malagocka, 2019, 349). Yet, Kuziemski and Misuraca (2020, 2) stress that "govern[ing] algorithms, while governing by algorithms" defines the very ambiguous situation that governments face, i.e., protecting their citizens by respecting their data privacy and security, and granting access to improve the efficiency of technological systems. Thus, designers of public data governance policies must consider individual privacy and data security, but also guarantee access to this data to improve the technology and keep innovating (Rosenbaum, 2010).

There is room for improvement regarding studies that deal with public data governance policies (Okuyucu and Yavuz, 2020; Liu, 2021). Yet, Alhassan, Sammon and Daly, (2017) highlight the need to investigate public data governance and AI policies. Moreover, Gleeson and Walden (2016) stress the public sector's dearth of maturity in this area.

Therein, to address this gap, we have used machine learning through RapidMiner text mining analysis to highlight the different approaches of public data governance and AI policies in the world's three main technological regions—China, the European Union, and the United States—based on scientific literature analysis. Moreover, by using machine learning to analyze most influential items related to public data governance and AI policies in each of the three regions, our research is congruent with Klyton et al. (2023, 142) that posit that "the language used by various stakeholders […] contributes to the construction of hegemonic power affecting (or supporting) organizational control".

In the remainder of this paper, we first highlight the relationship that exists between AI and data governance and the public data governance in the EU, United States, and China. Then we present our research design, discuss our results, and finish with our conclusion.

LITERATURE REVIEW

Artificial Intelligence as a tool for data governance

Artificial intelligence (AI) and data governance are interdependent and complementary (Matthews, 2019). The amount of data is fundamental when evaluating the accuracy of algorithms, whereas data quality and governance are essential prerequisites for the effective use of AI (Smith, 2019). The development of AI not only allows the transformation of data into action, but AI also learns from this information and creates new ones (Calzada and Almirall, 2020). Yet, AI relies above all on the strategies and public policies that governments put in place using their companies as application tools.

The development of AI and other machine-learning systems brings new challenges for data governance: "the scale and scope of data used by the algorithms and the opacity of the algorithms" (Winter and Davidson, 2017, 281) regarding the way data is used and transformed into results. AI has "the increased capability to collect, analyze and combine vast amounts of data from different sources, […] thus enhancing the capabilities of technology powers" (Mazurek and Malagocka, 2019, 348). AI can work on specific tasks without human monitoring, which enhances its analysis performance. Therefore, the definition of AI directly implies data privacy issues, as AI can easily deduce or predict sensitive and personal information.

However, data governance policies are far more difficult to implement nowadays because data can be collected through numerous different devices (e.g., smartphones, watches, GPS) that do not belong to a state but to a private company that can sell the data to another country. In this context, it is not the public authorities that own real-time data, but private companies such as network operators or big technological firms (Alemanno, 2018). Thus, the enormous amount of data and its stakeholders increase the difficulty of implementing a strict and efficient data governance policy. Therefore, international data sharing is a source of economic and commercial development, but it also represents a risk to the privacy of citizens who are potentially vulnerable to "foreign surveillance, hacking and data breaches" (Liu, 2021, 51).

EU, U.S., and Chinese public data governance: three different approaches

The General Data Protection Regulation: a strong but inadequate European regulation

The fast-moving digital environment and exponential growth of data has led the EU to implement strong regulations to protect its citizens' privacy: the General Data Protection Regulation (GDPR). Yet, very recently the EU parliament adopted the 'AI Act' that will be voted now in the EU council aiming to reach an agreement by the end of 2023 to become a law (EU Parliament, 2023).

In Europe, the protection of citizens' personal data constitutes a fundamental right because it is inherently related to a natural person. In doing so, data protection means: "preserving a natural person from the misuse of his or her personal information" (Fabiano, 2019, 58).

Implemented in 2018, the GDPR regulation demands that companies comply with a set of rules regarding the collection, storage, and processing of European's personal data in response to ethics and privacy concerns. These measures imply for companies major technological, functional, juridical, and cultural changes and challenges, not without impacts on businesses. These far-reaching changes are time-consuming and expensive—necessitating the mobilization of additional financial and human resources—and they represent high barriers for companies which must adapt their overall organization (processes, routines, procedures) to ensure that their activities meet GDPR rules.

