

A multi-disciplinary review of knowledge acquisition methods: From human to autonomous eliciting agents



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ABSTRACT

This paper offers a multi-disciplinary review of knowledge acquisition methods in human activity systems. The review captures the degree of involvement of various types of agencies in the knowledge acquisition process, and proposes a classification with three categories of methods: the human agent, the human-inspired agent, and the autonomous machine agent methods. In the first two categories, the acquisition of knowledge is seen as a cognitive task analysis exercise, while in the third category knowledge acquisition is treated as an autonomous knowledge-discovery endeavour. The motivation for this classification stems from the continuous change over time of the structure, meaning and purpose of human activity systems, which are seen as the factor that fuelled researchers' and practitioners' efforts in knowledge acquisition for more than a century.

We show through this review that the KA field is increasingly active due to the higher and higher pace of change in human activity, and conclude by discussing the emergence of a fourth category of knowledge acquisition methods, which are based on red-teaming and co-evolution.

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1. Introduction

Knowledge acquisition (KA) refers in a very broad view to gaining understanding about the processes underlying the observable behaviour of an entity. The immediate output of KA, the knowledge, is a representation of the real phenomenon at the level of detail and abstraction required by the purpose of the KA exercise. The representation takes the form of an ontological construct, i.e. a set of concepts considered necessary and sufficient to capture the understanding about the real phenomenon, which offers the possibility to re-instantiate it (replicate it in a different context), to improve it, or to further communicate the understanding about it to peers. The range of purposes for knowledge acquisition exercises is very broad, from the basis of learning in itself, to the creation of computational models and applications that improve the behaviours of the entities under investigation or solve problems on behalf of them (e.g. knowledge-based systems, expert systems).

The entities the KA can be performed on fall into three major categories—natural, man-made and humans—further referred to

throughout the paper as natural systems, technical systems, and human activity systems. An example of KA applied to natural systems can be the weather cycle in a certain region of the Earth, which one needs to understand in order to ensure safe aircraft operation over that region in different periods of the year. The tools available for gaining understanding about the weather are observations and measurements. The weather cycle is observed, measurements are taken on some relevant aspects such as air speed, temperature, pressure or humidity, and records of these observations and measurements are analysed and structured in order to understand how and why the weather behaves the way it does. This further allows the representation of the weather cycle in a manner that can be communicated to and used by aircraft operators. The same tools, i.e. observations and measurements, are available when applying KA to man-made technical systems, like in the case of an aircraft life-cycle. During its life-cycle, from design to manufacturing, operation and decommissioning, an aircraft is under permanent observation, and large amounts of measurements are performed in order to gain understanding on all possible aspects that allow normal operation. For example, before commissioning into operation, the design is tested in simulations, then in controlled realistic environments (e.g. wind tunnels) and finally in real flight tests in order to gain understanding about how all system components interact internally within the aircraft and externally with other systems such as the weather or the operators. The resultant

List of abbreviations: KA, Knowledge acquisition; HAS, Human activity system; CTA, Cognitive task analysis; SME, Subject matter expert; KD, Knowledge discovery; EC, Evolutionary computation; CRT, Computational red teaming.

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knowledge can be used to improve the design if the initial design assumptions are not met, or to release the aircraft into operation and communicate this knowledge to its operators.

Unlike natural and technical systems, in the case of human activity the processes underlying the observable behaviour can be unveiled not only through observations and measurements, but also by asking. Weather can be observed and measured, but cannot be asked about why it is the way it is. Similarly, the operation of an aircraft can be observed and measured, but the aircraft cannot be asked why it manifested a certain behaviour in some particular weather conditions. Humans instead, can be asked and thus knowledge can be elicited through various techniques that are unavailable in the case of natural and technical systems. For example, we assume an activity such as piloting an aircraft. This is a human activity system through that it involves the existence and the interaction of all types of entities: natural—the weather, technical—the aircraft and human—pilot's actions and decision making, with the human being the pertinent entity that steers the whole resultant system and is accountable for its behaviour. The pilot in this case makes use of its knowledge about the natural system, its knowledge about the technical system, and its innate or acquired cognitive-motor and decision-making skills in order to perform the task of flying the aircraft in good conditions. If one intends to improve the skills of this pilot (for purposes such as safety, flight duration, passenger comfort) or to transfer the existing skills to other pilots (through creation of training programs), then it is paramount to gain understanding about how and why the pilot takes decisions and performs various actions, and how are these yielding from the subsequent interactions with the natural and technical counterparts (the weather and the aircraft). Further, it is paramount to create and commit to an ontological construct that represents this understanding effectively, in order to be able to use it for fulfilling the established purposes.

In the light of the above examples, in this paper we concentrate on knowledge acquisition in relation to the generalised concept of human activity (described in the third example—the pilot), a research direction in which knowledge acquisition is employed as a facilitator for finding ways to improve human performance in various tasks in real-world contexts [142,182]. Historically, this research direction emerged in response to the need for improving the “workplace”, where the word workplace has a broad meaning, referring to the physical work-place itself, but also encompassing

the tasks performed by humans as part of their lucrative activity, their proficiency in accomplishing those tasks, their interaction with the technology they use in support of that lucrative activity, and the artefacts resulting from their activity. Roth et al. [182] see knowledge acquisition through a cognitive task analysis (CTA) lens, and note that KA is nowadays an indispensable tool used to understand the “cognitive and collaborative demands” that contribute to performance and facilitate the formation of expertise. They also note that KA is used as a support for designing ways to improve individual performance through various forms of training, user interfaces, human-machine interaction or decision-making support systems.

Today KA in relation to human activity systems is addressed in multiple fields of activity. In *Cognitive Systems Engineering* the KA methods are used to analyse the work environment in order to inform the design of various systems, focusing on the integration of humans, technologies and physical work space [142]. In *Cognitive Work Analysis* [101,181] the KA exercise is used for making real-world constraints more visible to human operators in order for them to make better-informed decisions in unanticipated circumstances. In *Naturalistic Decision Making* [157], some researchers proposed KA methods for investigating how human decision-making emerges in real world tasks, as a result of time pressure and risk [142,191]. *Human-Centered Computing* is another major field of research where KA techniques were used as a support for designing technology that amplifies or extend human capabilities [195]. KA was also considered essential for general *Knowledge Engineering* [49,51], where KA can be used in any or all of the knowledge elicitation, analysis and representation stages. In addition, in *Knowledge Discovery and Data Mining* [105] computational intelligence instantiations of KA exercises are used for autonomous knowledge discovery in problem domains that only offer access to inexact and imprecise artefactual data resulting from human activity systems. While this list is not exhaustive, it shows the magnitude of the KA paradigm and its importance in the investigation of what we can broadly consider, virtually any human activity system.

Fig. 1 summarises the above discussion in a visual manner, presenting broadly the position and scope of this study within the larger field of knowledge acquisition. More specifically, the review sees the human activity KA literature from an agent perspective and classifies it into three major categories of methods: human agents, human-inspired agents, and machine agents. In the most

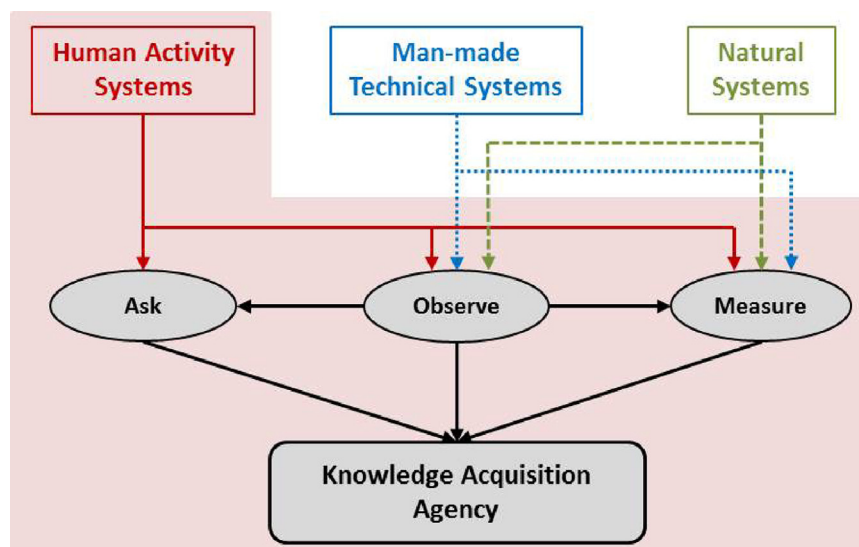


Fig. 1. The shaded area shows the position and scope of the review within the larger KA field.

general view, KA exercises assume various degrees of interaction between one or more elicitor entities and one or more subject matter expert (SME) entities. In the proposed classification the human agent category refers to the classic cognitive task analysis exercises, in which both the eliciting entities and the subject matter expert entities are humans. However, advances in computational intelligence and digital technologies made possible the replacement of either or both sides involved in the CTA exercise with their computer-based counterparts. Thus, the second category, human-inspired agents, consists of the classic CTA exercises in which the human elicitor entities are replaced by computer programs that emulate well-established human elicitors' actions (e.g. automated interviews, automated protocol analysis). The third category, the machine agents, include those KA exercises in which both the eliciting entity and the SME entity are replaced by computer programs with independent behaviour and no domain knowledge regarding the two entities. That means, the eliciting programs do not implement known behaviour of human elicitors, instead, they act autonomously for extracting knowledge from the SME entity. In the same time the SME entities are not any more human experts or known recorded behaviour of them, but rather unstructured and unsorted artefactual data resulted from unattended records of the human activity. Thus, in this category, the KA exercise becomes a knowledge discovery (KD) endeavour, in which the machine agents attempt to establish causal relations and meaning in an unstructured collection of artefactual data believed to be related to a task or human activity system of interest.

The paper is organised as follows. In Section 2, we present a historical view on KA, which provides an intrinsic chronology-based categorisation of the methods and provides the motivation for this study. Section 3 presents a discussion that highlights the fundamental stages of the KA process and sketches an architectural schema capturing general KA exercises. The fourth section presents the existing classifications of the KA methods and provides the foundation for the following sections. Sections 5–7 review the methods according to the three proposed categories, human agents, human-inspired agents and machine agents, respectively. In Section 8 we discuss major findings, the contribution of this paper, and future research directions. Section 9 briefly concludes the study.

