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Original Research

Determining the Knowledge Components Affecting Intelligent Knowledge Extraction: A Meta-Synthesis

Mila Malekolkalami
Ph.D. Student, Knowledge and Information Science, Management and Economics Faculty, Tarbiat Modares University, Tehran, Iran.
malekolkalami@modares.ac.ir
ORCID iD: https://orcid.org/0000-0003-2831-9307

Mohammad Hassanzadeh
Professor, Knowledge and Information Science, Management and Economics Faculty, Tarbiat Modares University, Tehran, Iran.
Corresponding Author: hasanzadeh@modares.ac.ir
ORCID iD: https://orcid.org/0000-0002-6175-0855

Atefeh Sharif
Assistant Prof., Knowledge and Information Science, Management and Economics Faculty, Tarbiat Modares University, Tehran, Iran.
Atefeh.sharif@modares.ac.ir
ORCID iD: https://orcid.org/0000-0003-4761-6761

Mansoor Rezghi
Associate Prof., Computer Science, Department of Mathematics, Tarbiat Modares University, Tehran, Iran.
Rezghi@modares.ac.ir
ORCID iD: https://orcid.org/0000-0003-4214-5008

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Abstract

Considering the importance of knowledge extraction as one of the stages of knowledge acquisition in the organization, this article aims to identify the effective components and dimensions of intelligent knowledge extraction and determine the importance of each one. Using the seven-step method of Wilson and Lipsey (2001), 280 research articles retrieved from databases were examined, and finally, 32 articles were evaluated. The critical Assessment Skills Program was used to score the articles. To extract codes and concepts, the articles were entered into the Atlas.ti software. Shannon's entropy was used to determine the importance of each component. In this research, 51 codes were categorized into six main dimensions (individual factors, education and learning, technology agents and smart technology, knowledge, dynamism and agility, and organizational factors). The results show that the component of "empowerment" has the most frequency and importance in extracting knowledge. This result shows the importance of training human resources in strengthening the organization. Also, in the spider diagram, the teaching and learning dimension has the highest weight among the identified dimensions. There is no organized study of the factors affecting intelligent knowledge extraction in this field. Therefore, as a pioneer, this research has achieved an organized framework for extracting knowledge and determining the importance of each identified dimension by categorizing themes. With the increasing importance of knowledge management in recent years, the attention of organizations and companies' managers has been attracted to processes leading to achieving, controlling, and making available their knowledge as an organizational asset. Knowledge as an organizational asset plays an extremely vital role today. Organizations necessitate knowledge related to their business field to achieve a competitive advantage.

Keywords*:* Knowledge Management, Intelligent Extraction, Meta-Synthesis.

Introduction

Different sources achieve technology-based knowledge extraction; the latest trends in knowledge management (KM), such as customer and vendor knowledge, mobile applications for KM, Collaborative Knowledge Management Systems (KMS), and social intranet can be integrated with business processes. KM also coincides with various business fields like marketing, sales, human resource, operations, supply chain, etc. Storing, processing, and analyzing extracted knowledge can increase business intelligence (Bharara, Sabitha & Bansal, 2017). And make the organization successful in the competitive environment and economic market. In an organization or an industry, there are different sources of knowledge to acquire and extract knowledge from. Acquiring and extracting knowledge from employees is as important as that from customers and the organization's target community. For example, to sustain a competitive advantage in the long term, an organization must keep its technological systems in harmony with social systems and use technologies to increase people's efficiency and facilitate the flow of knowledge. (Bhatt, 2001).

Earlier industrial revolutions sought to increase the automation of repetitive physical work, but the industrial revolution has made it possible to do intellectual or unusual tasks on a large scale using automation (Ménière, Rudyk & Valdes, 2017). Industrial Revolution 4.0 seeks to change how industries are managed by creating a convergence between physical and digital spaces that will lead to changes in management. Increasing productivity and flexibility and reducing costs are among the goals of the new generation of the industrial revolution, which requires the discovery and presentation of new patterns. (Guo et al., 2021). The industry's rapid movement towards digitalization has made knowledge managers cultivate valuable information per organizational goals. (Schniederjans, Curado & Khalajhedayati, 2020). On the other hand, since the advancement of technology, the techniques and methods of knowledge extraction have also changed in the knowledge acquisition process.

Knowledge extraction is one of the bases of artificial intelligence applications (Razniewski, Tandon & Varde, 2021). Knowledge extraction aims to extract key information such as entities, attributes, and relations from data (Xu, Gao & Li, 2021) and extract the knowledge elements from the collected data (Zhang et al., 2021a). Knowledge extraction aims to quickly refine deep knowledge and apply it to explain the path of simulation, analyze the reasons for the formulation of the phenomenon, define the hypothesis and the validity of the conclusion, and draw policy and strategic implications (Yang, Cai & Xue, 2022). The knowledge extraction technique will become the spine of any successful organization. Moreover, the knowledge extraction must be quick and efficient to apply the newly-obtained knowledge simultaneously.

Halder and Knapp (2013) state that two issues have hindered the growth of knowledge mining in the industry: one, the sheer volume of documents that must be processed, and second, the lack of expertise in knowledge mining (Ali, Latiff & Wahab, 2020). Considering the goals of knowledge extraction in organizations, and the problems that exist on the way to its growth, identifying the dimensions that influence knowledge extraction can create a clear path for starting and continuing the life of knowledge extraction in the organization. With these dimensions, knowledge managers and organizations can plan strategically to acquire their unique knowledge in the market. Identifying practical patterns between pieces of information in the organization is essential for making appropriate decisions. Today, one of the challenges of organizations is facing a large amount of information, and extracting knowledge from them is uncertain for the organization (Esposito, Del Buono & Selicato, 2021), while the resulting knowledge can lead to a competitive advantage. Therefore, the optimal use of this data is vital to the organization and will be useless if it is not converted into knowledge.

Therefore, there has been some research on intelligent extraction of knowledge models (Zuo, Chen, Qu, Huang, Wang & Chen, 2019; Zhou & Xue, 2020; Liu, Athanasiou, Padture, Sheldon & Gao, 2021; Noskova & Pavlova, 2020; Hu, Zhang, Luo & Chen, 2020) which discussed the methods, and special features from the perspective of artificial intelligence. Many of these studies have examined the method of extracting knowledge from different sources, such as extracting knowledge from chatbots (Arsovski, Osipyan, Oladele & Cheok, 2020), text databases (Yang, Kim, Hur, Cho, Han & Seo, 2018), organizations names (Chen & Chert, 2000), healthcare systems (Rencis, 2019), big data from the internet (Mani, Bari, Liao & Berkovich, 2014), Pharmaceutical Texts (Jofche, Mishev, Stojanov, Jovanovik & Trajanov, 2021), databases (Falle, Panhalkar, Jadhav, Kambl, Salunkhe & Mirajkar, 2017), Personal Knowledge (Tajedini, Sadatmoosavi & Esfandiarpour, 2018), Wikipedia (Kim & Lee, 2019), question-answer system (Xia, Boyu, Lixia & Ruidi, 2020).

