International Journal of Data Science and Analytics (2022) 14:99–111
https://doi.org/10.1007/s41060-022-00338-9

EDITORIAL

Collective intelligence and knowledge exploration: an introduction

Salma Sassi[1] · Mirjana Ivanovic[2] · Richard Chbeir[3] · Rajendra Prasath[4] · Yannis Manolopoulos[5]

Published online: 17 June 2022

Abstract
Collective intelligence and Knowledge Exploration (CI and KE) have been adopted to solve many problems. They are particularly used by companies as a support for innovation to efficiently obtain usable results. CI is usually defined as a group ability to perform consistently well across a wide variety of tasks, and it has to be combined with KD to ensure processes optimization, efficient management process, participative management, leadership, continuous teamwork, and so on. The importance of innovation grows the same way as the importance of mixing CI and KE, ensuring the successful exploitation of knowledge. Here, we present a quick review of current knowledge-oriented CI developments and applications. It aims at showing some observations about what's currently missing. Our editorial presents some recent interesting studies that we have gathered after a tight selection process. It also concludes by proposing avenue challenges to continue pushing CI and KE research forward, particularly regarding knowledge exploration.

Keywords Collective intelligence · Collective knowledge · Knowledge management · Knowledge exploration · Knowledge discovery · Knowledge community · Human-centered computer

1 Introduction

The concept of Collective Intelligence (CI) has been initially introduced in [1], where Wechsler states that "Collective behavior describes any cooperative enterprise in which individuals pool their resources to enhance task achievement. Collective intelligence is generally more innovative, though not necessarily more effective, than the intellectual capability of individuals working alone or in tandem". In [2], Wheeler, an entomologist, observed the close cooperation of the ants in the colony to form a single organism exhibiting intelligent behavior. In the mid-1990s, when Internet and digital communications had already been established and were undergoing exponential growth, Pierre Lèvy (a philosopher and cultural theorist) has introduced in [3] a new definition of collective intelligence as a new approach to generating and mobilizing skills by using communication systems, which provide users of delocalized communities with means and environments to coordinate their interactions toward collective endeavors in the same virtual environment. Thus, CI refers to skills and interactions and embraces the abilities, the capacities, and the possibilities that citizens have individually to achieve collective aims. CI has been studied by other researchers using other terms such as "Collective Intelligence" [4, 5], "group intelligence" [6], "wisdom of crowds" [7], "vox populi" [8], "collective mind" [9] or "organization mind" [10]. In [11], a new definition of CI is provided as a small group's general ability to perform a wide variety of tasks. Thus, to perform consistently well across a set of tasks, the group must have high CI (and a group with low CI would perform consistently poorly). This definition is based on the theory of individual intelligence and adopted theoretical and