2. A historical view

The KA concept has its roots in a long history of research on human activity, researchers tracing the work in the field to as early as 19th century. A brief historical view can be found in [142], while a comprehensive and in-depth discussion can be found in [98] in relation to four major periods acknowledged in the studies related to HAS: pre-1900, 1900–1920s, 1920–1960s, and 1970s to present. The first three are related to precursors of KA, while the fourth one represents the modern KA. The pre-1900 period was focused on self-reporting methods based on introspection and retrospection, in which knowledge about task and task performance was obtained from human subjects by asking them to perform the task and then provide retrospective reports. The second period, 1900–1920s, was dominated by the concept of “psychotechnics” which emerged as a result of the increased pace of industrialisation, which in turn generated the need for improving the human performance at work in order to increase productivity. Studies were concentrated on analysis of tasks, usually physical in nature, and targeted timing and motion during one task, or between several tasks, throughout the work place. Seminal for this period was the time and motion study of Taylor, first published in 1911 [200], where the focus was on understanding how proficient workers performed their tasks. The third period, 1920–1960s, was under the influence of large scale manufacturing, when mass produc-

tion in various industries introduced automation and high productivity assembly lines, changing dramatically the HAS. Task analysis shifted towards the study of human factors, work safety and human-machine systems, where the analysis of human activity was made with the purpose of adapting the tools and processes to the human operators for increasing productivity.

The fourth period, starting in the 1970s, is when KA in human activity systems emerged as a standalone high-level methodology covering all the fields previously addressed by precursor methods [49,77]. The technological advances shifted once more the human activities from predominantly physical to predominantly cognitive tasks, and consequently the human-technology interaction and integration problem reached levels unseen before [142]. We consider that the fourth period marks the most important contributions to the KA body of research, establishing the concept solidly in the scientific world through qualitative and quantitative studies. The fourth period, which continues today, was when most of the human agent (i.e. human-based or manual) KA methods and techniques were proposed and largely accepted by both researchers and practitioners. However, we note that since the early 2000s the amount of new methods and methodologies in the human agent KA area slightly declined, as evident through our inspection of the literature [49,142,207], while the amount of work on applications of the existing methods increased significantly. This is, we argue, due to the fact there was yet another shift in the HAS. It was the unprecedented development of the internet, the mobile communications, and lately virtual environments and social media/networks that gave birth to the information age, and transformed human activity systems to such extent that classical human agent KA exercises were no longer efficient or convenient. First, the physical interaction of human elicitors with human SMEs became less and less plausible and possible due to the nature of the new types of human activity. Then, the new range of activities generate behavioural artefacts in quantities and shapes no longer treatable with the capabilities provided by human-based methods.

As a response to the emergence of these new types of human activity, the human-inspired KA agents appeared as one direction of research, trying to implement some of the human agent methods in computer programs in order to replace human elicitors with their automated versions. However, these methods are still computer implementations of classical methods. A second direction of response consisted of methods that diverged from the human-related KA, bringing into the KA field human-independent approaches, the machine agents, which managed to better cope with acquisition of knowledge in cases where the human element became inefficient. This direction is marked by the full inclusion of agent-enabling technologies based on computational intelligence, such as statistical analysis, machine learning or evolutionary computation, into the KA exercises. We consider these two directions as belonging to a fifth significant period in the historical view on KA, starting from the 1990s to present days, which adds to the four historical periods acknowledged in the literature. We also note that despite the reduction in the amount of new methods belonging to the human agent methods, the fourth period did not cease to exist. Research on the classic human agent KA continued until the present days with valuable reiterations of the established methods in new contexts and application fields. Thus, the fifth period, which brings the human-inspired and machine agents to KA comes not as a replacement, but as an addition to existing paradigms, fuelled by the continuous expansion of the concept of human activity.

In the light of the above historical view on the KA research, and motivated by the historical evolution of the concept of human activity, we consider pertinent and useful to discuss the literature based on the three categories we mentioned in the introductory section: the human agents, the human-inspired agents and the machine agents. In order to keep the scientific discourse pertinent and

Table 1
The three stage KA process model.

Perspective	Process stages			References
KA	Data elicitation	Data interpretation	Knowledge modelling	[22]
KA	Knowledge elicitation	Knowledge explication	Knowledge formalisation	[49]
CTA	Knowledge elicitation	Data analysis	Knowledge representation	[51,210]
KD	Data preprocessing	Data mining	Knowledge interpretation	[29,148,152]

related to the KA concept, we provide in the next section a discussion on the core process of a KA exercise. This discussion will guide our review, and will ensure that the methods we describe throughout the paper are only included if they belong to the core KA process and suit the purpose of the KA exercises in relation with the concept of human activity.

3. Agent-enabled KA exercises: Core process and roadmap

To date, the literature focused more on the internal mechanism of the KA methods, and less on establishing an accurate description of the KA process, or a relation between the process and the purpose of the exercise [49,51,207,210,211]. Thus, the choice on how to conduct a KA exercise is strongly dependant on the purpose of the exercise. In [182] the authors consider, from a CTA perspective, that KA is still a task-related paradigm, “with no best practice, or general methodology in place”. Also, from a KD perspective Kurgan and Musilek [124] identified and reviewed the existing models for the KA process, where the models assumed a number of discrete activities or stages. They identified models consisting of 3–9 stages, and commented on the lack of guidance in defining the knowledge discovery process.

However, a certain consensus exists on the major stages of a KA process, regardless of the purpose. A majority of the studies assumes a “big 3 model” in support for the introduction of various KA methods. In [22] the three stages in KA are data elicitation from a human expert, data interpretation (which infers the underlying knowledge from the data) and knowledge modelling (which transfers the domain knowledge of the human expert into a computational model). In [49] KA is considered by Cooke as the front-end of knowledge engineering, which in turn is seen as part of the process of building a knowledge-based system in general. The author considers that the KA process consists of three major steps: knowledge elicitation, knowledge explication, and knowledge formalisation. She states that the final goal of the knowledge acquisition exercise is “to externalise the knowledge into a form that can be later implemented in a computer”, or in other words the creation of computational models; this idea is also present in [22,118] and [85]. This is achieved through the three stages of the process, where the elicitation provides the psychological data from human experts, the explication categorises and sorts those data and the formalisation transforms them into a computational model. The author also makes a distinction in the first stage between the knowledge elicited from humans and that extracted from other sources [53,71] such as task documentation, historical data, procedure manuals, etc. However, Cooke notes that the knowledge resultant from this extraction process should be verified, and enriched with that coming from elicitation in human SMEs. A decade later, the KA process is presented in [51] by Crandall et al. in a similar manner, with the three stages named knowledge elicitation, data analysis and knowledge representation. The authors enrich the description of the stages and also slightly shift their understanding. The elicitation stage is no longer differentiated in elicitation from humans and extraction from alternative sources, and is seen as the activity of collecting information about “judgements, strategies, knowledge, and skills that underlie performance”. The view of data analysis stage is similar to that of Cooke—it encompasses the set of

actions taken for “structuring data, identifying findings, and discovering meaning”. However, the knowledge representation stage is focused on externalising and presenting the data, which in Cooke’s study was the goal of the whole knowledge acquisition process. In Cooke’s study, the formalisation stage is explicitly associated with the formulation of a computational model, while Crandall and colleagues state that representation means “displaying data, presenting findings, and communicating meaning” that is, communicating the output of the analysis step. In a different approach to the ones described above, Yates and colleagues [210,211] acknowledge the three stages in the KA process; however, they note that the last two, analysis and representation, are usually treated together, being inseparable in the context of modelling the knowledge acquired through elicitation. Researchers in knowledge discovery also acknowledge the three stages model, with the three stages named: data preprocessing, data mining, and knowledge interpretation and evaluation [29,147,148,152]. The above discussion is summarised in Table 1, which shows the main studies supporting the three stage model of the KA process, from various perspectives.

In general, the need of a universal process model to support the KA exercises is obvious, and we showed in this section that there is no lack of preoccupation in the scientific world for investigating in this direction. In particular for this paper, it was necessary to summarise the existing work and to commit to a process model in order to highlight the relation between the proposed classification and the KA process. Assume that one must gain knowledge about how and why aircraft pilots perform various actions, in order to communicate this knowledge to pilot schools for purposes such as improving training programs. The first question is if the pilots are available in person for the KA exercise or the exercise is performed on artefacts of their activity, such as flight data from the on-board computers. If the pilots are available then it is important to establish how many of them will be participating in the KA exercise. In the case of one or few pilots, a team of human elicitors (i.e. human agency) is sufficient for performing the KA exercise, but if a large number of pilots needs to be involved, such as the whole population of pilots of an airline, then automated/computerised versions of human elicitors (i.e. human-inspired agency) may be needed in order to deal with the amount of data and analysis required. If on the other hand only artefactual data of pilot’s activity is available then again the amount of the available data triggers further choice options. If these data are in a low amount, such as simple tables with only the very important decisions like change of course, these can be analysed by humans, but if these data mean detailed records of all maneuvers, then machine agents should be chosen in order to mine the vast amounts of resultant data. In Fig. 2 we generalise this example and present in a visual manner how the proposed classification can contribute to a KA exercise by creating a preliminary decision tree that facilitates the choice of the appropriate methods to be used within the KA process. Thus, another merit of the agent perspective on KA is that it plays a decision support role in the KA exercises.