As mentioned, no study has been done on the dimensions and components affecting intelligent knowledge extraction. Besides having the skills related to artificial intelligence and targeted algorithms in knowledge extraction, the organization needs to know the types of resources and dimensions available to have a knowledge extraction system and its successful implementation. Identifying these components and dimensions can lead to standard and native intelligent extraction at the organizational level. The results of this research can help the organization make optimal decisions, save money and energy, plan practical knowledge strategies, evaluate the status of knowledge extraction, and be aware of all the sources and components affecting knowledge extraction. The results of this study can help the organization to know from which sources the knowledge that leads to competitive advantage is extracted and obtained and which components should be looked for to acquire knowledge. Recognizing and strengthening each of the sources of knowledge systematically in industries will help to find a way to extract knowledge intelligently. Researchers can find organized algorithms and focus on each component's goals in business processes to capture and extract knowledge intelligently.

In this paper, we are particularly interested in identifying and extracting the essential components and key themes used in knowledge extraction through the meta-synthesis method. By identifying these resources, algorithms can be defined specifically for each organization. The knowledge obtained by evaluating these components in an organization can lead to success and dominance among other peers.

Materials and Methods

The Meta-Synthesis requires the researcher to conduct a thorough and in-depth review and combine the findings of related qualitative research. The meta-combination method was used according to the model of Wilson and Lipsey (2001) to achieve the research goal.

Step 1: Set the purpose of the study

This study aims to identify the indicators and factors influencing the explanation of the intelligent extraction of knowledge model. As a result of this search and by entering the inclusion criteria, about 280 studies were found for review to achieve the following research questions (Table 1).

Table 1
Research Questions

Parameter	Research Question
What?	What indicators are used to measure the model of intelligent knowledge extraction?
Who? When?	What are the dimensions of effective factors in explaining the model of intelligent extraction of knowledge?
How?	Do the dimensions of effective factors affect the model of intelligent extraction of knowledge?

The keywords searched in this research are "Knowledge extraction framework", "Knowledge extraction model", and "Intelligent extraction of knowledge". In this study, the keywords used to identify the articles are shown in Table 2.

Table 2
Research Keywords

Keywords
Knowledge extraction framework
Knowledge extraction model
Intelligent extraction of knowledge

Step 2: A systematic review of the literature

Secondary data have been used to collect research data. These documents have been included in all models of intelligent extraction of knowledge. Articles and studies conducted from 2000 to 2020 have been studied. To collect and categorize the content of articles produced in the field of research, it was referred to the Google search engine and databases of scientific articles. A total of 280 studies were found by reviewing and identifying research through the National Library and other libraries' search systems, research institutes, and international databases such as Science Direct, Google Scholar, Springer, Emerald, Researchgate, Worldscientific, etc., with related keywords.

Step 3: Search and select appropriate texts

The researcher excluded some articles in each review that are not studied in the meta-synthesis process. This process is shown in Figure 1 (De Ridder, Lensvelt-Mulders, Finkenauer, Stok & Baumeister, 2018).

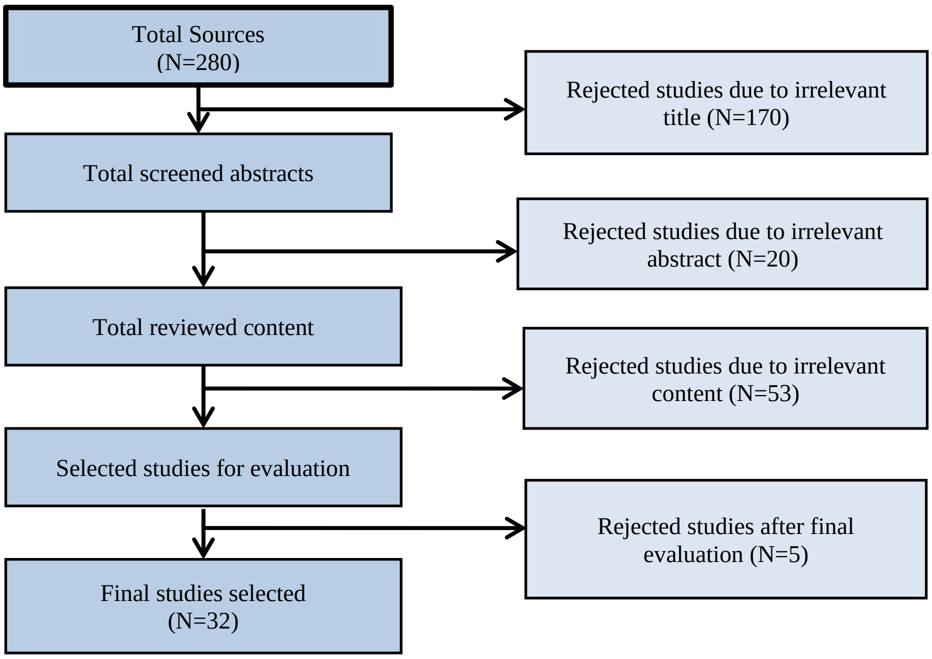

Figure1: Review and selection process

In this step, 280 studies found in the previous step were carefully reviewed in several steps to exclude studies that do not fit the research questions and finally to identify the most relevant studies to extract the answers to the questions. The review process includes reviewing the research's title, abstract, content, and methodology. The steps of the review process in this research are as follows:

1. At this stage, the reviewed studies whose titles were unrelated to the research questions were excluded. By reviewing the study title, 170 studies were discarded due to the lack of relevance of their title to the research questions, and 110 studies entered the next stage for further review.

2. At this stage, the reviewed studies whose abstracts were unrelated to the research questions were excluded. By studying the abstracts, 20 studies were discarded due to the lack of connection between the abstract and the research questions, and 90 studies entered the next stage for further study.

3. At this stage, the content of the studies was reviewed, and studies that were not related to the research questions were excluded. By reviewing the content of the studies, 53 studies unrelated to the research questions were discarded, and 37 studies were taken to the next stage for further investigation.

4. according to the final evaluation of the articles and their relationship with the subject of intelligent extraction of knowledge, 5 other studies were deleted due to lack of communication.