✉ Yannis Manolopoulos
yannis.manolopoulos@ouc.ac.cy

Salma Sassi
salma.sassi@fsjegj.rnu.tn

Mirjana Ivanovic
mira@dmi.uns.ac.rs

Richard Chbeir
richard.chbeir@univ-pau.fr

Rajendra Prasath
drrprasath@gmail.com

1 University of Jendouba, Jendouba, Tunisia

2 University of Novi Sad, Novi Sad, Serbia

3 University Pau and Pays Adour, Pau, France

4 Indian Institute of Information Technology, Tiruchirappalli, India

5 Open University of Cyprus, Latsia, Cyprus

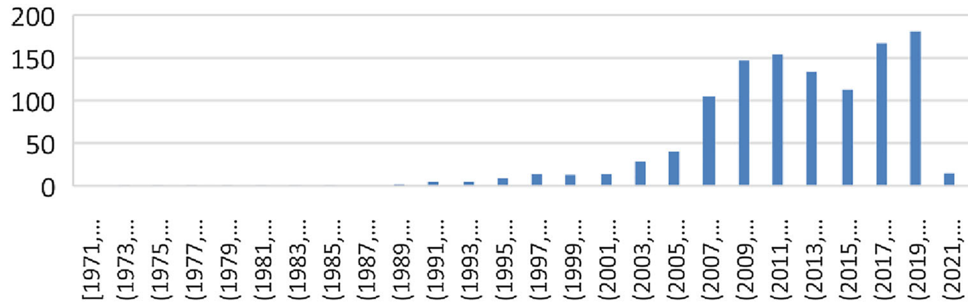

Fig. 1 Collective intelligence papers

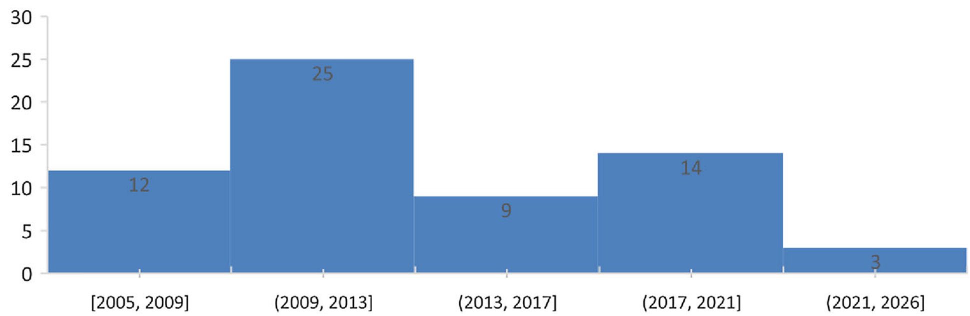

Fig. 2 Collective intelligence papers treating knowledge

measurement arguments from general intelligence as documented in [12]. Since the latter work, several other studies have been proposed confirming the initial results of the CI definition of Woolley et al. in human groups [13–15]. Nevertheless, other studies have discussed the obtained results [16, 17] and reached different results regarding the importance of individual skills in predicting group CI [18]. According to [19], CI is the synergistic and cumulative channeling of the vast human and available technical resources (over the Internet). Another definition reports that CI is a human–computer system where machines enable the collection and harvesting of amounts of human-generated knowledge [20]. Despite the discrepancy between results, all studies confirm that CI ensures better communication in the creation and management of innovation due to information technology tools.

Figure 1 shows a complete picture of research papers published during the last decades addressing collective intelligence within computer science communities. The list contains 1182 papers that have been generated using Google Scholar with the terms 'Collective Intelligence'. One can observe:

- The first paper has been published in 1971 by Wechsler [1]
- The number of publications has been increasing significantly since 2007 (with more than 60 papers per year).

It is important to note that CI is composed of three main and important steps: Data collection, Data Analysis, and Knowledge discovery/exploration. While the first two steps have attracted more attention from the communities, we observed that knowledge exploration remains partially addressed (Fig. 2 shows the list of 63 papers addressing knowledge in CI out of the 1182s). To define the Knowledge exploration in the CI process, there are a lot of possibilities for how to describe its meaning and the concept. In [21], the authors define it '*as a process that aims to improve the storing, creation, sharing and use of resources leading to improve the performance of individual employees and the organization as a whole entity*'. To better understand the importance of knowledge exploration, we can state that the knowledge is generally perceived neither as data nor information though it is related to both of them, and the differences between these terms are often commuted. Knowledge is broader, deeper, and richer than data or information.

In fact, the success of a CI system is related to its underlying architecture or framework. However, most existing approaches are based on specific problems [22] and are defined using system-specific elements, principles, attributes, requirements, or their combinations [23]. In other terms, current approaches are often presented with different entities. Indeed, the diversity of knowledge has not yet led to the development of a unified CI model [23] that can support the development of new CI systems based on exploring systematic knowledge [23]. Also, systems that are described in scientific literature focus more on theoretical foundations, usability, and future applications of collective intelligence [22], rather than focusing on how to explore individual and collective knowledge. This lack of well-defined and knowledge exploration has led us to initiate this special issue since we believe that the importance of innovation grows the same

Table 1 List of selected papers

Reference	Title	Publication type
Iandolo et al. [24]	Combining big data and artificial intelligence for managing collective knowledge in unpredictable environment —Insights from the Chinese case in facing COVID-19	Journal
Jian [25]	Improving situational awareness with collective artificial intelligence over knowledge graphs	Conference
Namnual et al. [26]	Development of digital repository system for knowledge management by using collective intelligence and big data for SMEs	Journal
Smirnov et al. [27]	Context-aware knowledge management for socio-cyber-physical systems: New trends towards human–machine collective intelligence	Conference
Li et al. [28]	The influence factors of collective intelligence emergence in knowledge communities based on social network analysis	Journal
Wang et al. [29]	An integrated open approach to capturing systematic knowledge for manufacturing process innovation based on collective intelligence	Journal
Nguyen et al. [30]	Intelligent collectives: Theory, applications and research challenges	Journal
Matzler et al. [31]	Leadership and the wisdom of crowds: How to tap into the collective intelligence an organization	Journal
Skarzauskiene et al. [32]	Modelling the index of collective intelligence in online community projects	Conference
Salminen [33]	The role of collective intelligence in crowdsourcing innovation	PhD Thesis
Georgi et al. [34]	Collective intelligence model: How to describe collective intelligence	Conference
Lykourentzou et al. [35]	Collective intelligence systems: Classification and modeling	Journal
Gregg [36]	Designing for collective intelligence	Journal
Schut [37]	On model design for simulation of collective intelligence	Journal
Vergados et al. [38]	A resource allocation framework for collective intelligence system engineering	Conference
Malone et al. [39]	Harnessing crowds: Mapping the genome of collective intelligence	Journal
Iandoli [40]	Leveraging the power of collective intelligence through IT-enabled global collaboration”	Journal
Boder [41]	Collective intelligence: A keystone in knowledge management	Journal

way as the importance of Knowledge Management (KM) and Collective Intelligence.

2 Current status of literature

2.1 Paper selection

Figure 2 shows the distribution of research papers (63 papers out of 1182) addressing knowledge in collective intelligence within computer science communities. In fact, this list has been extracted from the previous one by choosing those out of which the title or keywords contain the term “Knowledge”.

From this list, we selected and analyzed the following 18 most impacting papers in knowledge exploration in CI (see Table 1).

We applied a two-phase selection process. During this process, we analyzed and selected the most impacting studies related to knowledge exploration in collective intelligence. In the first selection phase, we studied the titles and abstracts of the identified articles and assessed them based on the primary inclusion criteria listed below:

- Primary criterion 1: explaining the theoretical foundations of CI systems
- Primary criterion 2: describing the role of collective intelligence in Information systems
- Primary criterion 3: describing architecture/frameworks of CI systems
- Primary criterion 4: describing CI systems/applications available on the Web
- Primary criterion 5: using knowledge generation and exchange in CI systems
- Primary criterion 6: using knowledge exploration in CI systems

After completion of this phase, we conducted a second selection phase where we applied the following quality assessment to the primary articles selected in Phase 1.