Thereby, to ensure data protection in cross-border flows, GDPR regulation has been added in every international trade agreement signed with the EU. Instead of applying different regulations according to the trading country, companies implement the European data protection law on a global scale. Therefore, the GDPR gets an extraterritorial scope as the foreign market follows this regulation with their partner countries in almost all their data transmission flows.

In practice, this regulation provides European citizens with the right to obtain an explanation regarding the decisions made by algorithms. However, Gordon-Murnane (2018, 41) highlights that "the GDPR lacks precise language as well as explicit and well-defined rights and safeguards against automated decision-making, and therefore runs the risk of being toothless." Hence, in the long run, the GDPR does not guarantee policies and technologies that comply with ethics and privacy. To be efficient, data protection law must be implemented in every step of the new technologies' development, from early stages to final processing. Unfortunately, our policymakers, industries, academia, and public sectors do not have the necessary resources to both develop efficient and innovative technologies and respect data protection law (Panagiotopoulos, 2019).

Yet, European regulators struggle to catch up and keep up with the growing pace of our digital evolution, and many measures that the GDPR has implemented conflict with the way global computer networks currently operate. The right to erase personal data is one of the most complex conditions to meet (Teixeira, Mira da Silva and Pereira 2019). In his report, Herian (2020) highlights this paradox, i.e., the right for European citizens to erase their personal data and the prohibition of storing personal data, which negatively impacts the possibility of improving control over one's own personal data.

Under GDPR regulation, data processing is governed by the purpose limitation concept: Data is collected and used only for a clearly defined purpose. However, the core principle of big data is to collect and analyze a very large amount of data and use it for different purposes, rather than a single defined purpose (Okuyucu and Yavuz, 2020). Thus, even if the data is not personal, platforms (e.g., Facebook) could reidentify a person by analyzing and triangulating enough data (Bendiek and Römer, 2018). As AI relies on big data systems, GDPR regulation on this technology is often discussed, with critics arguing both that this new law will slow down and limit innovation and that it threatens individual freedoms and fundamental human rights.

The Clarifying Lawful Overseas Use of Data Act: an instrument of U.S. digital supremacy

In democratic and liberal societies, privacy and data protection are tied to liberty. However, in the United States, privacy and data protection regulations are seen in another light, as "the focus is not on the protection of human dignity, but on freedom in the sense of liberty as a civil right of the individual, who wishes to be free of legal regulations" (Bendiek and Römer, 2018, 37). These different concepts can lead to conflicts of interest between states.

Implemented in 2018, the Clarifying Lawful Overseas Use of Data Act (CLOUD Act) enables the U.S. government to access every data center owned by a U.S. company, regardless of the geolocation of the servers. The CLOUD Act gives U.S. authorities permission to access U.S. cloud providers and request data on U.S. or foreign citizens and companies without their prior consent (Brincourt, 2021). Through bilateral agreements with national governments, the United States may also have access to data stored in the partner country. Thus, the CLOUD Act and the GDPR both have an extraterritorial characteristic involving numerous conflicts over the regulation of governance and digital sovereignty (Bendiek and Römer, 2018).

The CLOUD Act was enacted "in the name of protecting the public safety of the United States and fighting the most serious infractions, crimes, and terrorism" (U.S. Department of Justice, 2021). But this extraterritorial federal law expressly reflects the willingness of U.S. authorities to have access to data stored at service providers (Duboc and Noël, 2021). In accordance with a simple judge approval, service providers must communicate "the contents of electronic communications, any record, any information relating to a customer or subscriber, including personal data. The person who owns the data will not be notified" (The U.S. Department of Justice, 2021). The general characteristics of the law grant it a very broad scope of application:

individuals, companies, and the state, on all exchanges or data, wherever they are stored. This law breaches regulations concerning personal data protection, corporate data protection, and the protection of highly confidential elements of strategic state security. Considering that 85% of the global digital storage market is operated by U.S. firms, almost all European companies are potentially affected by this policy (Duboc and Noël, 2021).

China's data governance policies: a pillar of the Middle Kingdom's digital power

Liu (2021, 48) posits, "the Chinese government has long realized the strategic value of data." Since Xi Jinping came to power in 2013, the Chinese government has been building its big data national strategy and forging its way to becoming a "cyber superpower" (Segal, 2017) through:

- Strategic collaboration with digital firms
- Integration of big data into government statistics
- Upgrading of big data to a national strategy level
- Construction of a massive national data center

In 2017, the Chinese president enacted the Intelligence Law, its intention being to "strengthen the ability to protect the nation's crucial data resources, speed up relevant legislation, and improve protection of data property rights." (China Daily Newspaper, 2017). The extremely blurred framework of this law may give rise to fears of its extensive application, as with the U.S. CLOUD Act (Duboc and Noël, 2021).