4. Brief review of the existing KA classifications

As discussed in previous sections, KA is used in a very broad range of research fields and practitioner activities, and while

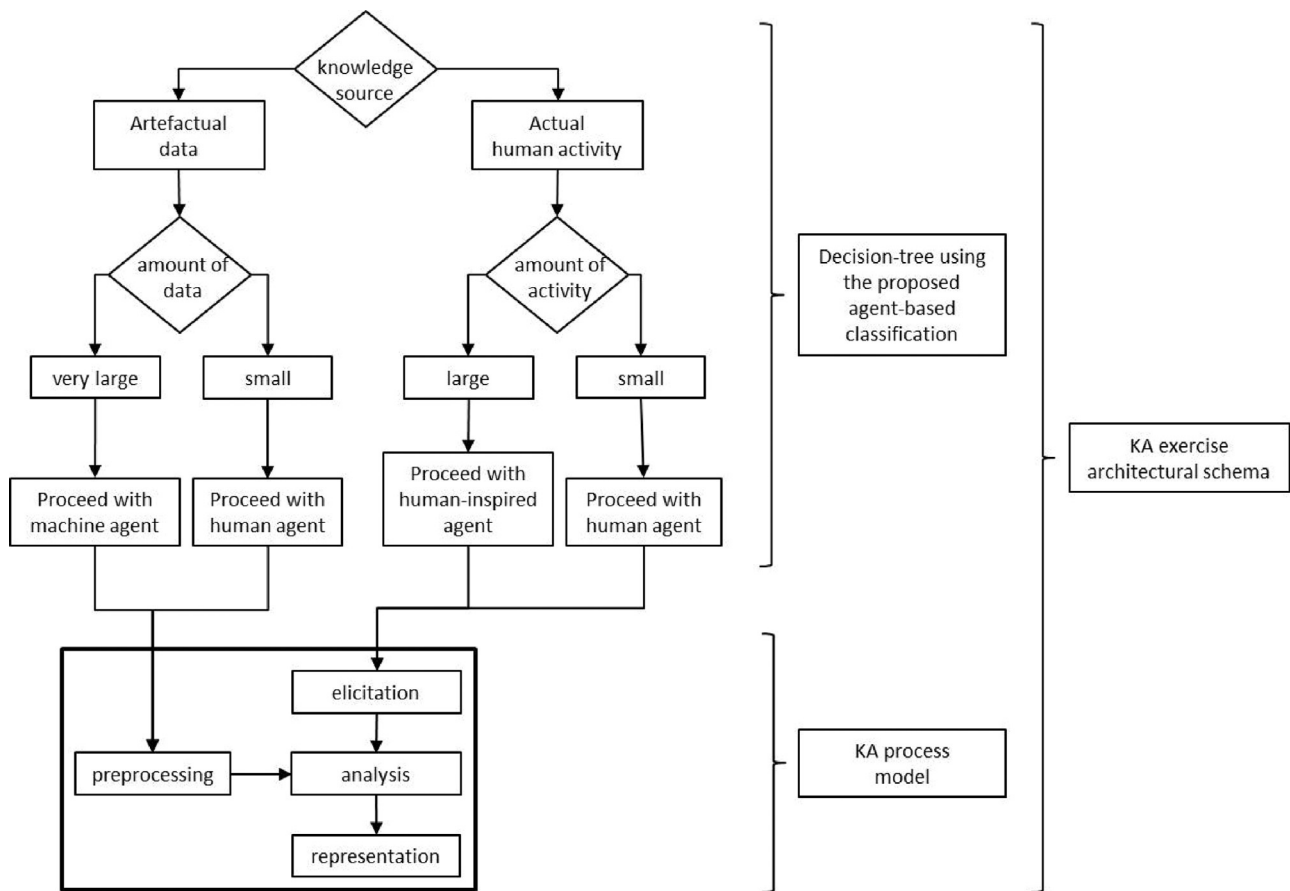


Fig. 2. The KA exercise—architectural schema.

having a fairly short history as a standalone concept, it includes numerous precursor techniques inherited from previous theoretical or practical approaches. This generated diverse paths of development for KA, which further generated numerous approaches customised for every field of research, purpose of the exercise, and even problem or task. This makes KA a highly problem-dependent concept, whose classification into a comprehensive taxonomy was very difficult. In [182] the authors note that while the need of conducting KA exercises is well established and acknowledged across many fields and problems, there is not much guidance about how to conduct it or evaluate its quality. The number of KA methods identified in the literature over the years is in the range of hundreds, as reported by some of the reviews of the field [49,98,190,207] which attempted to provide the basis for classifications of KA techniques. In the following, we provide a brief description of the most important classifications proposed over time in relation to the KA paradigm.

One of the first notable attempts to categorise KA methods belongs to Bainbridge [13], where the author proposed a matrix relating the acquisition method to the type of knowledge/information needed to be acquired. She introduced seven categories of “desired information”: general information on the effect of variables, general information on control strategy, numeric information on control strategy, the process, decision sequences, general types of cognitive processes and full range of behaviours. These were linked to acquisition methods such as observation and interviews, verbal protocol, questionnaires, etc. Later, Yates [210] notes that Bainbridge was also the first to suggest that a combination of techniques must be used in the KA process in order to ensure validity of the exercise; this became a common practice in KA, with

a majority of the researchers in the field supporting the idea [49,143,190,214].

From a different perspective Embrey [67] divided the KA techniques into two major categories: action oriented and cognition oriented. The action oriented techniques concentrate on describing and structuring the observed behaviours and tasks, while the cognition oriented techniques focus on the cognitive processes underpinning the observable behaviour. We add that this classification resembles the historical evolution of KA, which we briefly presented earlier in the paper, where in the research on human activity the initial work on studying the tasks was gradually enriched through the inclusion of cognition in the analysis process.

Another classification of KA techniques was based on the type of knowledge acquired by the KA exercise [49,70,211]. This classification uses the “differential access hypothesis” [95], that is, the belief that different acquisition methods uncover different types of knowledge. Most studies consider two categories of knowledge in this classification: declarative and procedural [46,210]. In [46] the authors state that complex human activity requires the seamlessly integrated use of both declarative (conscious, deliberative) and procedural (unconscious, automatic) knowledge. Thus, the resultant KA research focuses on either or both aspects, depending on the purpose of KA exercise. In a different view, substantive and strategic knowledge terms were first proposed by Gruber [87,88] and later discussed in [70] and [210]. The substantive knowledge is related to analytic activity, being used for describing and drawing conclusions about the domain of activity and/or state of the world, while the strategic knowledge is used at the decisional stage for deciding what action to perform next, based on the perceived state of the world. If we use the same aircraft pilot example we used

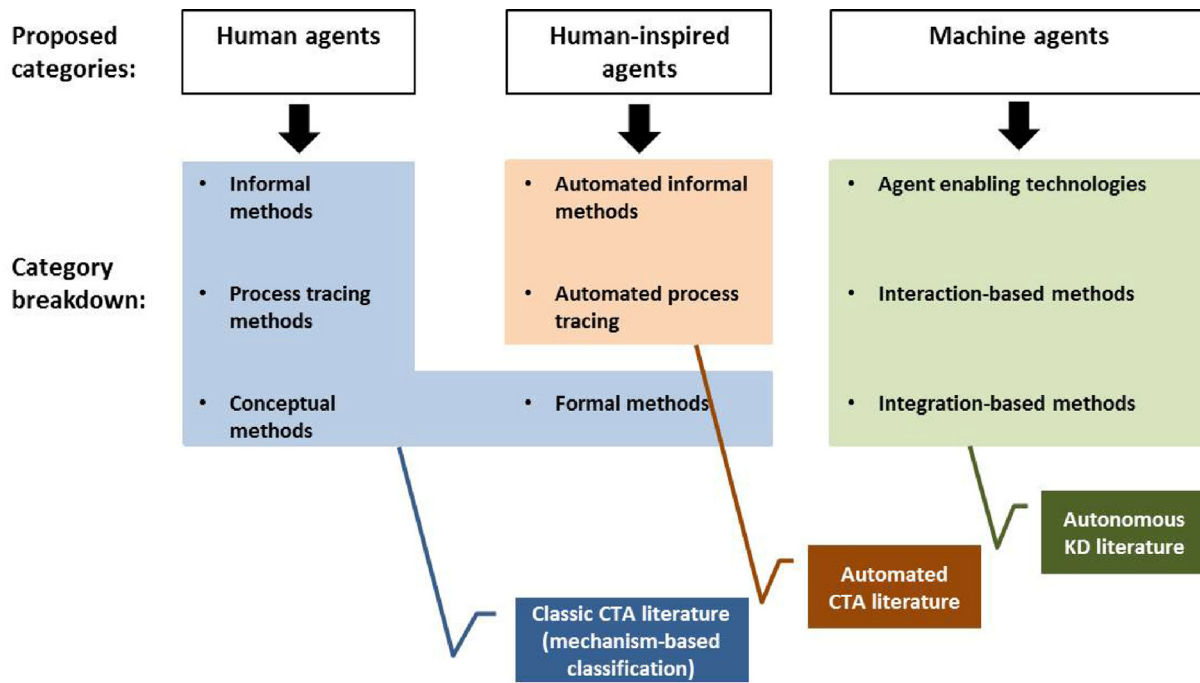


Fig. 3. The proposed classification and its relation to the existing mechanism-based classification.

earlier in the paper, a pilot uses substantive knowledge to conclude that the flight is in a high risk situation based on the weather data showing a potential storm, and uses strategic knowledge for deciding to descend in order to avoid the turbulent area.

A different taxonomy is based on the stage in the KA process in which the method is performed, where each stage is associated with an output of the acquisition exercise [156], e.g. data acquisition, analysis, representation. This categorisation is also indirectly presented by Cook in [49], even though the study is focused on classifying the internal mechanisms of the methods.

Recently, Yates and colleagues [210,211] proposed a taxonomy of KA methods which shows how different categories of purposes require the use of specific categories of methods. In essence, the authors assume that in practice the methods are not used individually, but rather in pairs of elicitation methods and analysis/representation methods coupled with specific purposes/activity types.

The most important, and perhaps most recognised and well-established classification of KA methods is based on the internal mechanism of the methods (the mechanism-based classification), that is, the way they acquire the knowledge. A classification that is generally accepted and largely used in the field [46,51,98,201,210,211] assumes four broad families of KA methods: informal techniques (observation and interviews), process tracing techniques, conceptual techniques, and formal models. The first three were proposed by Cooke [49], while the fourth is a later addition by Wei and Salvendy [207].