- Criterion 1: Providing a clear research objective (C1)
- Criterion 2: Proposing a new framework or providing technical details of an existing CI system (C2)
- Criterion 3: Providing a clear system architecture/framework/design/experiment (C3)

Table 2 Comparison of selected papers

Reference	C1	C2	C3	C4	C5	C6
Iandolo et al. [24]	Yes	Yes	Partial	No	Partial	No
Jian M. [25]	Yes	Yes	Yes	Partial	Partial	No
Namnual T. et al. [26]	Yes	Yes	Partial	No	No	No
Smirnov et al. [27]	Yes	Yes	Yes	No	Yes	No
Li et al. [28]	Yes	No	Partial	No	No	No
Wang et al. [29]	Yes	Yes	Yes	No	Partial	Partial
Nguyen et al. [30]	Yes	Yes	Partial	No	Partial	Yes
Matzler et al. [31]	Yes	No	Partial	No	Yes	Yes
Skarzauskiene et al. [32]	Yes	Yes	Partial	Partial	Partial	No
Salminen [33]	Yes	Yes	Yes	Yes	Yes	No
Georgi et al. [34]	Yes	Yes	Partial	No	Partial	No
Lykourentzou et al. [35]	Yes	No	Yes	Yes	Partial	No
Gregg [36]	Yes	No	Yes	Yes	No	No
Schut [37]	Yes	No	Yes	Yes	No	No
Vergados et al. [38]	Yes	Yes	Yes	Yes	No	No
Malone et al. [39]	Yes	Yes	Yes	Yes	Yes	No
Iandoli [40]	Yes	Partial	Partial	No	Partial	Partial
Boder [41]	Yes	Yes	Yes	Yes	No	No

- Criterion 4: Comparing the proposed CI architecture or framework to existing CI models or systems (C4)
- Criterion 5: Providing insights about the role, importance, and behavior of individuals (C5)
- Criterion 6: Proposing a solution to knowledge management issues in CI (C6)

These 18 studies were then used for data extraction and data synthesis (see Table 1).

3 Summary of selected studies

In the following, we summarized them.

In [24], the authors describe the potential role of big data and artificial intelligence in the path toward a collective approach to knowledge management. Thanks to the interpretative lens provided by systems thinking, a framework able to explain human–machine interaction are depicted and its contribution to the definition of a collective approach to knowledge management in unpredictable environment is traced. Reflections herein are briefly discussed with reference to the Chinese governmental approach to managing COVID-19 spread to emphasize the support that a technology-based collective approach to knowledge management can provide to decision-making processes in unpredictable environments.

In [25], the author presented a novel approach to improve representation learning and thus improve Situational awareness with collective AI over Knowledge graphs. He discussed four ideas for making prediction with collective AI: prediction ensemble, data aggregation, representation aggregation, and joint representation learning. He also described two state-of-the-art models to learn object representations from heterogeneous graphs: one is path-based embedding and the other is a graph neural network (GNN). Lastly, he presented a new GNN framework that jointly learns object representations from multiple agents. Experimental results demonstrate that collective AI performs significantly better than individual AI.

In [26], the authors designed a framework for a Digital Repository system for Knowledge management by using collective intelligence and Big data for SMEs. The authors also evaluated the appropriateness of the framework by experts in the field of Information Technology by purposive sampling. The data collection tools were the system and the assessment of an appropriate model using a 5-level rating scale. The statistics used in the data analysis were means and standard deviation. The results showed that the framework for a digital Repository system for Knowledge management by using collective intelligence and Big data for SMEs consisted of 3 components as followed: (a) Knowledge Management, (b) Cloud Knowledge Management System, and (c) User Interface.

The study of [27] presented new trends (including role-based organization, dynamic motivation mechanisms, and multi-aspect ontology) in knowledge management for socio-cyber-physical systems. Such trends can facilitate creation of innovative IT and Human Resource environments based on human–machine collective intelligence, where information and knowledge are shared between participants and across collectives of participants, who can be both people (collective intelligence as the methods used by humans to act collectively for problem-solving) and software services (based on artificial intelligence models). This paper considered examples of trends and their implementation experience in a global production company.

In [28], the authors aimed to discover the emergence mechanism and influence factors of CI in knowledge communities using the method of quantitative and qualitative analysis. The authors explained that a model theorizes that the two dimensions of social network (i.e., interactive network structure and participant's characteristics) affect two references of effectiveness (i.e. group knowledge production and participation in group decision). And this hypothetical model is validated with simulated data from "Zhihu" community. Their model has been useful since it offers some inspiration and directions to promote the level of CI in knowledge communities.