China is continuously updating its data governance strategy and agenda, which makes it more relevant to its external environment. In China, this concept is intrinsically linked to the broader notion of "cyber sovereignty," defined by Liu (2021, 52) as "state control of digital technologies, content and infrastructure under their jurisdiction." The six fundamental texts of the Chinese data strategy are: the cybersecurity law (2016), the information security technology guidelines for data cross-border transfer security assessment (2017), the draft measures on security assessment of the cross-border transfer of personal information (2019), the draft measures for data security management (2019), the data security law of the PRC (2021), and the personal information protection law of the PRC (2021).

Early in the summer of 2022, China enhanced its data governance policy, and especially the data cross-border arrangement. Since then, companies have had to follow a set of CAC-implemented rules to transfer abroad any data created in PRC. Any company operating in the country must store its data in China. If a data transfer is to be made to another country, the government conducts a preliminary risk assessment. China's data localization requirement applies to the personal data of Chinese nationals, but also to so-called "important data," a blurred definition that can include any type of data, and that is all available to the Chinese government.

Hence, the approaches in this matter as are embodied in the EU, U.S., and Chinese regulations result "in three inherently incompatible legislative paradigms, which has led to the restricted flow of personal data around the world as well as the free flow in three different regions, with the EU, the United States and China as the center of each region" (Zheng, 2021, 1).

RESEARCH DESIGN

Sampling and document preprocessing

We initially made requests on a selection (to which we had full access) of online databases— "Emerald Insights," "Open Edition," and "Science Direct"—to gather scientific documents about "public data governance" and "AI policy(ies)" and "EU" or "China" or "United States." This allowed us to get 62 documents as a sample. We used RapidMiner text mining software to conduct our text analysis of these 62 documents. For that purpose, we needed to correctly prepare documents to get the appropriate formats, clean the database, and obtain more meaningful results. Yet, we performed a tokenization of our texts by "non-letters" to obtain non-letter characters as segment cuts in our texts. As we changed the texts from PDF format to TXT format, the non-letter characters could only be spacing or dashing, therefore segmenting our texts by words. Thereafter, we undertook a data "cleaning" in our database before running the analysis.

First, we filtered the tokens by length, (4 to 20 characters) and by the stop words. Finally, we performed the stemming (snowball) process to restore all the words back to their roots (e.g., *connect*, *connections*, and *connected* all include the root *connect*).

Moreover, before processing the Terms Frequency-Inverse Document Frequency (TF-IDF) analysis, we labeled our texts now turned into segments by using their origins i.e., China, EU, and United States.

Methods

Terms Frequency-Inverse Document Frequency (TF-IDF)

Terms Frequency-Inverse Document Frequency (TF-IDF) is a common method used in text mining to retrieve information (Christian et al., 2016). Its goal is to show the importance of each word to a document in a corpus. Compared to a basic word count, TF-IDF helps to underline the most important word in each label. In this case, we used the prune method to take only into account terms that appear between 5 to 9,999 times in the corpus.

KNN algorithm

The K-Nearest Neighbor (KNN) algorithm is a supervised machine-learning algorithm mainly used for classification (Uddin et al., 2022). Our aim was to utilize KNN to automatically classify the documents by nationality with this content and see how accurate it was. As we worked on a small amount of data, we wanted the data set that we got from the TF-IDF operations to be at the same time the training set and the test set. To do so, we used cross validation, i.e., in our case we used 80% of the data set to train the algorithm and 20% to test the result accuracy. We defined a stratified sampling to determine which texts would be used as part of the training set and which would be used as part of the test set, while having the same percentage of each subset (here labeled as the country) in the training and in the test set. Yet, we utilized the cosine similarity between two documents based on their TF-IDF score, which we calculated previously to determine the similarities of the texts. Then, we determined the right number of K Neighbor.