As we stated earlier in the paper, in this study we classify the KA methods from the point of view of the type of agency involved in the KA exercise. However, in each of the categories belonging to the proposed classification we discuss the methods based on the way they implement the KA exercise, that is, based on the internal mechanism of the methods. Consequently, we will also use in our review the mechanism-based classification, and will redistribute the methods from this classification into our classification, accordingly. This redistribution is presented visually in Fig. 3 in support of the next sections. The diagram summarises the main categories

in the proposed KA method classification and shows how the sub-categories discussed for each category fall into the existing KA literature.

5. The human agents

The knowledge acquisition using human agents has been extensively covered in the literature, with numerous stand-alone methodologies, methods and techniques proposed in the last decades [46,49]. Very well documented reviews of these techniques have been published over the years, especially during the 1990s and early 2000s [22,49,190,207], however, several important reviews which include aspects related to more recent human agent techniques have been also published in the last decade [46,98,201,210]. From the point of view of the classification we propose in this paper, the human agent methods fall in general into the first three families of the mechanism-based classification [49]: informal methods, process tracing methods and conceptual methods. In this section, we provide for each of these categories a summary description of the category and a brief presentation of the most important methods belonging to it. Also, in order to guide the review of the literature on human agency in KA, in Fig. 4 we provide a mapping of the human agent methods onto the KA process.

5.1. Informal methods—Observations and interviews

Informal techniques are usually methods used for direct acquisition, in which a human elicitor watches human experts and/or talks with them in order to extract knowledge about task performance either from their observed actions, or from their active response to tasks-related enquiries. Methods in this category are highly informal, and are highly verbal and descriptive, requiring the elicitor to either possess certain levels of expertise in the task that is under assessment, or otherwise to be highly qualified and experienced in interviewing techniques. These methods are useful in the initial stage (elicitation) of the knowledge acquisition

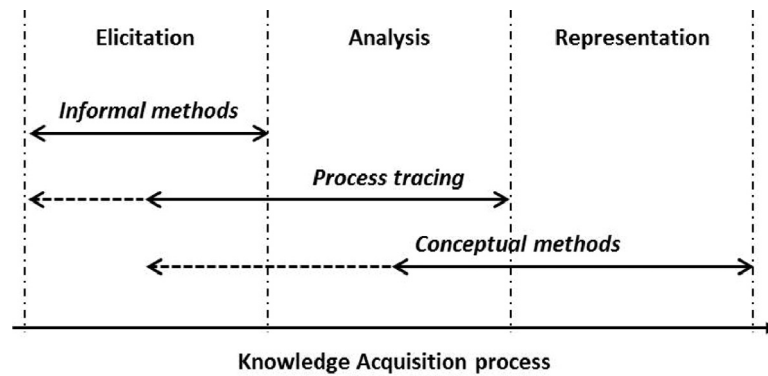


Fig. 4. Mapping of the human agent methods to the KA core process: solid line—ample explicit coverage and dashed line—limited implied coverage.

exercise (Fig. 4) for forming an initial view on the problem domain, however, the results may be difficult to interpret.

Observation methods involve extracting features from the observed human behaviour occurring during the performance of a task. The observation can be applied to the actual tasks or to records (video, audio, etc.) of the task performance [63,96]. In [141] the author states that observation is used in “manual” knowledge acquisition to familiarise the knowledge engineer with the domain. This familiarisation takes place before other techniques are applied, such as interviews or more formal methods, and facilitates further construction of knowledge models and representation. Observation is used to gather information about conscious and unconscious behaviour of subjects and to investigate the processes involved in the development of expertise. Cooke [49] identifies three observation methods: the active participation, the focused observation and the structured observation. While observation is by nature seen as a passive elicitation procedure, the active participation method assumes that the elicitor is involved together with the subjects in task performance. Hoffman [96] also provides a list of task types that can be subject to observations. He describes six families of tasks: familiar tasks, simulated familiar tasks, limited information tasks, constraint processing tasks, combined constraints tasks, and tough cases. In the elicitation process the subject is gradually exposed to situations belonging to various levels of familiarity and difficulty in relation to the domain of interest for the elicitor.

Interviews are another major type of informal human agent methods. They classify in unstructured and structured and can be direct or indirect, with questions that are explicit or implied [49,96,207]. In general they are retrospective—subjects are asked to retrieve information about certain tasks they performed in the past. The unstructured interviews are suitable for early stages of knowledge elicitation [49] due to the fact they do not require domain knowledge for the elicitor. The interviews do not follow a predetermined sequence or topic; the elicitor proceeds freely, and uncovers whatever information the subject can recall. For this reason they seem to be the preferred methods for initial stages of knowledge elicitation. However, the drawback is that the elicitor needs previous training and/or skills to facilitate the conversation and guide the interview. In addition, the data provided by unstructured interviews can be “copious and unwieldy”, as noted in [207]. The structured interviews are different from unstructured ones through that they follow a process that is in some extent predefined in terms of content and sequencing [49]. Depending on how strictly the process follows the predetermined format, they can be structured, semi-structured or prompted. The advantage of structured interviews over the unstructured ones is that they provide systematic, and thus, more complete views of the domains of interest. Also, the structured process tends to take less time, and the participants, both the elicitors and the experts tend to

be more comfortable throughout the elicitation exercise. However, structured interviews require more preparation time before the interview actually takes place. Nine types of structured interviews have been identified in the literature [46,49,141], as follows: focused discussions, teach-back, role play, twenty-questions, Cloze experiment, Likert scale items, question answering protocols, questionnaires and group interview techniques.

Starting from these broad families of techniques, in the following we describe the most popular methods, which generated the most important body of research to date.

Critical Decision Method [120,207] was proposed in the 1980s and is based on semi-structured interviews, using incidents as facilitators for testing decisions, judgements and general problem solving. The method is time consuming and requires elicitors to possess high level of expertise in the domain of interest, involving multiple-pass retrospection of past events guided by probe questions. However, the method generates information that is very rich and very specific in the same time. It is considered a method for high level KA, and was extensively used by both researchers and practitioners. Reviews of the method and its applications from various historical periods can be found in [49,51,78,97]. Recently, the method has been extensively applied especially in psychology and general medical practice [79,140,161,162,198,205], but also in ergonomics and human factors [168,169] or general critical decision-making problems [4,155].

PARI (Precursor-Action-Result-Interpretation) [91,92,207] is a nine stages structured interview methodology which elicits detailed information about procedural skills. The method was proposed in the 1980s and uses multiple experts on a set of problems, being considered to be time consuming and not feasible for usual operational contexts. However, it is considered a highly effective method which provides very detailed analysis of human skills. A simplified version of PARI (S-PARI) reduces the number of stages of the standard PARI from nine to three, and uses pairs of experts in relation to a specific problem. The method breaks down action, precursor and interpretation data into cognitive processes and investigates subtasks on only one task specific problem. The method is considered to be highly effective in analysing procedural skills, and easily usable in operational settings. Reviews of the PARI methodology and its applications from various historical periods can be found in [49,201,207], the literature showing that the most important body of research related to PARI methodology was concentrated in the 1990s and early 2000s. However, several important studies using PARI have been also reported in the recent years in instructional design in domains such as healthcare or engineering [45,160] or in virtual environments applications [47].

The Task Diagram approach [119,207] combines the diagram-based focused discussions with structured interviews and is used for generating task diagrams when a roadmap for task analysis

is not in place for the task of interest. The Task Diagram techniques generate an initial overview of the task, providing support for the rest of the cognitive task analysis; however, they have the disadvantage that they cannot handle very complex tasks. Comprehensive reviews of the major body of TD techniques and their applications can be found in [49,98,190,207]. Recently, task diagram methods have been used extensively in various fields, such as in medical domain in clinical research and pathology [205,209], in serious games [10,193], in ergonomics and human factors [149] or in instructional design [214] applications. In the last decade the classic task diagram methods also evolved towards a different elicitation approach called Graphic Elicitation [202] in which diagrams, photos or various forms of visual arts are used for stimulating experts' thoughts on task structure and performance, or in the reverse process experts are asked to provide visual representation of the personal understanding of tasks, concepts, experiences and behaviours. The literature on Graphic Elicitation reported a substantial number of studies in the recent years, in a variety of application fields [52,62,122,154,179].

The Knowledge Audit [119,207] is a structured interview method used in general when the elicitor needs to identify quickly the essential cognitive aspects associated with the task of interest. The method uses six compulsory probes related to past and future, big picture, noticing, task tricks, opportunities for improvement and expert-novice differences, and three optional probes related to anomalies in the task, equipment challenges and tough scenarios. The method is thought to be eliciting very detailed and specific information about the task performance, however the outcome is subjective and hence, may not be very accurate. The method was proposed in the 1980s and a number of reviews on knowledge acquisition describing various knowledge audit techniques and their applications are available in the literature [44,49,98,190]. Recently the knowledge audit methods have been used in various fields such as serious games [10,193], business and organisational development [54,83,174], transportation and energy sectors [44,173], and learning and instructional design [214].

The Simulation Interview method [119] is used for understanding the task process in which the elicitor brings out the major events throughout the task performance for highlighting the main cognitive elements of the task in relation to a specific incident. The method shows how the subjects perform the task, and also how they think about it, thus, it can deal with both experts and novices. Detailed description, historical notes and reviews on the simulation interview techniques can be found in [49,207]. In recent years simulation interviews have been used especially as part of ACTA (the Applied Cognitive Task Analysis methodology) [143], in fields such as clinical research [172], welfare [21,27,170] or ergonomics and human factor [56].

Another approach largely used in the classic human agent KA exercises is the Cognitive Demands Table method, which synthesises data from multiple interviews, finds patterns and organises them taking into account difficult elements, common errors, cues and strategies from SMEs' behaviour [119,207]. The method identifies the components of a task that are cognitively demanding and facilitates their further application in the task design cycles. Versions of the Cognitive Demands Table have been also used as part of ACTA [143], especially in very recent studies providing extensive coverage of a wide range of applications in numerous fields, such as medicine, ergonomics and human factors, psychology, economics, learning and instructional design, or games and virtual environments [21,27,54,56,83,170,172,214].

A recently emerging approach, thoroughly reviewed in [41], applicable in conjunction with any of the methods and family of methods described above, is the Elicitation by Critiquing, in which third party participants in the elicitation process are asked to critique SMEs actions or the resultant products of their actions in

order to generate meaningful knowledge about the tasks. The approach have been used especially, but not exclusively, in studies related to recommender system design [107,171,213].