In [29], the authors proposed an integrated approach to analyze the design of the process of Computer-Aided Process Innovation (CAPI) and technical features of open innovation. They proposed a novel holistic paradigm of process innovation knowledge capture based on collective intelligence (PIKC-CI) from the perspective of the knowledge life cycle. Then, authors applied a multi-source innovation knowledge fusion algorithm based on semantic elements reconfiguration to form new public knowledge. To ensure the credibility and orderliness of innovation knowledge refinement, a collaborative editing strategy based on knowledge lock and knowledge–social trust degree is explored. Finally, a knowledge management system MPI-OKCS integrating the proposed techniques is implemented into the pre-built CAPI general platform, and a welding process innovation example is provided to illustrate the feasibility of the proposed approach.

In [30], the authors advocated that "collective intelligence is considered as the power of Decisions 2.0" which is defined by Bonabeau in [42]. They provided a CI framework based on interesting characteristics and defined the following set of criteria required for a collective intelligence model as proposed by Surowiecki [43]:

(i) *Diversity:* defining those individuals that must belong to diverse backgrounds, knowledge bases, etc. [44],
(ii) *Independence:* defining the freedom for individuals to act according to their choice, without others influence [43–45],
(iii) *Decentralization:* facilitating individualism and assuring diversity in individuals [46], and finally
(iv) *Aggregation:* defining appropriate methods to integrate individual solutions [44, 47, 48].

In [31], the authors presented activities to promote collective intelligence within organizations. The study proposed 380 activities based on the work of Surowiecki [43]. All tasks are explained using case studies and real-world examples [31]. In this study, authors demonstrate that existing platforms (such as wikis, blogs, prediction markets, etc.) are inadequate to support collective intelligence within organizations. They propose that in order to improve the use of collective intelligence within organizations, it is imperative to follow the following steps:

(i) Creating cognitive diversity aiming at explaining cognitive diversity
(ii) Promoting independence so as to define to which extent the lack of independence or peer pressure may force employees to covey incorrect or sugar-coated information to their managers, which may lead to biased decisions [31].
(iii) Accessing decentralized knowledge and how knowledge was initially organized hierarchically in organizations, whereas of now, due to globalization, decentralization, and data ubiquity, knowledge within organizations is not limited to the organizations themselves [31], and
(iv) Effectively aggregating knowledge which consists of effectively aggregating dispersed knowledge.

In this study, the authors have briefly discussed some interesting techniques (such as averaging individuals' opinions) [31].

The authors in [33] proposed a conceptual framework for assessing the potential of CI [33] and defined three measures to quantify the minimum criteria required to transform community projects into CI systems. They proposed a three level-framework. The first level, named capacity level, describes possible user actions, both as individual and as a member of the community [35]. It also includes massive participant interactions [48] that promote knowledge creation and innovation [40]. The second level, named emergence level, describes a system state [35] that supports self-organizing, 'emergent' behavior, 'swarm effect' [49], and mechanic development [41]. The final level is the social Maturity Level describing the clarity of system goals [3] and community/individual objectives [35].

The study in [33] aimed at exploring the role of collective intelligence in crowdsourcing innovations [37]. The author conducted a systematic literature review of published case studies discussing three CI platforms (OpenIDEO, Quirky, and Threadless). After that, he observed user behavior on each of these platforms for over a month and gathered relevant data including web clips, diary entries, and statistics. The author also conducted a literature review of existing CI frameworks, and then proposed a new theoretical framework for CI through three levels of abstraction [49] such as micro, emergence and macro levels.

In [34], the authors aimed at building a comprehensive model based on available literature while recognizing the characteristics that describe collective intelligence. They confirmed the lack of research line dedicated to 'how to describe collective intelligence in general' despite the numerous scientific research that has been published about CI platforms, frameworks, and models [34]. To fill in this gap, they combined three models of collective intelligence: 'the collective intelligence genome' by Thomas W. Malone et al. [19], 'mitigating biases in decision tasks' by Eric Bonabeau [42], and 'the collective intelligent system' by Ioanna Lykourentzou et al. [50] and proposed five novel characteristics such as:

(i) The objective of task that can be described as the outcome of a collective intelligence model,
(ii) The size of contribution that represents the amount or volume of contribution, and can vary depending upon the complexity of the problem and form/structure of the collective intelligence,
(iii) The form of input that can be presented in form of rules or data/information and can be categorized as instructions, challenge descriptions, or raw material,
(iv) The form of output that can be of two types: knowledge (i.e., intangible) or products (i.e., tangible), and finally
(v) The stakeholder consisting of defining stakeholders of a CI system based on their roles (initiators, contributors, and beneficiaries) [34].

In [35], the authors proposed a modeling process aiming at identifying the common characteristics of CI systems. The proposed process aimed to identify challenges helping users to construct a generic CI system [35]. The proposed model was the first attempt in classifying the common shared characteristics of CI systems since authors confirm that all CI systems seem to share quite a few characteristics. Authors also proposed a new classification of CI systems (such as active and passive systems). The authors suggest in active CI to create a crowd behavior to be coordinated by the system itself [35]. However, in passive systems, groups of users would exhibit behavior of swarms, irrespective of whether the system requires such behavior or not. Finally, the authors modeled three types of CI systems (Collaborative: Wikipedia and open-source software development communities; Competitive: Innocentive, BootB, DesginBay, DARPA Network Challenge; Passive: vehicular ad-hoc networks) using the previously identified attributes [35].