Naïve Bayes algorithm

The Naïve Bayes algorithm allowed us first to come up with another system of classification to perform another accuracy that might do better than the KNN one (Prasad et al., 2022). Thus, we could investigate which word(s) the algorithm found more determining for each label to classify them as a Chinese, American, or European texts. Yet, we did the Laplace correction, since if an event never occurs then its conditional probability would be equal to 0; therefore, we added 1 to each count feed in the algorithm (Wang et al., 2022).

RESULTS AND DISCUSSION

TF-IDF results

When we ran the TF-IDF algorithm, it resulted in a table containing 62 rows (one for each document), and 3,029 columns, column 2 being the labels, columns 4, 5, 6 containing the metadata and the other 3,024 containing single terms with the TF-IDF scores. The scores are low as we have many terms in each document (see Table 1).

Table 1. TF-IDF results

Row No.	label	text	metadata_f...	metadata_...	metadata_...	aaai	abid	abil
3	China	Artificial inte...	AI and Chin...	/Users/g.ve...	Aug 26, 20...	0	0	0.013
10	China	The State an...	The_State_a...	/Users/g.ve...	Aug 26, 20...	0	0	0.007
9	China	The Rise of ...	The rise of ...	/Users/g.ve...	Aug 26, 20...	0	0.009	0.005
7	China	Vol.:(01234...	Roberts202...	/Users/g.ve...	Aug 30, 20...	0	0	0
14	China	1 | Decipher...	deciphering...	/Users/g.ve...	Aug 30, 20...	0.013	0	0
35	EU	Contents list...	Mapping the...	/Users/g.ve...	Aug 26, 20...	0	0	0.016
4	China	Editorial	Chinese soci...	/Users/g.ve...	Aug 26, 20...	0	0	0.003
16	China	Technology i...	factors influ...	/Users/g.ve...	Aug 30, 20...	0.039	0	0.025
46	USA	Data is diffe...	Data is diffe...	/Users/g.ve...	Aug 26, 20...	0	0	0.005
15	China	Discussion P...	dp1755.pdf	/Users/g.ve...	Aug 30, 20...	0	0	0.002
1	China	Bud1 .0...	.DS_Store	/Users/g.ve...	Sep 1, 202...	0	0	0
2	China	ol	1-s2.0-S20...	/Users/g.ve...	Aug 30, 20...	0.043	0	0.008
5	China	How Social ...	How Social ...	/Users/g.ve...	Aug 27, 20...	0.004	0	0
6	China	Start my sub...	Is China Em...	/Users/g.ve...	Aug 30, 20...	0	0	0
8	China	com	The promisi...	/Users/g.ve...	Aug 26, 20...	0.004	0	0.004

ExampleSet (62 examples, 5 special attributes, 3,024 regular attributes)

Table 2 indicates the 11 most frequently appearing words in our documents, allowing one to see the main subjects of our research, i.e., data governance, research, privacy, state, and policies. All those terms are important as they are the main subjects of most papers. However, it would be difficult to use this data for a classifier algorithm as it would use those terms as important terms, even though they are not discriminant.

Table 2. Most frequently appearing words

Word	Attribu...	Tot... ↓	Docum...	China	EU	USA
data	data	9035	51	1735	4579	2721
govern	govern	3126	53	1328	1210	588
china	china	2024	28	1816	139	69
inform	inform	1958	53	379	968	611
technolog	technolog	1828	53	609	876	343
research	research	1577	50	502	823	252
develop	develop	1553	50	560	576	417
system	system	1405	48	395	749	261
privaci	privaci	1356	41	177	598	581
state	state	1345	49	529	331	485
polici	polici	1301	53	358	595	348

We then fed those results into the KNN classifier.

KNN classifier results

First, we needed to determine the optimum parameter number of K neighbor. As we built a loop to be more efficient, we could thereby determine which number of K neighbor has the minimum error rate. Our results stress that the fourth iteration has the minimum error rate: 27%. Therefore, we know that 5 K neighbor is the optimum parameter with an accuracy of 73% (see Figure 1).