5.2. Process tracing techniques

Process tracing techniques typically capture an expert's performance of a specific task through a think-aloud protocol during the performance of the task, or through a subsequent recall of it. Similar to the informal methods, these methods are also highly customised and task-dependant, requiring the elicitor to possess certain expertise in the problem domain. However, unlike the informal methods, they do not necessarily require direct interaction (i.e. subjects can be recorded), and the data to be monitored and extracted from the expert are predefined. Process tracing techniques have a slightly higher degree of formalisation compared to observations and interviews, and can be used in either or both the elicitation and the analysis stages of knowledge acquisition (Fig. 4), allowing the exploration of the cognitive structure of task performance. In the literature most of the classic KA studies consider that the process tracing approaches can be split into five major approaches: verbal reports, non-verbal reports, protocol analysis, decision analysis, and cognitive walk-through [49,207]. Several detailed descriptions and historical notes on process tracing can be found in [49,98,207], while a very recent, thorough and comprehensive review can be found in [17]. In the following we briefly describe the five main categories and provide references to their most recent applications.

The Verbal Report methods assume that the elicitors extract knowledge from SMEs based on what the latter are able to express through verbal description of what they believe they do for accomplishing the tasks of interest. The verbal communication can be on-line, if the expert provides a verbal report in real-time while performing the task, or off-line if the expert comments retrospectively on how they performed the task in the past. It can be also self-reported, when the expert reports own experience, or shadowed, when a second expert reports the facts experienced by the expert performing the task. Verbal reports are used in the initial stage of knowledge elicitation, and provide the raw data which is further used for protocol analysis. Recent studies on verbal reports have been reported especially in psychology related applications [75,89,129].

The Non-Verbal Report methods [49,75,84,188] assume the collection of data other than verbal, for process tracing purposes. Examples of non-verbal data can be bodily communication (e.g. eye movement, facial expression), inputs for computer-based tasks (e.g. keystrokes, mouse, touch screen), or physiological data from sources such as EEG (electroencephalography), EOG (electrooculography), EMG (electromyography), X-Ray etc. Non-verbal reports are also used in the initial stage of knowledge elicitation, like their verbal counterparts, especially when the verbal communication of the process involved in task performance is impaired due to various reasons. The data provided by non-verbal reports are then further used for protocol analysis [49].

The Protocol Analysis methods [46,49] emerged from the need of improving the consistence of data resulted from knowledge elicitation process. Informal methods, as well as the verbal and non-verbal reports are in general time-consuming and generate large amounts of data that are qualitative in nature, complex and unordered, which are usually interpreted with a certain amount of subjectivity by the elicitors, depending on the methods and/or their skills. Protocol analysis methods are in general ways of organising large amounts of so-called "open-ended" [49] material through objective and systematic identification of specific characteristics. Various techniques have been proposed over time, since the approach emerged in the 1970s, such as content analysis [13],

which searches for predefined patterns as part of the hypothesis testing process, interaction analysis [156], which parses the recorded interaction between the elicitor and the expert for identifying patterns in the expert's statements, or grounded theory [167], which is similar to content analysis except the patterns are not predetermined. Recent applications in various fields of the protocol analysis methods can be found in [132,164,206].

The Decision Analysis methods emerged in the 1980s [25,49,207] and are used for producing quantitative analysis of decision points within a task, when such points are previously identified using verbal and non-verbal protocols or protocol analysis. Thus, these methods are applied in the analysis stage of the KA process, after the initial raw data extraction. Decision analysis uses formal statistical methods and probability theory in order to provide quantitative information and prediction in relation to the decision points of interest. Recent work on decision analysis can be found in [64,114], including a comprehensive review of the period between 2000 and 2011 in [102].

Another category of techniques, is the Cognitive Walk-through [55,125,136,207] in which one or more elicitors work through the task of interest ask a set of questions from the perspective of the user. The procedure involves a task analysis that establishes the sequence of steps a human subject needs to take for performing the task, and the system responses to subject's actions. This is followed by the actual questioning sequence, when the elicitor goes through the task steps asking questions to itself at each step. The data obtained through the walk-through exercise are also in the form of verbal protocols, and can be further analysed with one of the protocol analysis methods. However, the method is an exploratory process and is believed to be easy to implement, having low time and cost requirements [207].

5.3. Conceptual techniques

In contrast to the first two categories, conceptual techniques produce structured, interrelated representations of relevant concepts within a problem domain. They are mostly indirect, requiring less or no introspection and verbalisation, and can use multiple sources of problem domain expertise, such as multiple human experts and/or task documentation and logs, historical data, practitioner's literature etc. The output of these sources can be aggregated in order to generate a composite structural representation of the acquired knowledge (Fig. 4).

Several broad families of methods are described in the literature in relation to conceptual methods [49,196]. Concept Elicitation methods focus on establishing a set of key concepts that are essential for understanding the domain/task of interest. These concepts and their interaction can be inferred using various informal techniques, such as structured interviews or focused discussions, if the techniques are adapted for elicitation of essential elements of the domain, rather than the extraction of general data. Cooke [49] identifies structured interviews as the most appropriate to be used for concept elicitation. The interviews are adapted to concept elicitation through that the experts/subjects are guided towards building dictionaries of concepts related to the task of interest, in which the concepts are grouped based on a set of criteria relevant to the associated domain. The concept elicitation methods can be also based on goal decomposition, involving the construction of hierarchies of concepts which generate taxonomies of concepts. Another notable family of conceptual methods is the data collection, which involves the estimation of the degree of correlation between two concepts belonging to a domain of interest. In [49] the author refers to this correlation as "relatedness" or "proximity". These methods are used in general after the initial elicitation of concepts, in conjunction with informal methods or through process tracing, and constitute the immediate support for representation stage of

the KA process. The data collection techniques generate one or several matrices of proximity, depending on the number of experts involved in the elicitation exercise, in which the rows and columns represent various domain concepts. Methods in this family include "rating and ranking" [57,93], repertory grid [26], sorting [57,184], event co-occurrence [49], and correlation/covariance [49]. Another important group of methods is gathered in the structural analysis family, where the techniques are based on descriptive multivariate statistics [49] and are in general used for reducing the taxonomies of concepts and the subsequent relatedness estimate matrices to simpler forms which are more appropriate for further knowledge representation. Important methods for structural analysis are multidimensional scaling [24], discrete techniques (e.g. clustering) [106], direct structure elicitation [196], and structure interpretation [156].

In the following we describe a number of conceptual techniques considered to be of major importance in a variety of fields of research from a human agent KA perspective.

The Conceptual Graph Analysis [82] method creates a conceptual map of the task in the form of graphs, in which nodes represent conceptualised states, events, goals or actions, and directional links represent relations between the concepts captured in nodes. The graphs can represent taxonomic, spatial and causal structures of the concepts and create the support for knowledge representation through information integration and organisation. The method represents a structured framework for transferring knowledge from an implicit form to an explicit one.

The Consistent Component methods [73,207] investigate procedural knowledge and are used in the intermediate or late stages of analysis. They decompose the task of interest and identify decision points and the automated skills associated to them, providing in the same time measurements for the degree of interference between simultaneous tasks and detailed information about action and skill performance timing [186].

The Diagramming methods are knowledge representation techniques which show the key concepts that tie all the other concepts related to the task/domain of interest [177,207]. Diagrams are very intuitive and in general require low time and cost, being simple ways to represent fairly complex tasks. However, above a certain level of task complexity the diagrams themselves may become too complex to provide good representation of the domain, and require the analysts to employ other methods in order to produce better representations.

The Error Analysis methods [207] focus on identifying error sources and on classifying these errors. The errors made by subjects throughout the task performance process are systematically analysed in order to establish their relationship with the cognitive processing, i.e. they are mapped to the corresponding cognitive processing failures. Error analysis produces in-depth insights into the intimate cognitive processes and functions and create the premises for realistic representation of thought processes. However, their use is in general appropriate for tasks which are susceptible to errors, such as critical incidents or safety critical domains [116].

The Psychological Scaling methods belong to the rating and ranking class described in [49], and focus on the relations between concepts related to a task/domain of interest, with inclusion of subjective aspects such as individual preference and perception. The relations are expressed using estimated proximity between concepts, which are mapped into proximity matrices. The concepts are ranked by using each of them at a time as reference and measuring the similarity with the remaining ones [187,207].

The Paired Comparison methods are also part of the rating and ranking class, and involve the rating of pairs of concepts in relation to a standard pair [49]. Based on relatedness/proximity measures, the techniques generate magnitude estimations for each pair;

however, if the number of concepts increases [207] the methods may become time consuming. Another drawback of the methods is that they only consider relatedness along one specified dimension.

The Repertory Grid methods [26,207] are particular cases of general rating and ranking methods, in which the concepts related to the task of interest are rated along “dichotomous dimensions” called constructs [49]. The constructs can be organised in hierarchies and used for separating the domain concepts. The subjects provide to the elicitor ratings of various constructs, which are then placed into grids, on rows and columns. Overall relatedness/proximity is then extracted from the grid, by calculating the correlation between ratings constructs and concepts. The result of repertory grid methods is usually further used for knowledge modelling, through structural modelling techniques such as hierarchical clustering.

The Sensori-Motor Process Charts are techniques that focus on mental activities [109,207]. They take into account sensors and sensory information and their relation to the task of interest and produce skill charts based on the patterns observed during the task performance. In general they follow a predefined set of steps, equivalent to the key mental activities involved in psycho-motor tasks: plan, initiate, control, end, and check [207].

The Sorting methods focus on high-level conceptual structures [49,57,184,207]. The experts are required to order concepts based on relatedness/proximity and place them into piles, accordingly. In addition, due to the fact the experts are not restricted in terms of number and content of piles (one concept can be placed in multiple piles), these can be also asked to label the piles. In general the sorting techniques are considered to be less time-consuming than the paired comparison, with which they are alike, but instead they have a lower level of sensitivity to relatedness/proximity differences. In general sorting techniques are considered fast and simple ways of eliciting conceptual information of a quality that is good enough to be used reliably in further analysis of data.