As shown in Figure 1, after studying and reviewing 280 articles, 32 articles entered the final evaluation stage. These 32 selected studies are presented in Table 3.

Table3
List of Final articles

Article Code	Title	Authors
C01	Intelligent Information Extraction	Neumann & Xu (2004).
C02	Advanced Information and Knowledge Processing	Jain & Wu (2009).
C03	Digital Transformation and Knowledge Management in the Public Sector	Alvarenga, Matos, Godina & Matias (2020).
C04	An Intelligent Knowledge Management System from a Semantic Perspective	Mazilescu (2008).
C05	Foundations of intelligent knowledge management	Zhang, Li, Shi & Liu (2009).
C06	Using ICT to enhance Knowledge Management in higher education: A conceptual framework and research agenda	Omona, van der Weide & Lubega (2010).
C07	Information Extraction for Effective Knowledge Management	Palshikar, Srivastava, Deshpande & Bhat (2015)
C08	The Intelligent Enterprise and Knowledge Management	Wiig (1999)
C09	Intelligent Systems and Knowledge Management	Kanellopoulos, Kotsiantis & Pintelas (2008).
C10	A conceptual framework of contextual factors affecting knowledge transfer using the meta-synthesis method	Shoelh, Golabchi & Haji Yakhchali (2019).
C11	Business intelligence for business Processes: the case of it incident Management	Goby, Brandt, Feuerriegel & Neumann (2016).
C12	Advances in Knowledge Management: An Overview	Razmerita, Phillips-Wren & Jain (2016).
C13	Adaptations of data mining methodologies: a systematic literature review	Plotnikova, Dumas & Milani (2020).
C14	Information Extraction: Methodologies and Applications	Tang, Hong, Zhang & Li (2008).
C15	Study on Process-oriented intelligent knowledge management Meta-Synthesis system model	Zhang, Song & Li (2007).
C16	A Multi-intelligent Agent Architecture for Knowledge Extraction: Novel Approaches for Automatic Production Rules Extraction	Kadhim, Alam, & Kaur (2014).
C17	Effectiveness and efficiency of cross-border knowledge transfer: An empirical examination	Pérez-Nordtvedt, Kedia, Datta & Rasheed (2008).
C18	From imitation to innovation: The discursive processes of knowledge creation in the Chinese space industry	Bi et al. (2017).
C19	Integration, knowledge creation and B2B governance: The role of resource hierarchies in financial performance	Adams & Graham (2017)

Article Code	Title	Authors
C20	Extending data mining methodologies to encompass organizational factors	Debuse (2007).
C21	Current Practices OF Virtual Community and Their Influence on Social Cohesion	Md Dahalin et al. (2015).
C22	Mining Knowledge from Text Using Information Extraction	Mooney & Bunescu (2005).
C23	Knowledge acquisition for decision support systems on an electronic assembly line	Gebus & Leiviskä (2009).
C24	Artificial Intelligence: Structures and Strategies for Complex Problem Solving	Luger (2005).
C25	To Develop Tool, an Intelligent Agent for Automatic Knowledge Acquisition In Rule-based Expert System	Kadhim & Alam (2012)
C26	Just talking? Middle managers negotiating problem ownership in gender equality interventions	Lansu, Bleijenbergh & Benschop (2020).
C27	Exploring knowledge creation processes as a source of organizational learning: A longitudinal case study of a public innovation project	Brix (2017).
C28	Knowledge creation processes as critical enablers for innovation	Esterhuizen, Schutte & Du Toit (2012).
C29	Knowledge sharing motivational factors of using an intra-organizational social media platform	Vuori & Okkonen (2012).
C30	Knowledge extraction and representation using quantum mechanics and intelligent models	Kim, Choi & Kwak (2012).
C31	Zadehian Paradigms for Knowledge Extraction in Intelligent Manufacturing	Ullah & Harib (2006).
C32	Intelligent information extraction based on artificial neural network	Ansari, Maknojia & Shaikh (2016).

After removing the articles according to the process, the methodological quality of the research was also examined. This stage aims to eliminate research in which the researcher does not trust the findings. The most common tool used to evaluate the quality of primary qualitative research studies is the Critical Assessment Skills Program (CASP), which helps to determine the accuracy, validity, and importance of qualitative research studies by proposing ten questions. These questions focus on the following: 1. Research objectives. 2. Methodological logic, 3. Research design, 4. Sampling method, 5. Data collection, 6. Reflection (which refers to the relationship between the researcher and the participants), 7. Ethical considerations, 8. Accuracy of analysis and Data analysis, 9. Clear expression of findings, 10. Research value. To use this tool, all studies have been reviewed, and each study is given a score between 1 and 5 in terms of having the above characteristics. Based on the 50-point scale of the Critical Appraisal Skills Program, the researcher proposes the following scoring system and categorizes studies according to their degree of methodological quality: very good (50-41), good (40-31), moderate (moderate) 21-30), weak (11-20), very weak (0-11).

Based on the Critical Appraisal Skills Program (Table 4), the researcher performs the above scoring system and removes any research below a good score (below 31) (Chenail, 2011; De Ridder, Lensvelt-Mulders, Finkenauer, Stok & Baumeister, 2018). The research content and method were evaluated in the previous section using CASP. Based on this, 32 articles were evaluated based on ten criteria. The result of the structural and content analysis of the articles was the approval of 32 articles.

Table 4
The outcome of the Critical Assessment Skills Program (CASP)

Criteria / Article	Research purposes	Methodological logic	Research plan	Sampling method	Collecting data	Reflexivity	Ethical considerations	Accuracy of data analysis	Clear expression of findings	Research Methods	Total points
C01	4	4	3	4	4	3	5	4	4	4	39
C02	3	4	4	3	4	3	5	4	3	3	36
C03	4	4	4	4	3	4	5	4	3	3	38
C04	3	3	3	4	4	4	5	4	3	4	37
C05	4	4	3	3	3	4	5	4	3	4	37
C06	5	4	4	4	3	4	5	4	4	3	40
C07	4	4	4	4	4	4	5	4	4	4	41
C08	4	4	4	4	3	4	5	4	4	4	40
C09	2	3	2	3	4	3	5	2	3	2	29
C10	3	4	3	4	4	3	5	4	4	3	37
C11	2	3	4	4	3	4	5	3	4	3	35
C12	5	5	4	5	4	4	5	5	4	4	45
C13	4	3	2	3	2	3	5	3	3	2	30
C14	4	4	4	3	4	4	5	4	3	4	39
C15	2	3	3	4	4	3	5	4	3	3	34
C16	3	3	4	2	3	3	5	2	3	2	30
C17	5	4	3	4	4	4	5	4	4	4	41
C18	4	4	3	4	4	4	5	3	3	4	38
C19	3	4	4	3	3	2	5	3	2	2	31
C20	3	3	4	2	4	3	5	4	5	4	37
C21	3	4	5	4	3	4	5	4	4	4	40
C22	5	4	4	3	4	4	5	3	4	3	39
C23	5	4	5	4	4	5	5	4	4	4	44
C24	2	3	2	4	4	3	5	3	3	3	32
C25	3	3	4	3	3	3	5	3	2	3	32
C26	3	4	3	3	2	3	5	4	3	2	32
C27	4	4	3	4	3	3	5	4	3	4	37
C28	2	4	3	2	3	3	5	4	2	3	31
C29	2	3	2	4	3	4	5	3	4	3	33
C30	2	3	4	4	3	2	5	4	3	2	32
C31	4	4	3	4	4	4	5	3	3	4	38
C32	3	4	4	3	3	2	5	3	2	2	31