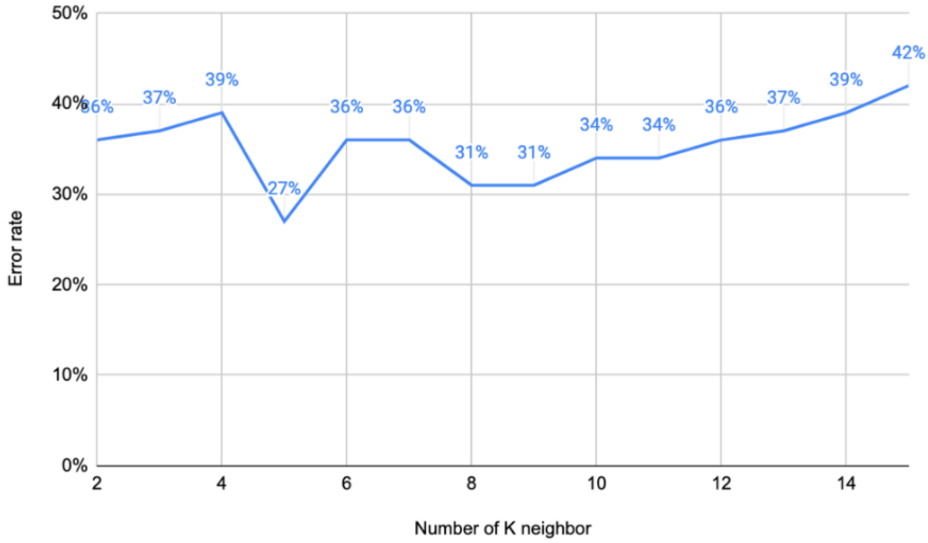

Figure 1. Error rate number of K neighbor

Thereafter, the confusion matrix of our KNN algorithm with 5 K neighbor set as parameter was done. As Table 3 indicates, the algorithm performs very well with predicting text coming from China—a 94.12% accuracy, with only one error of a European text predicted as Chinese. Hence, Chinese texts are highly recognizable, as they have a clear tendency on the topics (half of texts deals with Covid-19 and AI). Most of the Chinese texts mention the role of the state and its tight influence on research and companies.

The KNN algorithm performs rather well with the European text, with an accuracy of 80%. However, the accuracy drops below 50% for the American texts, with a tendency to label similarly to European texts, predicting nine texts as European and nine correctly predicted as American. The fact that there are also more European texts than American might additionally create a negative effect for the classifier, which has less data to train with to recognize the American label.

Table 3. KNN confusion matrix

accuracy: 64.49% +/- 4.43% (micro average: 64.52%)

	true China	true EU	true USA	class precision
pred. China	14	1	3	77.78%
pred. EU	2	19	10	61.29%
pred. USA	1	5	7	53.85%
class recall	82.35%	76.00%	35.00%	

Naïve Bayes algorithm results

Table 4. Naïve Bayes confusion matrix

Attribute	Parameter	China	EU ↓	USA
item	standard deviation	0.006	0.223	0.248
data	mean	0.064	0.189	0.155
data	standard deviation	0.083	0.171	0.139
ethic	standard deviation	0.078	0.155	0.107
gdpr	standard deviation	0.007	0.148	0.045
word	standard deviation	0.005	0.143	0.159
procur	standard deviation	0.021	0.141	0.014
machineri	standard deviation	0.006	0.129	0.001
cloud	standard deviation	0.006	0.124	0.016
reproduct	standard deviation	0.003	0.122	0.001
artifici	standard deviation	0.003	0.106	0.005
citi	standard deviation	0.021	0.103	0.129
explan	standard deviation	0.006	0.103	0.004
utilis	standard deviation	0.008	0.100	0.001
reproduc	standard deviation	0.002	0.086	0.006

The confusion matrix of the Naïve Bayes' classifier (see Table 4) didn't perform as well as the KNN classifier: 64.5% performance (as average). The algorithm performs less well when classifying all three labels, with a 12% drop in classification of the Chinese ones.

To investigate which terms influence each label the most, we checked the distribution table. This table shows two values per attribute, i.e., the mean deviation and the standard deviation. Our results highlight that there are more similarities among the influential terms between Europe and the United States (see Table 5), and the most influential word for the U.S. label also has strong influence on the EU one (thereby the classifier struggles to differentiate between the two classes).