5.4. Summary of human agents

We included in this section those methods which suited the perspective depicted earlier in the paper in Fig. 2. In Table 2 we summarise this section in a tabular manner and through this, we

emphasise the contribution of this class of methods to the creation of the roadmap that facilitates the KA process, and we show how each of the methods can fill an appropriate branch in the decision tree, corresponding to human agency. Thus, overall, this section contributes to demonstrating the decision support role of the human agent class of methods in the KA exercises.

6. The human-inspired agents

As we explained earlier in the paper, we consider the human-inspired agent methods as those methods that automate some of the human agent methods in order to increase the speed of the exercises or to allow the exercises to be performed in cases where physical presence or participation of human elicitors in the KA exercise is impeded or inefficient/inconvenient due to various reasons. From the point of view of the classification we discuss in this study, the human-inspired agents represent a significant contribution to the KA body of research through that they are a significant step in the process of advancing the KA field from purely human-based activities to purely human-independent activities. While the human-inspired agent methods have been extensively used for a variety of KA exercises, they do not present novel approaches regarding the intrinsic mechanisms of the acquisition, but rather they bring novelty in the way the human-based methods, such as interviews or analysis of verbal protocols, are implemented in computer programs. Thus, the contribution stays in the ability of those programs to accurately emulate and automate the well-known human elicitor actions, and to increase the speed and convenience of the KA exercises.

In this category, the literature contains a variety of human-inspired agent methods which are used for implementing automated versions of some of the informal methods (especially automated interviews), process tracing methods (especially analysis of verbal and non-verbal protocols) and conceptual methods (especially psychological scaling and repertory grid implementations) [49,76]. However, from the mechanism of the method point of view, most of the human-inspired agents are those belonging to the class of formal KA methods proposed by Wei and Salvendy [46,207]. In order to guide the review of the literature on

Table 2
Summary of human agent methods: agent perspective roadmap and KA process.

KA approach	Agent perspective roadmap		KA process model			References
	Amount of activity	Richness of analysis	Elicitation	Analysis	Representation	
Critical Decision	Very low	Very rich	Yes	Yes	No	[49,51,78,97]
PARI	Very low	Very rich	Yes	Yes	No	[49,201,207]
Task Diagram	Very low	Moderate	Yes	Partial	No	[98,119,190,207]
Knowledge Audit	Low	Rich	Yes	Partial	No	[44,49,98,190]
Simulation Interview	Moderate	Moderate	Yes	Partial	No	[49,143,207]
Cognitive Demands Table	High	Moderate	Yes	Yes	Partial	[119,143,207]
Elicitation by Critique	Very low	Moderate	Yes	No	No	[41,107,171,213]
Verbal Reports	Very low	Low	Yes	No	No	[17,75,89,129]
Non-Verbal Reports	Very low	Moderate	Yes	No	No	[49,75,84,188]
Protocol Analysis	Moderate	Rich	No	Yes	No	[13,46,49]
Decision Analysis	Moderate	Rich	No	Yes	No	[25,102,207]
Cognitive Walk-through	Very low	Low	Yes	Yes	No	[55,125,136,207]
Conceptual Graph Analysis	High	Rich	No	Yes	No	[49,82]
Consistent Component	Moderate	Rich	Yes	Yes	No	[73,186,207]
Diagramming	Moderate	Rich	No	Partial	Yes	[177,207]
Error Analysis	Low	Moderate	Yes	Yes	No	[116,207]
Psychological Scaling	Moderate	Rich	No	Yes	Yes	[49,187,207]
Paired Comparison	Moderate	Moderate	No	Yes	Yes	[49,207]
Repertory Grid	Moderate	Rich	No	Yes	Partial	[26,207]
Sensori-Motor Process Charts	Low	Moderate	Yes	Yes	Partial	[109,207]
Sorting	High	Moderate	Yes	No	No	[49,57,184,207]

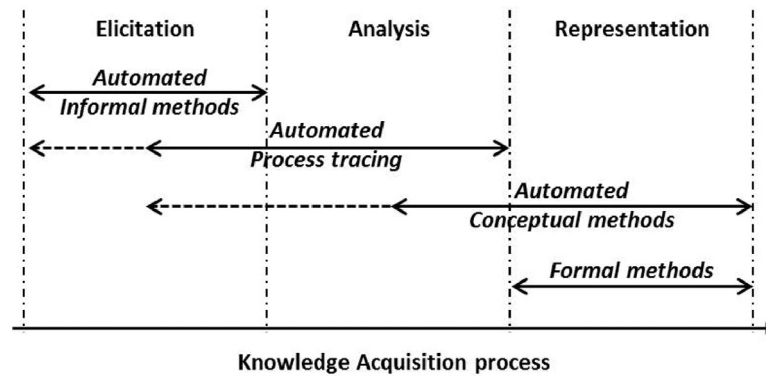


Fig. 5. Mapping of the human-inspired agent methods to the KA core process: solid line—ample explicit coverage and dashed line—limited implied coverage.

human-inspired agency in KA, in Fig. 5 we provide a mapping of the human-inspired agent methods onto the KA process.

6.1. Automation of human agent methods

For the human agent informal methods most of the human-inspired counterparts consist of computer-based tools which include support for fully automated or mixed-initiative (semi-automated) interviews. Some of the most important tools reported in the literature [49] are Cognosys [208], which transfers the SME domain knowledge into a graph structure, MORE [111] and its enhanced version MOLE [69] which were largely used for generating models of diagnosis knowledge able to disambiguate under-specified domains and to refine incomplete knowledge bases, SALT [137], which was used for problems such as configuration and scheduling for generating expert systems able to handle propose-and-revise problem-solving strategies, and ASK [88] which interviews the SMEs for eliciting strategic knowledge about the domain of interest. Other computer based tools containing automated interviews have been also reported in the literature, such as ETS (expertise transfer system) and its enhanced version AQUINAS [23] which were mainly used by Boeing, IRA-Grid [133] which acquires descriptions of prototypical situations through a grid-based interview component, or KRIMB (Knowledge Representation for Intelligent Model Building), which acquires descriptive information about complex reliability systems [59].

For human agent process tracing category of techniques, most of the human-inspired counterparts concentrate on implementing computer-based verbal protocol analysis methods in order to automatically record and analyse transcripts from SMEs thinking aloud about tasks. Popular tools reported in the literature were Cognosys, which contained a protocol analysis component in addition to the automated interview capabilities, and KRITON [59] which transforms verbal protocols into propositions based on pauses in the speech, along with other tools such as LAPS [99], MACAO [12], or MEDKAT [104].

Conceptual human agent methods were also addressed by various automated tools. Automated counterparts of psychological scaling, including multi-dimensional scaling, were largely used in the literature for structuring knowledge, i.e. AQUINAS, KRITON, IRA-Grid with variations such as FLEXIGrid, KSS0 and others [22,37]. Also a consistent body of research concentrated on repertory grids and used various personal-construct psychology-related methods to elicit and analyse knowledge, such as AQUINAS, ETS and IRA-Grid, FLEXIGrid, KRITON, KSS0, KITTEN, SMEE [74,150].

Recent work that applies the above methods has been reported especially in domains that are new and less explored by the classic KA community, such as games and virtual environments, virtual worlds and societies, or serious games [14,94,159,166], where the

knowledge is not acquired (automated or not) from entities that are humans or artefactual data of human activity, but rather from computer generated artificial entities. Such an approach was used in [159], where the authors created automated data collection entities for virtual worlds, which they tested in the Second Life environment. They demonstrated that the entities were capable to capture a variety of behavioural data about various avatars populating the Second Life, data that were further analysed using Social Network Analysis methods. They concluded that a combined approach utilising manual and automated techniques can provide valuable knowledge about elements of interest in virtual worlds and social networks, such as structural and functional aspects, or key players. In a different study Yee and Bailenson [212] describe a method for collection of longitudinal behavioural data from virtual worlds, and introduce a technical framework for capturing avatar-related data for several weeks in real-time, at a resolution of less than one minute. Also, in [94], the authors used the game Second Life to implement human-inspired agents in embodied survey “bots”, in the form of software-controlled avatars, in order to obtain automated data collection in 3D virtual worlds. In their framework a human elicitor controlling an avatar and a “bot” artificial elicitor controlling another avatar cooperated to perform a survey interview on various characters (both human-controlled avatars and computer generated avatars) populating the game Second Life. They found that both the human-based and the bot interviewer performed the survey in good conditions, however, the bot had a slightly lower response rate compared to the human. While a difference existed, the authors concluded that the findings provided sufficient support for the idea of using bots as virtual research assistants.

6.2. The formal methods in the mechanism-based KA classification

The formal methods use computer simulations to model human activity, thus they account for the knowledge representation stage only (Fig. 5), in the KA process. The acquisition of knowledge does not rely on actual performance of the tasks or records of it, instead is based on cognitive models built on various assumptions which lead to descriptions of the tasks/domains of interest convenient for the purpose of the KA exercise [207]. The methods in this category are considered by Wei and Salvendy [207], and further acknowledged by other authors [46,51,98] as KA methods inspired from assumed understanding of the human mind and cognition, and formalised into computational models that plausibly emulate human activity. We complement this view by saying that the methods in this category consist of attempted cognitive architectures for general intelligence, emerging from the corresponding cognitive theories, and aiming to emulate human problem-solving and decision-making capabilities. Thus, these methods are inherently automated, without human agent counterparts, and therefore, we discuss them

in our classification (1) as part of the category of human-inspired agents and (2) separate from the automated versions of the human agent methods. In the following we present the most notable approaches belonging to this category.

The ACT model (Adaptive Character of Thought) comes from the “ACT*” cognitive theory initially proposed by Anderson in 1983 [8], and further instantiated as a cognitive agent architecture [9,28,189]. In ACT the authors consider that cognition emerges from the interplay between procedural and declarative knowledge. Procedural knowledge is modelled through units called production rules encoding transformations in the environment. Declarative knowledge is modelled through units called chunks encoding objects in the environment. The ACT model is focused on skill acquisition and can be applied only to problem solving domain, assuming a “means-ends” problem solving structure [207]. It can represent both declarative and procedural knowledge and represents a way to understand the learning of complex problem solving skills.