The author in [36] demonstrated the requirements for designing CI applications. Based on the work of Tim O'Reilly [46], he proposed the following key requirements for CI application: representing task-specific, considering the data as a key for CI, considering the users as an added value, facilitating data aggregation, facilitating data access and considering the new feature that must be added to CI systems depending on community needs and requirements [36]. The author developed a web-based CI application named DDtrac application for children with special needs. The proposed CI supports decision-making in special education and therapy. DDtrac has two main objectives: the first one consists of facilitating communication between therapists and teachers so that they could share information about the needs of the children. The second goal aims at analyzing data to understand a child's progress and to determine adjustments necessary for a better development of the child [36].

In [37], the author provided systematic guidelines and instructions to develop CI models. Based on the literature, he defined a list of properties of CI systems and classified them into 'enabling CI properties' and 'defining CI properties [37]. After that, the author proposed a 'systematic approach for designing CI system models' and illustrated the proposed methodology using two case studies namely the 'Chinese Whispering Room' and the 'Braitenberg collectivae' [37].

The authors in [35] proposed a novel framework aiming at raising the emergence of collective intelligence in web community. The proposed system is based on three main components: human community, machine intelligence, and system information [38]. They described the following characteristics:

(i) System attributes defining possible individual actions, system states and community and Individual objectives [35, 38],
(ii) Functions defining expected community member action functions, future system state functions, and objective functions [36, 39], and finally
(iii) Other characteristics defining resource allocation algorithms, critical mass, and the motivation [38].

In [39], the authors described and analyzed 250 web-enabled CI systems and tried to deduce the building blocks or 'genes' (analogy adopted from biology) of collective intelligence. Based on their analysis, they classified these building blocks, using two pairs of fundamental questions: 'Who is performing the task? Why are they doing it?' and 'What is being done? How is it being done?' [40]. After that, the authors defined a new framework explaining the underlying model of CI systems.

In [40], the author aimed at providing a model to manage collective intelligence, and to raise issues that must be considered when designing CI systems. He confirmed that although there are several open issues in collective intelligence, all of these issues could be organized into two macro-areas: management of collective intelligence' and 'design of collaborative tools' [40]. The author defined the communities

Fig. 3 The keywords cloud of the selected studies

as organizations and thus proposed five characteristics of online/virtual communities 'when modeled as organizations' [38, 40]. Those characteristics are clear goals and objectives, a large number of participants, a set of processes and rules. He also explained that considering communities as organizations would still face major governance issues, because of the many differences between virtual communities and real organizations. Three of these issues are attention governance, participation governance, and community governance [40].

In [41], the author provided a new model for collective intelligence in organizations and explained insights that enable transformation from tacit to explicit knowledge within and among organizations from a collective intelligence perspective [41]. He also provided the building blocks of organizational collective intelligence. The first block, *Block A,* is the development of competencies [41]. The second block, *Block B*, is the development of a common representation of the goals [51]. And finally, the last block, *Block C*, is the development and alignment of processes into mechanics of interactions between entities involved [41].

3.1 Analysis of selected studies

The 18 papers covered a wide spectrum of knowledge exploration in CI providing models, frameworks, platforms, essential characteristics, and criteria to be included in systems and business domains and applications. Figure 3 illustrates the cloud of keywords of the selected studies.

Different observations have been noticed:

- *Different Components of CI systems:* The review of existing studies clearly shows that collective intelligence is a multidisciplinary field drawing concepts and techniques from many disciplines such as computer science [52], organizations [53], social media [54], complexity sciences [37] and psychology [55]. The review shows also that three definitions of collective intelligence have been widely adopted in CI systems (where two of which have been proposed during this decade) by Pierre Lévy [56], Jerome Glenn [52], and Thomas Malone [39]. Although these definitions describe collective intelligence in their own distinct ways, they are based on one of the three main components: individuals (with data/information/knowledge); coordination and collaboration activities (according to a predefined set of rules); and means/platform for real-time communication (viz. hardware/software). This means that a nice attempt would be combining these components in the same definition, allowing intelligent behavior in groups or crowds. Table 4 aggregates these characteristics/attributes and their relationshipto the three main components of collective intelligence.
- *Different used terminologies*: After a deeper analysis of the described studies, we observed that various definitions with different terminologies have been used to describe the main CI concepts (see Table 3). Table 4 summarizes the list of main CI terminologies used in these models. This shows the first need to provide common and clear definitions and classifications.
- *Lack of research in knowledge exploration*: Last but not least, none of them aimed to properly explore embedded (individual or collective) knowledge. Whereas the existing models provide procedures and rules helping in designing a CI system-based knowledge and highlighted challenges to be faced in order to achieve a robust and adaptive CI system, most studies proposed specific CI models aiming at only describing collective intelligence and manage knowledge in specific domains.

4 Special issue focus

Given the discussion on current research in the previous section, we envision that more efforts on "Collective Intelligence and Knowledge Exploration" are needed to tackle major societal challenges by using computation to combine human intelligence in better ways [3, 21]; yet our knowledge of supporting planning in Collective Intelligence is incomplete. Existing Collective Intelligence efforts vary according to the tasks that human contributors complete, and the expertise of humans who plan those tasks. In some systems, humans with domain expertise decompose a complex task into smaller ones without special planning expertise [57]. In other studies, complex tasks are automatically decomposed into well-defined tasks [58]. Finally, a third understudied kind of CI system—called novice-based collective innovation—requires domain novices to plan highly complex, ill-structured tasks [51].