Table 5. The EU sort Naïve Bayes distribution table

Attribute	Parameter	China ↓	EU	USA
china	mean	0.309	0.018	0.007
china	standard deviation	0.270	0.043	0.015
rumor	standard deviation	0.204	0.003	0.001
brain	standard deviation	0.186	0.016	0.001
outbreak	standard deviation	0.142	0.002	0.011
chines	mean	0.130	0.008	0.003
contract	standard deviation	0.118	0.030	0.007
chines	standard deviation	0.118	0.021	0.007
firm	standard deviation	0.117	0.033	0.043
densiti	standard deviation	0.113	0.003	0.003
virus	standard deviation	0.098	0.001	0.004
weibo	standard deviation	0.089	0.001	0.001
coronavirus	standard deviation	0.088	0.010	0.006

However, the most-influential Chinese terms are unique to its label. With almost no influence on the two other classes, this explains why China is the best-labeled category, with an error rate of 18% (see Table 6). It is congruent with Zeng (2020, 1442) who highlighted "the successful employment of digital technologies in China is made possible by [China's] unique socio-political environment." Thus, for China, we observe many terms related to the Covid-19 pandemic (e.g., *outbreak*, *virus*, *coronavirus*, *epidemic*). The term *authoritarian* appears in Row 16, thereby allowing them to focus only on the technical part of AI, and not on public opinion nor law limitations, which is in line with what was stated in our literature (Zeng, 2020; Liu, 2021).

Table 6. The Chinese sort Naïve Bayes distribution table

If we add up the 15 most influential attributes for China, we reach the number 2.155; the same attributes for the EU reach 0.205 and 0.160 for the United States. This means that the influential terms for China are unique for this specific label. If we perform the same analysis on the EU, we find that its 15 most influential terms reach the number 2.041, which is quite a shift when compared with China, for which those terms score 0.321. However, those terms do have an influence on the U.S. label, where they score 1.029. This confirms that the difference between the EU and U.S. texts is not as wide as the difference between the EU and the Chinese texts. Moreover, the 15 most influential terms for the United States and EU share three terms: *data*, *item*, *word*.

Attribute	Parameter	China ↓	EU	USA
china	mean	0.309	0.018	0.007
china	standard deviation	0.270	0.043	0.015
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virus	standard deviation	0.098	0.001	0.004
weibo	standard deviation	0.089	0.001	0.001
coronavirus	standard deviation	0.088	0.010	0.006

Yet, it is very interesting to find words such as *GDPR* and *ethic* as the fourth and fifth most influential terms for European-labeled texts. As defined in the literature review, there is a difference between the way China and EU countries are working on AI. The EU is trying to build a different model based on the spectrum of data privacy (first and thirty-first terms ranked) and prioritize the rights of its citizenry (city ranked 12th). This, according to Hlávka (2020), is one of the reasons why the EU lags in terms of AI-related technological advances. Furthermore, this is where we can see the difference between the EU and the United States.

Even though it is not as relevant as the differences that the EU and the United States have with China, there is still a difference between the United States and the EU. Our algorithms allow us to obtain more terms coming from U.S. private industry, as well as potential application of AI (same as China, and a few words being related to Covid-19), as we have medical terms like *health* ranked fourth, *healthcare* ranked seventh, *medic* 11th, and *patient* 13th—but also, terms that are related to company property, such as *court*, *venture*, and *copyright*. Therefore, as Duboc and Noel (2021) stressed, even if the United States created the CLOUD Act (which is still very vague on different subjects), it still allows massive collections of data—wherever their tech companies do business in the world— to feed their algorithm and maintain their competitiveness against the Chinese tech companies that are government-sponsored.

CONCLUSION

Data constitutes the main vector today of the success of companies and countries. Yet, data represents "the most important factor to ensure successful AI algorithms" (Lee, 2018, 34) as it "feeds" the AI algorithm constructed. AI importance is growing, as pointed out in 2017 by Russia's President Putin: "whoever leads in artificial intelligence will rule the world." (Meyer, 2017). Therein, to control the internet and data, states define public data governance policies (Woods, 2018). Alhassan et al. (2017) amplified the need to investigate public data governance and AI policies. In an aim to help address this gap, we've used machine learning through RapidMiner text mining analysis to highlight the different approaches to public data governance and AI policies as they exist in the Chinese, European, and U.S. literature. We've sought to determine whether a classification of the texts obtained in scientific databases is possible according to the key words characterizing the approach to public data governance and AI policies and depending on the three geographical areas selected.

We obtained a 72% accuracy with the KNN algorithm using the cosine similarity with the number of neighbors set to 5- and it performed well on the Chinese' texts and less well when differentiating U.S. labeled text from European text.