The ARK model (ACT-based Representation of Knowledge) [49,80,139,207] is a technique similar to the goal decomposition, which is part of the informal methods in Cooke’s taxonomy [49]. The model uses a process that breaks goals into sub-goals and/or actions and generates a network of objects and their interaction by using ACT-inspired production rules for modelling goal-subgoal and goal-action relations. The model is thus able to emulate both the network-based representation of the domain knowledge and the corresponding procedures performed on that knowledge.

The Human Processor model is based on the theory of human information processor [33,34]. It was developed as a model of human–computer interaction, and consists of a series of three processors—perceptual, cognitive and motor—and a set of general purpose memory stores [134]. From a KA perspective the approach can model various parameters which participate in breaking down of complex tasks into relevant components, taking into account timing attributes. The task decomposition is very detailed, with the associate cognitive processes and skills reaching an “atomistic” level [207]. The model is considered to be very accurate, especially for modelling simple tasks, where detailed task decomposition can be easily done.

GOMS (Goals, Operators, Methods and Selection rules) was also developed as a human–computer interaction model, based on human information processor [11,36,66,86,115]; however, the task modelling and decomposition focuses on higher levels of cognitive processes, i.e. goals, operators, methods and selection. From a KA perspective GOMS is applicable to error-free tasks for which the sequence of actions needed to perform them is known. Based on that particular sequence GOMS is able to provide good understanding of the cognitive interaction between the system user and the system, based on that particular sequence. Consequently, the model is functional for the specificity of the task and needs major rework in order to be ported to different tasks. A number of versions of GOMS model have been proposed over time, such as Basic GOMS, Keystroke Model, Model Unit Task, Natural GOMS Language or Cognitive-Perceptual-Motor GOMS [197,207].

The Grammar methods [65,207], such as Cognitive Grammar [178] or Task-Action Grammar [163], describe the tasks requiring human–computer interaction in a formal language, in which a syntax is associated to the actions taken throughout the task performance. Grammars are considered appropriate for complex systems, and fairly easy ways of modelling languages for human–computer interaction. In Cognitive Grammar methods the grammar is modelled using five types of symbols: terminal—are associated to actions that involve learning and remembering, non-terminal—represent sets of actions that can be grouped based on their similarity, starter—are associated to high-level tasks, meta-symbols—refer to operators/operations such as *and*, *or*, *inclusion*, and rules—

which define interactions within the grammar structure. The Task-Action Grammar methods usually identify primitive tasks that do not require control frameworks, and can be performed without involvement of problem solving skills. These tasks are then described in a dictionary using semantic categorisation. Based on the dictionary, rules that associate the simple tasks to actions are generated.

The Object-Oriented Models use object oriented technologies for integrating procedural models, such as GOMS and semantic models, such as grammars [20,197,207]. In general it is considered that GOMS-type models are limited to specific types of tasks and subsequent functionality, while semantic models are entirely task-dependant. Object Oriented modelling allows variation of functionality through addition/removal of classes and methods, and due to this flexibility can generate semantic structures for virtually any task. From the KA point of view it can handle both declarative and procedural knowledge, especially in human–computer interaction contexts, and bridges a gap between high-level semantic description of task domain and procedural description of the sequence of actions.

The standalone Cognitive Simulation methods [183,207] use inputs from domain scenarios to generate realistic cognitive computational models which can then be compared to observed human behaviour for the same scenarios. In general, such models evolved towards cognitive agent architectures for general intelligence, where the resultant cognitive models were intended to produce behaviour not limited to the same scenarios used for building the models. However, from a KA perspective, the cognitive simulation limits its scope to reproducing, through simulation, plausible behaviours related to the tasks of interest; behaviour that can be further analysed and decomposed towards increasing levels of detail. CES (Cognitive Environment Simulation) is a Cognitive Simulation approach proposed by Roth and colleagues [183] for modelling the cognitive activity of operators in nuclear power plants, in order to capture the cognitive demands involved in dynamic fault-management situations. CES monitors and tracks process changes, identifies unexpected behaviours and formulates hypotheses related to these, builds and revises a situation assessment, and formulates proposed actions based this assessment. Other important cognitive simulation approaches such as SOAR [126], CLARION [199], CogAff [48] or SoM (Society of Mind) [130] have been also proposed and continuously improved over time, emerging towards complex cognitive architectures largely used nowadays for modelling knowledge and behaviour in a variety of application fields [130].

6.3. Summary of human-inspired agents

We included in this section those methods which suited the perspective depicted earlier in the paper in Fig. 2. In Table 3 we summarise this section in a tabular manner and through this, we emphasise the contribution of this class of methods to the creation of the roadmap that facilitates the KA process, and we show how each of the methods can fill an appropriate branch in the decision tree, corresponding to human-inspired agency. Thus, overall, this section contributes to demonstrating the decision support role of the human-inspired agent class of methods in the KA exercises.

7. The machine agents

In the previous two categories (human agents and human-inspired agents) the KA relies on human or human-like agents to extract the underpinnings of the observable behaviour of humans. The third category, machine agents, opposes to them in two aspects, as we explained in the introductory section. First, the machine agents acquire knowledge in ways that no longer resemble or depend on the human ways of performing the acquisition tasks.

Table 3

Summary of human-inspired agent methods: agent perspective roadmap and KA process.

KA approach	Agent perspective roadmap		KA process model			References
	Amount of activity	Richness of analysis	Elicitation	Analysis	Representation	
Automated Informal Methods	High	Rich	Yes	Yes	No	[23,59,69,88] [133,137,208]
Automated Process Tracing	High	Rich	Yes	Yes	Partial	[12,59,99,104]
Automated Conceptual Methods	High	Rich	No	Yes	Partial	[22,37,74,150]
ACT	Moderate	Moderate	No	No	Yes	[8,9,28,189]
ARK	Moderate	Moderate	No	No	Yes	[49,80,139]
Human Processor	Low	Rich	No	No	Yes	[33,34,134]
GOMS	Moderate	Moderate	No	No	Yes	[36,66,86,197]
Grammars	Moderate	Moderate	No	No	Yes	[65,163,178]
Object-Oriented Models	Moderate	Low	No	No	Yes	[20,197,207]
Cognitive Simulation	Low	Rich	No	No	Yes	[48,126,130,199]

Thus, the acquisition process implemented by the machine agents is not intended to be plausible from the point of view of human elicitor actions, while still delivering consistent results in terms of the KA output. Second, the machine agents no longer acquire knowledge from humans or planned/attended records of their behaviour, but rather from unattended artefactual data resulted from human activity systems. Thus, the machine agents employ a variety of computational intelligence technologies that enable them to perform a human-independent autonomous knowledge discovery process, in order to generate models of the knowledge hidden in the artefactual data. In order to proceed with the survey on the machine agent KA literature, we first describe in a brief manner the most important of these agent-enabling technologies.

7.1. Agent-enabling technologies

In this study we consider three classes of computational intelligence methods which are of high importance in enabling the machine agents for KA: statistical analysis, machine learning, and evolutionary computation. The methods in these categories are used either individually or combined in order to implement agents capable to act autonomously for performing the acquisition process.

7.1.1. Statistical analysis

Numerous statistical methods have been used over the years for knowledge acquisition, especially in autonomous knowledge discovery contexts, for extracting both the structure [108] and the causal relations [100] existing in artefactual data. Statistical analysis can be seen in the KA perspective as the mathematical way to capture and disseminate data, with the purpose of defining models for prediction.

Bayesian networks [151], rule sets (crisp, rough or fuzzy) [105], k-means techniques [113], regression analysis [61], or decision tree analysis [180] are some of the most popular approaches, which generated a significant body of research in the general KA field, as well as in the KA related to human activity systems, which is of interest in this paper. Comprehensive reviews of these techniques can be found in [2] in relation to their mathematical foundation, and in [19,112] in relation to their application in the KA field.

Methods in the statistical analysis family of agent-enabling technologies benefit from a strong mathematical foundation, through which they can provide well defined and reliable insights into the mechanisms underpinning the artefactual data. However, they [18] can only infer the knowledge models from well structured data, while they produce less clear results when dealing with complex and highly non-linear data or multidimensional datasets.

In machine agents for KA, the statistical analysis methods are mainly used as part of the inference modules [40,110], especially

for the early stages in the knowledge discovery process, such as data preprocessing, but also in clustering or rule mining.

7.1.2. Machine learning technologies

Machine learning technologies employ a variety of techniques in order to endow artificial entities (machines) with the ability to autonomously learn facts about various phenomena, which from a KA perspective equals to the ability to uncover and understand the inherent structures and causal relations underlying the artefactual data of interest. The machine learning techniques may be supervised, where the supervised learning methods assume the existence of prior (historical) domain knowledge, or unsupervised, where the machine entities act entirely independent in the knowledge discovery process.

Inductive Logic Programming [50,153], Support Vector Machines [158,176], Reinforcement Learning [121,128], and Artificial Neural Networks [35,38,105] are the most popular approaches in machine learning which generated the largest body of research in the KA field. Detailed reviews of the machine learning field and techniques can be found in [112,144] and [138].

Often machine learning techniques are used in conjunction with statistical methods for extracting the meaningful information out of the non-linear and multidimensional datasets, i.e. neural networks can be used in conjunction with symbolic production systems in the form of a rule sets, where the rules can be crisp (if-then), rough or fuzzy. Consequently, the machine agent methods for KA can employ one or more machine learning techniques, which in turn may make use of statistical methods, resulting in complex integrated machine agents covering more than one stage/sub-process in the KA process.

7.1.3. Evolutionary computation technologies

The motivation for applying evolutionary computation (EC) techniques to knowledge acquisition is that they are robust and adaptive search techniques that perform a global search in the solution space. Evolutionary computation techniques are not used *per se* as standalone methods to implement acquisition tasks such as feature selection, rule mining, clustering or classification. Rather, they are used to evolve the parameters of other methods in order to improve the quality of the incipient knowledge extracted by those methods. Thus, evolutionary computation techniques have been found particularly useful in automatic processing of large quantities of raw noisy data, where large numbers of parameters used by various other KA techniques needed to be optimally set in order for those methods to be able to discover, extract and represent significant and meaningful information [72,152].