This evaluation was performed on extractive codes. The coding status of the first and second researchers is shown in Table 5.

Table5
Codification table of 1st and 2nd encoders

The total score of 1st encoder	2nd encoder's opinion			
	No	Yes		
30	2	28	Yes	1st encoder's opinion
2	0	2	No	
32	2	30	The total score of 2nd encoder	

The analysis results obtained from the SPSS statistical software are shown in Table 6.

Table 6
Agreement measurement values

	Value	Significant
Agreed to Kappa	0.840	0.001
Number	32	

As can be seen, the significant number obtained from Cohen's kappa coefficient is less than 0.05, so the assumption of the independence of the extracted codes is rejected and the dependence of the extracted codes on each other is confirmed, so it can be claimed that the 32 papers used to extract the codes were sufficiently reliable.

Step 4: Information extraction from articles

Next, the articles were entered into Atlas to extract the codes and concepts.ti software. In Figure 2, the qualitative analysis software specifies a view of extracting codes from the articles**.**

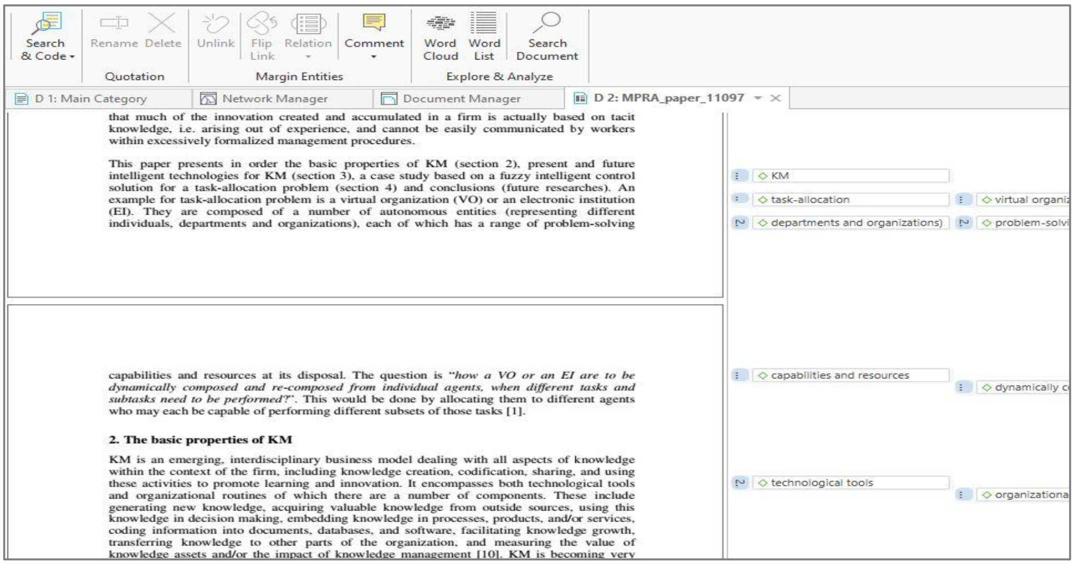

Figure 2: A view of Code Extraction in Atlas.ti Software

In this study, research information was categorized in Table 7. This table contains the following information:

Research ID: Name of the authors, year of publication
Information of main findings: Extracted components (Honorton, Ferrari & Hansen, 2018)

Table7
Codes Extracted from Selected Articles

Primary code	Source
Formal and informal relationships	C1, C2,C19
Self-education and personal development	C1, C22, C31, C32
Trust	C3,C4, C14, C30, C38
Acceptance of technology	C6, C10,C11,C12, C19,C26, C28,C30
Perception	C6, C10,C11,C12, C19,C23, C28
Individual feelings and attitudes	C14, C20, C29
Communication skills	C5,C6,C17, C21, C26, C29, C30, C31
Motivation	C3, C9, C12, C21, C28,, C32
The spirit of cooperation and interaction	C1,C11,C19, C25
Empowerment	C22, C27, C29
Job Satisfaction	C1,C2, C5, C11,C15, C20, C26, C27
Organizational Culture	C8,C9, C12, C18, C22, C30,
Organizational reward system	C1,C16, C22
Organizational motivation system	C12, C18, C23, C27
Manager support	C1, C5, C11,C29
Culturalization	C3-C10-C19-C30-C32
Organizational Structure	C14, C21, C25, C32
Organizational Commitment	C7, C12, C19, C25
Knowledge extraction opportunities	C7,C8,C9,C10,C11,C19, C20, C28
Characteristics of organizational leaders	C10,C16, C17, C27
Organizational strategy	C15, C19, C27, C29, C32
Institutional Relations	C23, C32
Learning	C19, C20, C28
Organizational rules and regulations	C25, C30
Financing	C3,C4,C17, C20, C22, C26, C31,
team work	C3,C4,C12, C19, C20, C24, C28, C31
Management infrastructure	C1,C2,C3,C4,C21, C25, C31
Organizational capital (human resources, internal resources)	C1,C2, C8,C9,C10,C11,C12,C13, C14C17, C24, C27
Social software (smart site, messenger, software Knowledge management tools)	C4,C5,C6,,C11,C12,C13,, C18, C19, C21
Information and communication technology (Internet, software and hardware according to the type of company)	C9-C21
technological infrastructure	C1-C2-C6
Semantic web (virtual discussion, subscription types Social Networks)	C10-C17
Knowledge management systems	C1-C2-C5-C9
Ability to use new technology in bulk data analysis	C13-C16-C22
Application of artificial intelligence	C17-C25-C30
Data mining application	C18