We used the Naïve Bayes algorithm and obtained a 64% accuracy, which is not as good as that which was achieved with KNN. However, it enabled us to understand better how the algorithm weighted each probability to classify the text. We determined that Chinese top discriminant terms were more unlikely to also be discriminant for the EU and U.S. texts. While the EU and U.S. texts tend to be more similar and so have similar discriminant terms.

Our results emphasize that China has no legal limit in terms of developing its big database's algorithm. Yet, the United States tends to focus more on its data sovereignty, but with more mentions of ethics or privacy than in China. Regarding the EU, it highlights that the EU is trying to build a model that focuses on data privacy and rules to protect its citizens' privacy.

The survey has some limitations due to the limited number of databases used as well as the limitations of RapidMiner.

REFERENCES

Aaronson, S.A. 2019. Data is different, and that's why the world needs a new approach to governing cross-border data flows. Digital Policy, Regulation and Governance 21(5): 441–460.

Alemanno, A. 2018. Big Data for Good: Unlocking Privately-Held Data to the Benefit of the Many. European Journal of Risk Regulation 9(2): 183–191.

Alhassan, I., Sammon, D. and Daly, M. 2018. Data governance activities: a comparison between scientific and practice-oriented literature. Journal of Enterprise Information Management 31(2): 300–316.

Bendiek, A. and Römer, M. 2019. Externalizing Europe: the global effects of European data protection. Digital Policy, Regulation and Governance 21(1): 32–43.

Bisson, C. 2013. Guide de gestion strategique de l'information pour les PME. Montmoreau : Les 2Encres.

Brincourt, L. 2021. Géopolitique de la Datasphère. Le "Cloud Act", trois ans après : révélateur du besoin de définition de notre souveraineté dans l'espace numérique. Accessed November 17, 2022. https://www.diploweb.com/Le-Cloud-Act-trois-ans-apres-revelateur-du-besoin-de-definition-de-notre-souverainete-dans-l-espace.html

Calzada, I. and Almirall, E. 2020. Data ecosystems for protecting European citizens' digital rights. Transforming Government: People, Process and Policy 14(2): 133–147.

China Daily Newspaper. 2017. 习近平：实施国家大数据战略加快建设数字中国. Accessed November 21, 2022. http://www.chinadaily.com.cn/interface/flipboard/1142846/2017-12-12/cd_35280418.html.

Christian, H., Pramodana Agus, M and Suhartono, D. 2016. Single Document Automatic Text Summarization using Term Frequency-Inverse Document Frequency (TF-IDF). ComTech: Computer, Mathematics and Engineering Applications 7(4): 285-294.

Data Governance Institute 2022. Definitions of Data Governance. Accessed November 21,2022. https://datagovernance.com/the-data-governance-basics/definitions-of-data-governance/

Duboc, S. and Noël, D.-J. 2021. Economie et gouvernance de la donnée. Accessed November 17, 2022. https://www.lecese.fr/sites/default/files/pdf/Avis/2021/2021_06_eco_gouv_donnee.pdf

EU Parliament. 2023. EU AI Act: first regulation on artificial intelligence. Accessed June 25, 2023. EU AI Act: first regulation on artificial intelligence | News | European Parliament (europa.eu)

Fabiano, N. 2019. Ethics and the Protection of Personal Data. Journal of Systemics Cybernetics and Informatics 17(2): 58–64.

Gleeson, N. and Walden, I. 2016. Placing the state in the cloud: Issues of data governance and public procurement. Computer Law & Security Review 32(5): 683–695.

Gordon-Murnane, L. 2018. Ethical, Explainable Artificial Intelligence - Bias and Principles. Online Searcher 42(2): 22–44.

Herian, R. 2018. Regulating Disruption: Blockchain, GDPR, and Questions of Data Sovereignty. Social Science Research Network 22(2): 7–16.

Hlávka, J.P. 2020. Security, privacy, and information-sharing aspects of healthcare artificial intelligence. In Artificial Intelligence in Healthcare, ed. A. Bohr and K. Memarzadeh, 235–270. Amsterdam, Netherlands: Elsevier.

van Klyton, A. Arrieta-Paredes, M.-P., Palladino, N. and Soomaree, A. 2023. Hegemonic practices in multistakeholder Internet governance: Participatory evangelism, quiet politics, and glorification of status quo at ICANN meetings. The Information Society 39 (3): 141-157.