This special issue focuses on presenting a number of state-of-the-art papers on mining Collective Intelligence and Knowledge Exploration and in developing methodologies, techniques, approaches, and successful applications. This special issue aims at contributing to the paradigm shift from

Table 3 Definition of components of collective intelligence according to CI characteristics

Component	Properties
Individuals (data, information, knowledge)	Heterogeneity Diversity Independence Motivation Crowd Critical mass Users and value Sensory information Digital repository
Coordination and collaboration activities (according to a predefined set of rules)	Competencies development Self-organization Emergence Trust and respect Community and individual objectives Clear goals and objectives Wisdom of crowd Task and workload allocation Set of processes
Means for real-time communication (viz-hardware/software)	Aggregate knowledge Knowledge discovery Big data Artificial intelligence Access to decentralized knowledge Roles & responsibilities Massive interactions System state Predefined input/output types Task specific representation Data is key Robust

"data-centered pattern mining" to "domain-driven Actionable Knowledge Discovery (AKD)" for next-generation Knowledge Discovery in Databases (KDD) research and applications. Herewith, it is identified how mining human intelligence techniques can better contribute to critical domain problems in practice and strengthen society intelligence in complex problems. Some challenges and future trends for future mining Collective Intelligence research and development are also reported. Here, we highlight two major research areas in Collective Intelligence and Knowledge Exploration:

a. Topics focusing on developing workable AKD methodologies, including:

- *Evolutionary computation:* including algorithms for global optimization inspired by biological evolution, and

Table 4 Terminologies used to define CI systems

Reference	Terminologies
Iandolo et al. [24]	Knowledge management Collective knowledge Bigdata Artificial intelligence Viable systems approach
Jian M. [25]	Knowledge Graphs Sensory information Artificial intelligence Prediction Aggregation
Namnual et al. [26]	Digital repository knowledge management collective intelligence big data SMEs
Smirnov et al. [27]	Socio-Cyber-Physical Systems Collective Intelligence Knowledge management Hybrid Systems Context-aware Knowledge Management Ontology Role-based Organization
Li et al. [28]	Collective Intelligence Knowledge Community Social Network Analysis
Wang et al. [29]	Manufacturing process Innovation computer-aided innovation Open innovation Collective intelligence knowledge management knowledge-based engineering
Nguyen et al. [30]	Diversity Independence Decentralization Aggregation
Matzler et al. [31]	Cognitive diversity Promote independence Access decentralized knowledge Effectively aggregate knowledge
Skarzauskiene et al. [32]	Capacity level Emergence level Social maturity level
Salminen [33]	Micro-level Level of emergence Macro-level
Georgi et al. [34]	Objective of a task Size of contribution Form of input Form of output Stakeholder

Table 4 (continued)

Reference	Terminologies
Lykourentzou et al. [35]	Set of possible individual actions System state Community and Individual objectives Critical-mass Task and workload allocation Motivation
Gregg [36]	Task-specific representation Data is the key Users add value Facilitate data aggregation Facilitate data access Facilitate access for all devices The perpetual beta
Schut [37]	Enabling CI properties Defining CI properties
Vergados et al. [38]	System attributes Other elements
Malone et al. [39]	Staffing Incentive Goal Structure/Process
Iandoli [40]	Clear goals coherent with mission Large number of motivated participants A set of processes Rules, Roles & Responsibilities
Boder [41]	Competencies development Goal development Mechanic development

the subfield of artificial intelligence and soft computing studying these algorithms.

- *Computational intelligence:* including theory, design, application, and development of biologically and linguistically motivated computational paradigms.
- *Computational security:* including solutions to the real-world attackers that are computationally limited unlike information theoretic security, e.g., one-time pad.
- *Knowledge Exploration in IoT*: including changing the way knowledge is managed within IoT, calling for a new and inventive knowledge management-based IoT system.
- *Knowledge integration:* including the process of synthesizing multiple knowledge models into a common model.
- *Knowledge representation:* incorporating new models about how humans solve problems and represent knowledge to design formalisms making complex systems easier to design and build.
- Knowledge-based system including new techniques based artificial intelligence (AI) aiming to capture the knowledge of human experts to support decision-making.
- *Experience-based Knowledge Exploration:* exploring new methods for user-driven Knowledge Exploration where users are actively involved in the ideation and design process.
- *Uncertainties in Knowledge Exploration:* including research on how dealing with the available knowledge having multiple causes leading to multiple effects or incomplete knowledge of causality in the domain.
- Medical image analysis, pattern analysis, and computer vision including studies on the development of integrated systems for use in pattern analysis, enabling both imaging analysis and the automatic assessment of the resulting data.
- *Artificial intelligence:* refers to wide-ranging branch of computer science concerned with building smart machines capable of performing Knowledge Exploration using Collective Intelligence.
- *Advances in Machine Learning:* including new technologies allowing for recent breakthroughs that promote faster and more efficient business intelligence, using abilities ranging from facial recognition to natural language processing.
- *Algorithms for Intelligent Learning:* including analysis and development of algorithms for intelligent systems with their applications to various real-world problems.
- *Context aware techniques:* designing context-aware systems to understand and analyze context in real-world problems.

b. Topics focusing on novel KDD domains and the corresponding techniques, exploring the mining of emergent areas and domains such as:

- Data mining and Information retrieval is an emerging interdisciplinary discipline dealing with Information Retrieval and Data Mining techniques. This topic includes the advances in mathematics, statistics, information science, and computer science.
- *Distributed Mining of human expertise:* including studies around discovering knowledge and human expertise generated from parts of the entire training data set.
- *Text Mining and Natural language processing:* including research leading to identify facts, relationships, and assertions that would otherwise remain buried in the mass of textual big data.
- *Learning to Data/Text mining:* also known as text data mining including process of transforming unstructured text into a structured format to identify meaningful patterns and new insights.
- *Real-time applications of text mining:* including frameworks to detect a potential crisis and discover product flaws or negative reviews in real time and so prioritize urgent matters.