Primary code	Source
Types of knowledge (specialized, practical, qualitative, general knowledge and management of various types of knowledge, etc.)	C13-C35
Knowledge management processes (knowledge planning, knowledge acquisition, knowledge organization, knowledge retrieval, knowledge application, knowledge retention, knowledge evaluation)	C1-C3-C7
Dimensions of knowledge (tracking, representation, flow, map, audit, ontology, classification, clustering, etc.)	C9-C21
Accelerate response	C1-C2-C6
Smart tools (Internet of things, artificial intelligence and other cases)	C5-C8-C19-C30
Speed in decision making	C1-C4-C6-C8-C16
Flexibility in action	C19-C21-C25
The power to face challenges	C1-C2-C5-C9
Facilitate matters while complying with regulations	C3-C4-C8-C18
Use of intelligent knowledge in decision making (dynamics)	C1,C16, C22
Creativity and innovation	C12, C18, C23, C27
Experimental and oral teaching and learning	C1, C5, C11,C29
Distance and virtual education	C14, C16, C25, C32
Exchange ideas and storytelling	C19, C21
Collaborative teaching and learning	C26, C29

It can be seen in Table 7 that some primary codes are in common in different articles. Figure 3 shows the cloud created from extracted codes in Atlas.ti software.

Figure 3: Cloud Codes Formed in Atlas.ti Software

Step 5: Analyze qualitative findings

In this research, first, all the factors extracted from the studies were considered as identifiers, and then by considering the meaning of each of them, identifiers were defined in a similar concept; Next, similar concepts were categorized in explanatory categories to identify the fields explaining the factors affecting the context of the intelligent knowledge extraction model in the form of the main components of research. Table 8 presents the main and sub-categories of qualitative analysis:

Table8
Main categories and related codes

Main Category	Related codes
Individual factors (9)	Formal and informal relationships
	Self-education and personal development
	Trust
	Acceptance of technology
	Perception
	Individual feelings and attitudes
	Communication skills
	Motivation
	The spirit of cooperation and interaction
Teaching and learning (19)	Empowerment
	Job Satisfaction
	Organizational Culture
	Organizational reward system
	Organizational motivation system
	Manager support
	Culturalization
	Organizational Structure
	Organizational Commitment
	Knowledge extraction opportunities
	Characteristics of organizational leaders
	Organizational strategy
	Institutional Relations
	Learning
	Organizational rules and regulations
	Financing
	teamwork
	Management infrastructure
	Organizational capital (human resources, internal resources)
Technology agents and intelligent technology (8)	Social software (smart site, messenger, software Knowledge management tools)
	Information and communication technology (Internet, software and hardware according to the type of company)
	technological infrastructure
	Semantic web (virtual discussion, subscription types Social Networks)
	Knowledge management systems
	Ability to use new technology in bulk data analysis

Main Category	Related codes
	Application of artificial intelligence
	Data mining application
Knowledge (3)	Types of knowledge (specialized, practical, qualitative, general knowledge and management of various types of knowledge, etc.)
	Knowledge management processes (knowledge planning, knowledge acquisition, knowledge organization, knowledge retrieval, knowledge application, knowledge retention, knowledge evaluation)
	Dimensions of knowledge (tracking, representation, flow, map, audit, ontology, classification, clustering, etc.)
Dynamics and agility (8)	Accelerate response
	Smart tools (Internet of things, artificial intelligence, and other cases)
	Speed in decision making
	Flexibility in action
	The power to face challenges
	Facilitate matters while complying with regulations
	Use of intelligent knowledge in decision-making (dynamics)
	Creativity and innovation
Organizational factors (4)	Experimental and oral teaching and learning
	Distance and virtual education
	Exchange ideas and storytelling
	Collaborative teaching and learning

We observe from Table 8 that there are 6 main categories explaining the factors affecting the context of the intelligent knowledge extraction model. They include Individual factors (9 codes), Teaching and learning (19 codes), Technology agents and intelligent technology (8 codes), Knowledge (3 codes), Dynamics and agility (8 codes), and Organizational factors (4 codes). Figure 4 shows the identified factors in the form of 6 main dimensions.

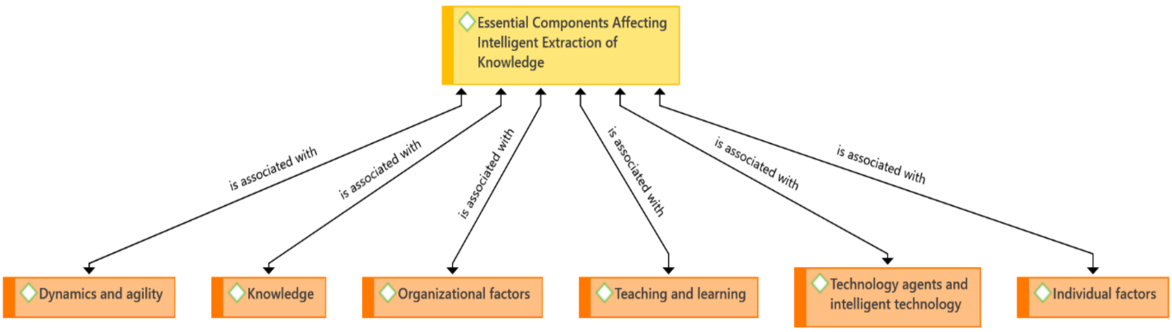

Figure 4: Identified 6 main dimensions

Step 6: Control of analysis quality

Four quantitative criteria have been used to assess validity, transferability, verifiability, and reliability: The Holstein coefficient, Scott's Pi coefficient, Cohen's kappa coefficient (κ), and Krippendorff's alpha (α). The correlation of the experts' viewpoints with the calculation of the Holstein coefficient or "Percentage of Observed Agreement" (PAO) is obtained at 0.823, which is a significant value. According to the drawbacks of the Holstein method, Scott's Pi coefficient has also been calculated, which is 0.786. The fourth indicator for assessing the validity of qualitative research is Cohen's kappa coefficient. The Cohen's kappa coefficient in this study is 0.76. Finally, Krippendorff's alpha has been used, estimated at 0.790 in this study.

Step 7: Presenting the report and studying the findings

In this step of the meta-synthesis method, the findings of the previous steps are presented. At this stage, using the Shannon entropy method, the support level of previous studies from the findings of this study is shown statistically.

Shannon entropy

According to the Shannon entropy method, data processing in the discussion of content analysis is presented with a new perspective, quantitatively and qualitatively (Lin, 1991).