Kostka, G. 2019. China's social credit systems and public opinion: Explaining high levels of approval. New Media & Society 21(7): 1565–1593.

Kshetri, N. 2014. Big data′s impact on privacy, security and consumer welfare. Telecommunications Policy,38(11): 1134–1145.

Kuziemski, M. and Misuraca, G. 2020. AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. Telecommunications Policy 44(6): 101976.

Lee, K. 2018. AI Superpowers: China, Silicon Valley, And The New World Order. Houghton: Mifflin Harcourt Company.

Liu, L. 2021. The Rise of Data Politics: Digital China and the World. Studies in Comparative International Development 56(1): 45–67.

Matthews, K. 2019. How AI is slowly changing data governance. Information Management 27 November.

Mazurek, G. and Małagocka, K. 2019. Perception of privacy and data protection in the context of the development of artificial intelligence. Journal of Management Analytics 6(4): 344–364. McLuhan, M., & (1967). The medium is the massage: An inventory of effects.

McLuhan, M. and Fiore, Q. 1967. The Medium is the Massage: An Inventory of Effects. Berkeley, CA: Gingko Press.

Meyer, D. 2017. Vladimir Putin Says Whoever Leads in Artificial Intelligence Will Rule the World. Accessed Oct 20, 2022. https://fortune.com/2017/09/04/ai-artificial-intelligence-putin-rule-world/,

Mureddu, F., Schmeling, J. and Kanellou, E. 2020. Research challenges for the use of big data in policy-making. Transforming Government: People, Process and Policy 14(4): 593–604.

Okuyucu, A. and Yavuz, N. 2020. Big data maturity models for the public sector: a review of state and organizational level models. Transforming Government: People, Process and Policy 14(4): 681–699.

Panagiotopoulos, A. 2019. Data protection law and ethics: Where do we stand? Information and records management society (212): 8–11.

Prasad, R., Agrawal, R. and Sharma, H. 2022. Modified Gabor Filter with Enhanced Naïve Bayes Algorithm for Facial Expression Recognition in Image Processing. In Advances in Computational Intelligence and Communication Technology, Lecture Notes in Networks and Systems, ed Gao, XZ., Tiwari, S., Trivedi, M.C., Singh, P.K., Mishra, K.K., 371–383. Singapore: Springer.

Rosenbaum, S. 2010. Data Governance and Stewardship: Designing Data Stewardship Entities and Advancing Data Access. Health Services Research 45(5): 1442–1455.

Segal, A. 2021. When China Rules the Web: Technology in Service of the State. Foreign Affairs 24 November.

Seurre, X. 2020. L'intelligence artificielle, un enjeu stratégique pour la puissance chinoise. Accessed November 17, 2022. https://www.iris-france.org/notes/lintelligenceartificielle-un-enjeu-strategique-pour-la-puissance-chinoise/

Smith, D. 2019. AI in Data Governance Strategic Finance, 1 November. Accessed November 17, 2022. https://sfmagazine.com/post-entry/september-2019-ai-in-data-governance/

Teixeira, A. G., Mira da Silva, M. and Pereira, R. 2019. The critical success factors of GDPR implementation: a systematic literature review. Digital Policy, Regulation and Governance 21(4): 402–418.

Uddin, S., Haque, I., Lu, H., Moni, M.A. and Gide, E. 2022. Comparative performance analysis of K-nearest neighbour (KNN) algorithm and its different variants for disease prediction. Sci Rep 12, 6256.

The US Department of Justice. 2021. Cloud act resources. Accessed November 22, 2022. https://www.justice.gov/dag/cloudact

Wang Y, Li T, Liu M, Li C, Wang H. 2022. Study on token shuffling under incomplete information based on machine learning. International Journal of Intelligent systems 37(12): 1-23.

Winter, J.S. and Davidson, E. 2018. Big data governance of personal health information and challenges to contextual integrity. The Information Society,35(1): 36–51.

Woods, A.K. 2018. Litigating Data Sovereignty. Yale Law Journal 128(2): 328–406.

Zeng, J. (2020).Artificial intelligence and China's authoritarian governance. International Affairs 96(6): 1441–1459.

Zheng, G. 2021. Trilemma and tripartition: The regulatory paradigms of cross-border personal data transfer in the EU, the U.S. and China. Computer Law &Amp; Security Review 43: 105610.