Fig. 4 The word cloud of the special issue collection on Collective Intelligence and Knowledge Exploration

- *Data mining for Social Networks:* applying data mining techniques to large social media data sets to improve search results for everyday search engines, realize specialized target marketing for businesses, help psychologist study behavior, provide new insights into social structure for sociologists, and personalize web services for consumers.
- *Events extraction in unstructured text mining:* including text mining techniques depending on the user, the available content, and the scenario of use employed for various event extraction purposes.
- *Visual analytics for text mining/exploration:* exploring visual text analytics using visual interactive machine learning, visualization of scientific simulation data, visualization of biological data, etc.

The current special issue on Collective Intelligence and Knowledge Exploration was open to new original research submissions on the above themes. We originally attracted 16 submissions, among which 5 regular papers were finally selected for inclusion in the present issue after a rigorous review process. The accepted papers illustrate the highly innovative and informative venue for essential and advanced scientific and engineering research in the fields of Collective Intelligence and Knowledge Exploration. A brief presentation of selected papers follows. Figure 4 provides an initial picture of this collection of research as indicated by the frequently occurring keywords identified in accepted papers conforming to the special issue topics.

The first paper is entitled "Conspiracy theories on Twitter: Emerging motifs and temporal dynamics during the COVID-19 pandemic" and have been authored by Veronika Batzdorfer, Holger Steinmetz (Leibniz Institute for the Social Sciences, Germany), Marco Biella (Eberhard Karls University of Tuebingen, Germany) and Meysam Alizadeh (Harvard University, USA). The authors show that COVID-19 pandemic resulted in an upsurge in the spread of diverse Conspiracy Theories (CTs) with real-life impact. However, the dynamics of user engagement remain under-researched. They leverage Twitter data across 11 months in 2020 from the timelines of 109 CT posters and a comparison group (non-CT group) of equal size. Within this approach, they used word embeddings to distinguish non-CT content from CT-related content as well as analyzed which element of CT content emerged in the pandemic. Subsequently, they applied time series analyses on the aggregate and individual level to investigate whether there is a difference between CT posters and non-CT posters in non-CT tweets, as well as the temporal dynamics of CT tweets. The narrative motifs, characterized by word embeddings, address pandemic-specific motifs alongside broader motifs and can be related to several psychological needs (e.g., epistemic, existential, or social). Moreover, the aggregate series of CT content revealed two breaks in 2020 and a significant albeit weak positive trend since June. On the individual level, the series showed strong differences in temporal dynamics and a high degree of randomness and day-specific sensitivity. The results stress the importance of Twitter as a means of communication during the pandemic and illustrate that these beliefs travel very fast and are quickly endorsed. The COVID-19 pandemic resulted in an upsurge in the spread of diverse conspiracy theories (CTs) with real-life impact.

The second paper is entitled "HUFTI-SPM: High utility and frequent time-interval sequential pattern mining from transactional databases" and have been authored by Ritika Ritika (I.K. Gujral Punjab Technical University, India) and Sunil Kumar Gupta (Beant College of Engineering and Technology, India). Authors focus on sequential pattern mining based on support or frequency as a threshold. Authors extended the sequential pattern by including time information and later the concept of utility mining emerged. This work aims to provide a novel hybrid pattern growth-based approach for the discovery of sequential patterns along with time intervals and satisfying both frequency and utility as a threshold. All the three parameters are taken into consideration while mining. A support-utility table is also introduced for maintaining information on support and utility at various time intervals. The hybridization of constraints increases the usefulness of patterns. Experimental results also showed that the proposed work gives good results as compared to the existing hybrid algorithms.

The third paper is entitled "Telugu Named Entity Recognition using BERT" and has been authored by SaiKiranmai Gorla, Sai Sharan Tangeda, Lalita Bhanu Murthy Neti, and Aruna Malapati (Birla Institute of Technology and Science Pilani, India). This study performs the Named Entity Recognition (NER) task on Telugu Language using Word2Vec, Glove, FastText, Contextual String embedding, and Bidirectional Encoder Representations from Transformers (BERT) embeddings generated using Telugu Wikipedia articles. These embeddings have been used as input to build deep learning models. Authors also investigated the effect of concatenating handcrafted features with the word embeddings on the deep learning model's performance. Their experimental results demonstrate that embeddings generated from

BERT added with handcrafted features have outperformed other word, embedding models.