After identifying the research indicators based on content analysis and determining the units of analysis (words and themes), the Shannon entropy method will be used to analyze the data as follows:

- First, the frequency of each identified category must be determined based on content analysis.
- The intended matrix must be normalized. For this purpose, the linear normalization method is used:

$$n_{ij}= \frac{\mathrm{xij}}{\Sigma \mathrm{xij}}$$

The information load of each category must be calculated. The following equation is used for this purpose:

$$k = \frac{1}{Ln(a)} \quad a = \text{Number of options}$$

$$Ej=-k\Sigma[n_{ij}LN(n_{ij})]$$

The coefficient of importance of each category must be calculated. The higher the information load, the more important each category is. The following equation is used for this purpose:

$$w_{\mathrm{j}} = \frac{\mathrm{Ej}}{\Sigma \mathrm{Ej}}$$

Therefore, in the first step, the decision matrix is formed. The scores obtained from the decision matrix on the issue are presented in Table 9:

Table 9

Determining the importance and emphasis of previous research on identified factors

Code	Frequency	$\Sigma \boldsymbol{Pij} \times \boldsymbol{k}\mathrm{n}\boldsymbol{Pij}$	Unreliability Ej	Significance factor Wj	Rank
Empowerment	14	-0.1523	0.0386	0.0405	1
Organizational motivation system	12	-0.1373	0.0348	0.0365	2
Job Satisfaction	11	-0.1294	0.0328	0.0344	3
Organizational Culture	11	-0.1294	0.0328	0.0344	3
Self-education and personal development	10	-0.1211	0.0307	0.0322	4
The spirit of cooperation and interaction	10	-0.1211	0.0307	0.0322	4
Formal and informal relationships	9	-0.1125	0.0285	0.0299	5
Organizational reward system	9	-0.1125	0.0285	0.0299	5

Code	Frequency	$\Sigma Pij \times k\mathrm{n}Pij$	Unreliability Ej	Significance factor Wj	Rank
Knowledge extraction opportunities	8	-0.1034	0.0262	0.0275	6
Exchange ideas and storytelling	8	-0.1034	0.0262	0.0275	6
Organizational Structure	8	-0.1034	0.0262	0.0275	6
Dimensions of knowledge (tracking, representation, flow, map, audit, ontology, classification, clustering, etc.)	8	-0.1034	0.0262	0.0275	6
Acceptance of technology	8	-0.1034	0.0262	0.0275	6
Types of knowledge (specialized, practical, qualitative, general knowledge and management of various types of knowledge, etc.)	7	-0.0939	0.0238	0.0250	7
Knowledge management systems	7	-0.0939	0.0238	0.0250	7
Collaborative teaching and learning	7	-0.0939	0.0238	0.0250	7
Individual feelings and attitudes	6	-0.0839	0.0212	0.0223	8
Trust	6	-0.0839	0.0212	0.0223	8
Organizational Commitment	6	-0.0839	0.0212	0.0223	8
Organizational rules and regulations	6	-0.0839	0.0212	0.0223	8
Organizational strategy	6	-0.0839	0.0212	0.0223	8
technological infrastructure	6	-0.0839	0.0212	0.0223	8
Semantic web (virtual discussion, subscription types Social Networks)	6	-0.0839	0.0212	0.0223	8
Motivation	5	-0.0733	0.0185	0.0195	9
Culturalization	5	-0.0733	0.0185	0.0195	9
Accelerate response	5	-0.0733	0.0185	0.0195	9
Distance and virtual education	5	-0.0733	0.0185	0.0195	9
Manager support	5	-0.0733	0.0185	0.0195	9
teamwork	5	-0.0733	0.0185	0.0195	9
Communication skills	4	-0.0619	0.0157	0.0165	10
Smart tools	4	-0.0619	0.0157	0.0165	10
Data mining application	4	-0.0619	0.0157	0.0165	10
Perception	3	-0.0496	0.0125	0.0132	11
Financing	3	-0.0496	0.0125	0.0132	11
Knowledge management processes (knowledge planning, knowledge acquisition, knowledge organization, knowledge retrieval, knowledge application, knowledge retention, knowledge evaluation)	3	-0.0496	0.0125	0.0132	11
Ability to use new technology in bulk data analysis	3	-0.0496	0.0125	0.0132	11
Speed in decision making	3	-0.0496	0.0125	0.0132	11
Flexibility in action	3	-0.0496	0.0125	0.0132	11
Facilitate matters while complying with regulations	3	-0.0496	0.0125	0.0132	11

Code	Frequency	$\Sigma \boldsymbol{Pij} \times \boldsymbol{k} \mathrm{n} \boldsymbol{Pij}$	Unreliability Ej	Significance factor Wj	Rank
Characteristics of organizational leaders	2	-0.0360	0.0091	0.0096	12
Institutional Relations	2	-0.0360	0.0091	0.0096	12
Learning	2	-0.0360	0.0091	0.0096	12
Management infrastructure	2	-0.0360	0.0091	0.0096	12
Social software (smart site, messenger, software Knowledge management tools)	2	-0.0360	0.0091	0.0096	12
Information and communication technology (Internet, software and hardware according to the type of company)	2	-0.0360	0.0091	0.0096	12
The power to face challenges	2	-0.0360	0.0091	0.0096	12
Use of intelligent knowledge in decision-making (dynamics)	2	-0.0360	0.0091	0.0096	12
Creativity and innovation	2	-0.0360	0.0091	0.0096	12
Organizational capital (human resources, internal resources)	1	-0.0205	0.0052	0.0055	13
Application of artificial intelligence	1	-0.0205	0.0052	0.0055	13
Experimental and oral teaching and learning	1	-0.0205	0.0052	0.0055	13

As seen in the table, empowerment with a rank of 1 and frequency of 14 is one of the most important factors in the intelligent extraction of knowledge model, which has been mentioned in previous studies. On the other hand, organizational capital (human resources, internal resources), application of artificial intelligence, and experimental and oral teaching and learning with a rank of 13 and frequency of 1 are among the least used factors in an intelligent extraction of knowledge model. Finally, the weight of all 6 dimensions has been determined based on the obtained frequency.

Based on the designed diagram (Figures 5, 6), the weight of the teaching and learning dimension is 0.31, the Individual factors dimension is 0.21, the Technology agents and intelligent technology dimension is 0.19, the Knowledge dimension is 0.17, Dynamics and agility dimension is 0.16, the Organizational factors dimension is 0.14. The teaching and learning dimension has the most weight in intelligent knowledge extraction. As mentioned, the rank of each component in the categorized theme was determined. Empowerment is the first place of ranked components. Organizational capital (human resources, internal resources), Application of artificial intelligence, and Experimental and oral teaching and learning are ranked 13th. The frequency of each theme is as follows:

1. Individual factors theme with 9 components is applied in the articles with a frequency of 61.
2. Teaching and learning theme with 19 components is applied in the articles with a frequency of 118.
3. Technology agents and intelligent technology theme with 8 components is applied in the articles with a frequency of 31.
4. Knowledge theme with 3 components is applied in the articles with a frequency of 18.

5. Dynamics and agility theme with 8 components are applied in the articles with a frequency of 24.

6. Organizational factors theme with 4 components is applied in the articles with a frequency of 21.

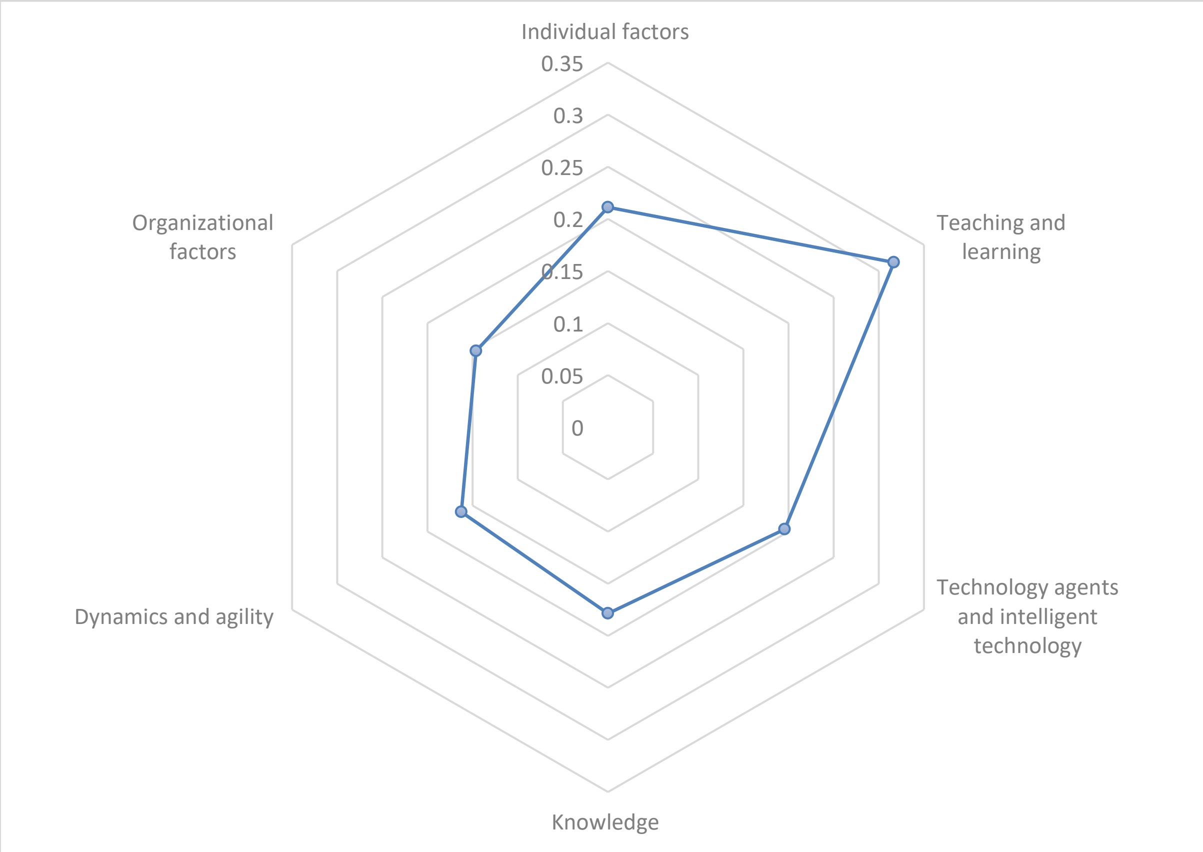

Figure 5: The Spider Web Diagram of the Weighting of the Identified Factors

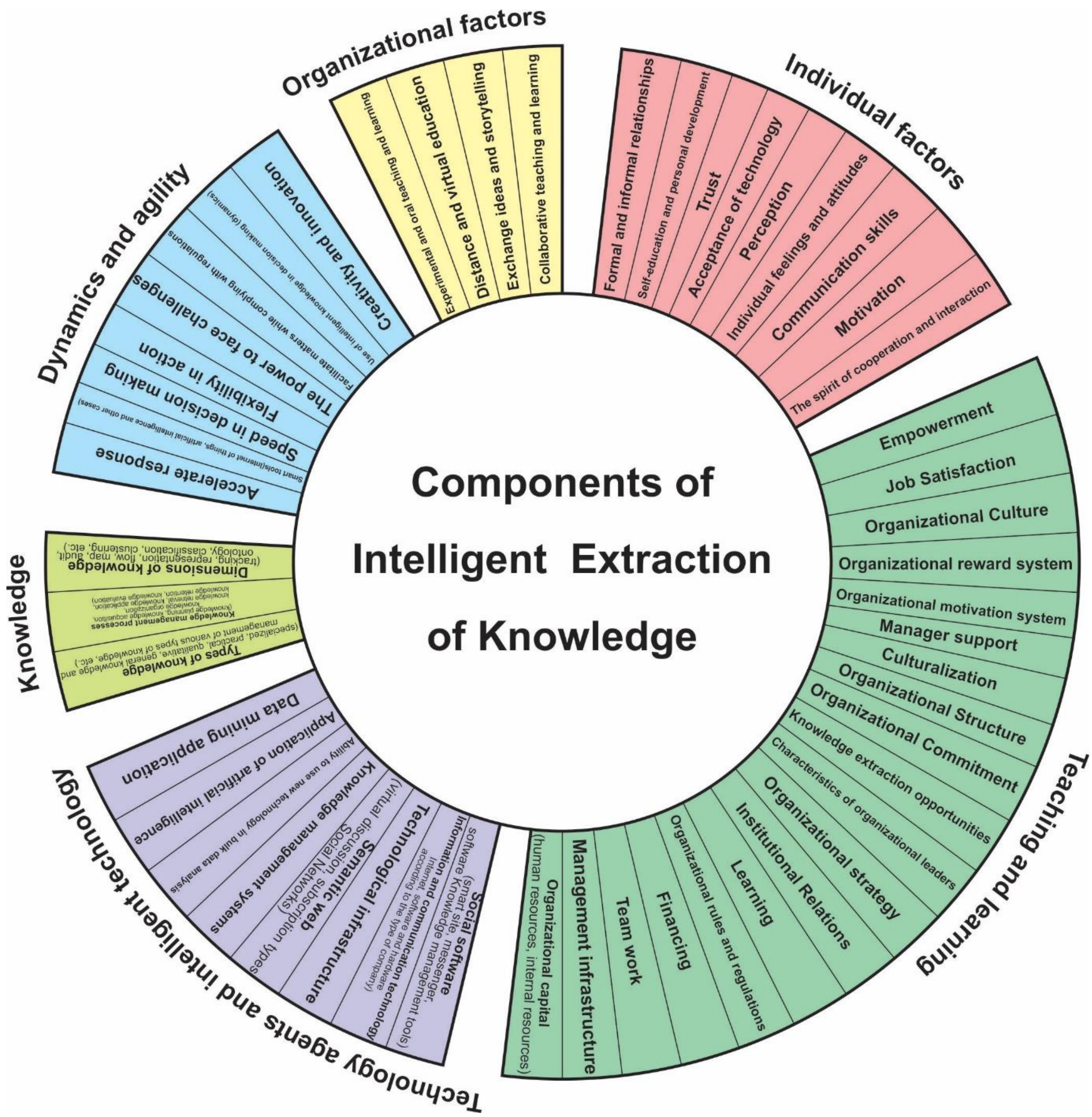

Figure 6: Components of Intelligent Extraction of Knowledge

Discussion

This study's teaching and learning dimension is the most significant in knowledge extraction. Human sources training can affect the process of knowledge intelligence extraction. For example, with the emergence of Covid-19 and its destructive impact on human society, we witnessed the nature of our human shortcomings and realized the importance of vital knowledge even more.

As Willet (2004, quoted in Antone, 2005) says, "Without the critical knowledge, we are operating in a vacuum. With the application of artificial intelligence and the use of big data in knowledge acquisition, the teaching and learning of human resources lead to the acquisition of new knowledge and skills that help them develop the organization's goals and promote their careers. In the field of knowledge extraction in organizations, teaching, and learning aims to train human resources equipped with the knowledge, skills, and attitudes necessary for participation (Hang, 2022) in work processes and integration with artificial intelligence. New research has focused on identifying key features of industry Evolution 4.0 that have highlighted the importance of humans in this process (Ansari, Erol & Sihn, 2018; Vaidya, Ambad & Bhosle, 2018; Ginting, 2020; Inshakova, Frolova, Rusakova & Kovalev, 2020; Guo et al., 2021). Empowerment is one of the most important issues in the industry, which is also mentioned in the definition of Industry 5.0. Knowledge extraction requires modern equipment and methods that human resources need to learn.

Individual factors are second-ranked in this study. Some studies support the components in this dimension. Being taught and learned are critical for specialists and managers in knowledge extraction. A part of this learning can be progressed by self-human.

Self-education and personal development are essential to a specialist's life (Khachirova, 2020). This development should happen in a continuous process of education and training aimed at forming a system of knowledge, skills, and value orientations (Duysenbaeva & Baisalbaeva, 2019). Acceptance of technology and trust are bases of using modern equipment and methods in knowledge extraction. There may be some concerns about individual privacy, so it is hard for people to accept and trust technology such as AI-based systems (Zhdanov, Bhattacharjee & Bragin, 2022). Individual feelings and attitudes and communication skills can have an impact on conducting knowledge extraction as a study showed people with introverted, silent, and isolated personalities seem to have poor communication skills in interacting with others, which is one of the barriers to knowledge sharing in virtual communities (Mokhtari Nouri, Ebadi, Rezaiye & Babajani Vafsi, 2022) and as it has been shown in our study is in interaction with people by technology and its acceptance are critical.