The fourth paper is entitled “AutoML: State-of-the-art with a focus on anomaly detection, challenges, and research directions” and has been authored by Maroua Bahri (Télécom Paris, France), Flavia Salutari, Andrian Putina, and Mauro Sozio (INRIA, France). In this work, the authors report an overview of the Automated Machine Learning (autoML) field with a particular emphasis on the automated methods and strategies that have been proposed for unsupervised anomaly detection. In their study, the authors show that the performance of multiple machine learning algorithms is very sensitive to multiple ingredients (e.g., hyper-parameters tuning and data cleaning) where a significant human effort is required to achieve good results. They also demonstrate that building well-performing machine learning algorithms requires domain knowledge and highly specialized data scientists. To conclude their review, authors demonstrate that autoML aims to make easier and more accessible the use of machine learning algorithms for researchers with varying levels of expertise. Besides, research effort to date has mainly been devoted to autoML for supervised learning, and only a few research proposals have been provided for the unsupervised learning.

The fifth paper is entitled “Comparative Analysis of Different Crossover Structures for Solving a Periodic Inventory Routing Problem” and has been authored by Salim Amri (University of Tunis, Tunisia). This study proposes a novel system that integrates two of the most important logistics activities, namely inventory holding, and transportation, known as the Inventory Routing Problem (IRP). The proposed replenishment network consists of a supplier that uses a single vehicle to distribute a single type of item during each period to a set of customers with independent and deterministic demand. The objectives considered in this work are the management of supplier and customer inventories, the assignment of customers to replenishment periods, the determination of optimal delivery quantities to avoid customer stock-outs, the design and optimization of routes. A Genetic Algorithm (GA) is developed to solve the IRP problem. Different crossover structures are proposed and tested in two sets of reference instances. A comparison of the performance of different crossover structures is established. Then, the model is used to find the most appropriate crossover structure that provides better results in a minor computation time. The obtained results show the competitiveness of GAs compared to literature approaches and demonstrate the performance of the proposed approach.

5 Challenges and future trends

The association of knowledge exploration and the collective intelligence creates indeed a new perspective on innovation and brings its management into a new dimension. Our special issue aimed to show the importance of the processes of knowledge exploration in new CI systems and how it is related to the development of modern information technology. Through this special issue, we observed that the systematic support of innovative CI systems requires effective exploration of knowledge with regard to activities such as acquisition, development, enrichment, retrieval, reuse, and combinations of these skills.

The full-fledge usage of knowledge exploration in CI systems consists of developing new CI frameworks to solve knowledge-based problem [59]. Collective Intelligence needs to rely on in-depth: data intelligence, human intelligence, domain intelligence, network intelligence, and organizational and social intelligence. It seems important to synthesize such intelligence in actionable knowledge exploration, discovery, and delivery [60–64]. Based on the current studies, we identified several key aspects and challenges that need to be addressed further so as to enforce knowledge exploration in CI systems such as:

- How to consider the environment referring to any factors surrounding the CI systems?
- How do incorporate environmental elements and domain experts dynamically and iteratively?
- How to design an infrastructure to improve engagement of environmental elements and humans at runtime in a dynamic and interactive way?
- How to develop an open system considering closed loop interaction and feedback?
- How do consider dynamics dealing with data distribution and solving problems from training to testing and from one domain to another?
- How do evaluate when designing new models based on the interestingness needs to balance between technical and business goals?
- How to cope with security intelligence?

These challenges are also related to technical and engineering aspects related to handle CI system architectures by proposing effective and flexible architecture to incorporate and consolidate specific environmental elements, knowledge exploration process, evaluation systems, and final deliverables. It seems also critical to facilitate supporting the knowledge exploration process and workflow, from business understanding, data understanding, and human system interaction to result assessment, delivery, and execution of the deliverables. The *interaction* is also an important challenge consisting of catering to interaction with users along knowledge exploration process by providing appropriate user interfaces, user modeling, and services to support individual and group interactions. Another challenge consisting of providing *adaptive CI systems* based on knowledge exploration and discovery, models, and evaluation metrics to handle differences and changes in dynamic data distributions, cross domains, changing business situations, and user needs and expectations. Finally, to enhance knowledge actionability, domain-related Collective Intelligence is crucial. It consists of intelligence of human, domain, environment, society, and cyberspace, combined with data intelligence. Thus, the domain-related Collective Intelligence involves many challenging issues need to be studied and experimented with in real-world scenarios.

Acknowledgements Special gratitude and appreciation are extended to all the authors for their high-quality submissions as well as the reviewers for volunteering their time and expertise to evaluate the scientific merit of the submitted papers: Sabri Allani, Salim Amri, Sabeur Aridhi, Ali Ayadi, Mongi Boulehmi, Imene Dlala, Ravi Doddavaram, Sabeur Elkosantini, Sana Fakhfakh, Fethi Gazouani, Inserm, Azza Harbaoui, Wissem Inoubli, Sarika Jain, Abderrazek Jemai, Mouna Jouini, Marouane Kachroudi, Mourad Khayati, Elio Mansour, Neila Rjeibi, Mattia Samory, Brian Schwartz, Akram Sellami, Mokhtar Sellami, Sana Sellami, Mouna Selmi, Michele Starnini, Anis Tissaoui, Taoufik Yeferni, and Sami Zghal. Finally, special thanks are due to the Editors-in-Chief of the JDSA for providing the opportunity to work on this special issue project.

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