Appropriate technological infrastructures are important in starting and continuing the knowledge extraction process, as it is ranked in this study, and different infrastructures in knowledge extraction have also been mentioned in the literature (Omidipoor, Toomanian & Samani, 2018). The purpose of using data mining as one of the most important steps in knowledge extraction is to extract knowledge from data by discovering hidden patterns between data (Kocakoç & Türkölmez, 2022). Technology agents and intelligent technology have been studied in knowledge extraction fields (Chen, 2020; Zhang et al., 2021b). The new generation of the industry sees technology as a tool for developing and implementing other new technologies to improve business processes, so it should support the empowerment of resources by technology (Wisnujati, 2020).

Different types of Knowledge exist in the databases, and the knowledge extraction methods can differ for them, i.e., structured or unstructured data. On the other hand, taxonomies and knowledge graphs are the tools for knowledge extraction. Levels of knowledge extraction, different types of knowledge bases and sources, and existing evaluation procedures are considered in these tools (Abu-Salih, AL-Qurishi, Alweshah, AL-Smadi, Alfayez & Saadeh, 2022). To find a proper knowledge extraction method, different types of knowledge are relevant to a decision problem (Aerts, Deryck & Vennekens, 2022). Breakthroughs in IT have changed knowledge management processes, and some phases, such as knowledge storage or knowledge sharing, and knowledge extraction in this process could not be possible without IT tools (Gribovskis, 2021).

As the fifth-ranked dimension, dynamics, and agility are critical in this process. It is stated in previous studies that the lack of development in the process may be concluded from a lack of the necessary dynamics and agility (Quintela, Carneiro & Ferreira, 2019). Dynamics and agility are knowledge management investments in company knowledge (Jain, 2021). They are the tool for competitive advantage in the business management ecosystem (Jabeen, Al Zaidi & Al Dhaheri, 2021).

Organizational factors, the sixth and last dimension, can drive the knowledge extraction process in organizations in various ways. Danylyuk (2018) mentioned distance and virtual education in knowledge extraction in his study. Storytelling videos, Storytelling chatbots, and knowledge management systems using a storytelling-based approach have been mentioned in some studies, too (Osman, Noah & Saad, 2022; Jabbari, Mantegh & Akhgar, 2022; Jackson & Latham,2022).

Conclusion

Knowledge is increasingly essential in modern organizations (Rahimi, Rostami, Shad & Vafaei, 2017). Knowledge management is a systematic and organizational-specific framework to capture, acquire, organize, and communicate tacit and explicit knowledge (Alavi & Leidner, 1999; Davenport & Prusak, 1998). As one of the processes in knowledge management, knowledge extraction has been increasingly considered in organizations; on the other side, technological advancement has changed the techniques of knowledge extraction as far as emerging artificial intelligence in knowledge management processes. Therefore, to extract knowledge successfully, it is significant to identify the important components from which knowledge is acquired.

Empowering the employee is affected by information systems and knowledge management. It can positively influence the relationship between knowledge management and the performance of employees (Abualoush, Obeidat, Tarhini & Al-Badi, 2018). Hence, it should be considered in training courses and organizations' policies to make knowledge flows victoriously; and by applying technology, as mentioned in the technology theme, we will be able to create an intelligent extraction of knowledge in the organization.

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