The largest body of research on EC in the KA consists of EC methods that can be included in the standard genetic algorithms

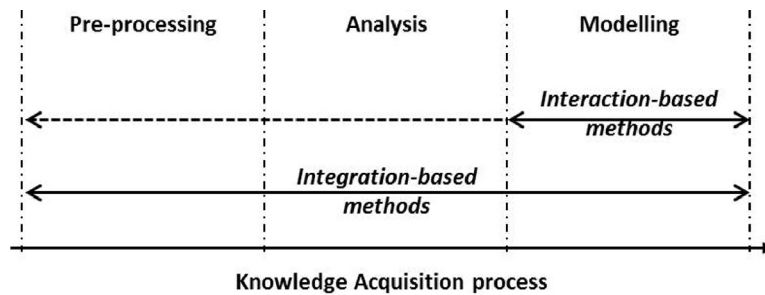


Fig. 6. Mapping of the machine agent methods to the KA core process: solid line—ample explicit coverage and dashed line—limited implied coverage.

(GA) category, either in single or multi-objective variants. The algorithms follow in general the broad guidelines of classic GAs, i.e. they use classic encoding methods such as binary or decimal (real, integer) with one feature in one chromosome, fixed sized populations with no sub-populations, genetic operators such as single-point and multi-point crossover and mutation, classic selection techniques such as roulette wheel selection or stochastic universal selection, etc. [81]. Applications and reviews of these algorithms can be found in [16,58,117,123] and [146].

Apart from those considered standard GAs, a number of non-standard evolutionary techniques have been largely employed in KA tasks, such as the Non-dominated Sorting Genetic Algorithm [7,103], the Niched Pareto Genetic Algorithm [68], the Evolutionary Multi-Objective algorithm for Feature Selection [203], or the Evolutionary Local Search Algorithm [117,215].

A very recent and comprehensive review of the EC methods employed in KA is offered in [148] and [147], where the authors identify the most used evolutionary techniques for feature selection, classification, clustering and association rule mining, and provide detailed guidance for adapting the design of each component of the evolutionary algorithms (e.g. encoding, genetic operators, selection strategies, objective functions) to the desired knowledge acquisition task.

Similar to the other agent-enabling technologies, in the EC technology case too the machine agents can employ one or more EC techniques, which in turn can make use of either or both statistical methods and machine learning methods, resulting in complex integrated machine agents covering more than one stage/sub-process in the KA process.

7.2. The mining machine agents

The machine agents have been extensively used in KA as part of the autonomous KD paradigm. In [30,31] the authors note that agents—generally seen through the lens of autonomous agents and multi-agent systems, and knowledge discovery—generally seen as a data mining exercise, initially emerged and established as separate standalone research fields but in the last two decades methods from both fields merged into a new field of research, the “agent mining”. The agent mining concept was largely supported by numerous studies in the literature [15,32,40,110,145], which proposed agents for agent mining applications under various names such as knowledge driven agents [15], knowledge collector agents [145], or miner agents [6,40]. In [30] Cao et al. identify three approaches on agents and knowledge discovery that are essential for the emergence and establishment of the machine agents in knowledge acquisition: the data mining-driven agents, the agent-driven data mining, and the agent mining itself, where the former two were precursors of the latter. In the data mining-driven agents, the agents are empowered and their capabilities are enhanced by data mining and knowledge discovery techniques. Conversely, in the agent-driven data mining the agents or agent tech-

nologies in general are used to improve data mining processes. The agent mining encompasses both paradigms, and merges agent and multi-agent technologies with data mining and knowledge discovery techniques. This brief historical view on agent mining is important for understanding the convergence of the research interest towards autonomous knowledge discovery through the use of machine agents.

However, from the point of view of this paper we are interested in the mechanics of the methods and therefore we identified in the literature two categories of machine agents for autonomous KD, the interaction-based and the integration-based agents, which we describe in the following. However, in order to guide the review of the literature on machine agency in KA, in Fig. 6 we provide a mapping of the machine agent methods onto the KA process.

7.2.1. Interaction-based agents

The interaction-based methods present multi-agent approaches in which the learning mechanisms underlying the knowledge acquisition process are implemented using various types of social interactions and behaviours, such as collaboration, cooperation, negotiation, competition or imitation [90,175,185,216]. However, we found that of the many types of agent interactions reported in the general agent literature, only collaboration, cooperation and negotiation have been used in a significant amount for knowledge acquisition as part of the autonomous knowledge discovery paradigm, while the rest are only implied by some methods, rather than explicitly used as standalone methods.

In [90] the authors proposed a Collaborative Exploration System for knowledge discovery in biomedical multivariate time series data, in the form of a multi-agent system in which the subsequent learning is the result of cooperation between five types of agents (a data segmentation agent, a data classification agent, a symbolic translation agent, a scenario construction agent, and a system agent), which are grouped in two “triads”: the symbolic triad and the system triad. In the symbolic triad the segmentation, classification and symbolic translation agents mutually interact to generate a symbolic representation of the raw data. In the system triad the symbolic interpretation, scenario construction and system agents interact to generate the knowledge representation. Further, a triad-to-triad interaction is also implemented in the form of a feedback cycle in order to refine and improve the resultant knowledge representation. Another collaborative system, MAS-KS (the Multi-Agent System based on Knowledge Sharing), was proposed by Schroeder and Bazzan [192], for improving individual learning models through knowledge sharing. In their approach each agent is derived from a machine learning algorithm which generates a set of rules. The method considers collaboration through a pair-wise interaction, in which two agents can match or merge their rules based on their performance in the knowledge extraction. Through this they update parameters of their models in order to improve the quality of the generated rules. A collaborative multi-agent system based on fitness-proportional knowledge

sharing was also used in [131] for cognitive skill modelling in the context of puzzle solving, where for the extraction of clue patterns from puzzles, procedural visual scanning skills must be developed by human players. The authors model computationally the cognitive skill acquisition process through a society of agents that search the puzzle grids and learn socially from the knowledge discovered and shared by fellow searching agents. An agent in the society updates its features by borrowing new features from another agent in the society considered to be its best fit. The amount of features borrowed is proportional to the fitness level, where the fitness considers agent feature compatibility and searching proficiency in the same time. In web search and web content mining, Chau et al. [39] propose CS (the Collaborative Spider), a multi-agent system that allows user search collaboration for more accurate search results based on own and shared search history. Another collaborative environment was used in [175] for gaining knowledge about the dynamic strategies of companies involved in cartel formation. The authors introduced the AGent-Mining tool consisting of a society of collaborating agents grouped in specialised teams, and defined the interaction within and between the teams based on a standard released by the Foundation for Intelligent Physical Agents, called the “FIPA Contract Net Interaction Protocol” [3].

Cooperation and negotiation were also addressed in a number of studies [43,60,127]. A cooperative approach is used in [6], where Albashiri and colleagues introduce EMADS, an extendible multi-agent data mining system. The authors describe the proposed system as “an anarchic collection of persistent, autonomous (but cooperating) KD agents operating across the Internet”, in which individual agents of different types, such as data agents, user agents, task agents, mining agents and “house-keeping” agents interact to provide pertinent knowledge models to whomever lodges a knowledge discovery request. In [60] the authors use cooperative negotiation in a multi-agent distributed learning system consisting of several learning agents and a mediator agent, where the former implement different machine learning algorithms and the latter controls the negotiation-based interaction of the former. Using their own predefined subsets of the total available data, the learning agents extract rules and construct their own models of knowledge, which are then evaluated based on rule accuracy and used in negotiation. In the negotiation process the mediator agent collects proposals (models) from each learning agent, and filters them based on a threshold value. The models above the threshold are returned to the society of agents to be used in further search of rules with better accuracy. In [127] a multi-agent system using adaptive probabilistic negotiation agents is proposed for knowledge discovery in e-marketplaces. The method uses a Bayesian learning mechanism that enables the agents to dynamically improve their negotiation skills by discovering key negotiation knowledge through mining and monitoring the interaction with and between the opponent agents. Further, a similar approach to negotiating agents has been presented in a different study by Cheng et al. [43] who discussed the concept of automated negotiation by autonomous agents. The automated negotiation agents jointly search for a mutually acceptable solution in the space formed by negotiable issues, where the negotiable issues are knowledge discovery aspects such as the fuzzy rules extracted by individual agents, if agents are seen as fuzzy inference systems.

7.2.2. Integration-based agents

The integration-based methods describe complex intelligent (autonomous) agents which fulfil the mining role individually, by implementing the learning mechanism implied by the knowledge discovery exercise through integration of one or more techniques from various fields, such as machine learning or evolutionary computation in order to implement one or more of the knowledge discovery tasks, such as rule extraction, classification or clustering

[42,110,145]. From the integration point of view, Chemchem and Drias identify three major types of agents [40]: agents based on expert systems, which use inference engines for constructing knowledge, agents based on machine learning, which extract knowledge using machine learning techniques, and agents based on data mining which rely on knowledge discovery methods for extracting the knowledge more efficiently. Most of the work on integrated mining agents uses various frameworks that in essence integrate in more or less extent these three major types of agents under different names, such as sub-agents, modules, components, units or processes [15,40,110].

In [40], based on the classification they proposed, the authors integrate the three approaches and introduce the Miner Intelligent Agent (MIA), a scalable knowledge-based cognitive agent that consists of a knowledge base, a meta-knowledge base, an induction rule mining module, and an inference engine. The knowledge base contains all the knowledge perceived and developed by the agent in the form of if-then rules, the rules are clustered and relations between the rules are found in the form of meta-rules. The meta-knowledge base contains the clustering information related to the clusters of knowledge, as well as the meta-rules associated to the clusters. The induction rule mining module continuously re-clusters new knowledge and the subsequent meta-knowledge, using two different K-means based algorithms for each of the knowledge base and meta-knowledge base. The Inference Engine creates the feedback loop that reinforce the rule base in order to emulate the reasoning process. Following the same type of integration framework as the one described in [40], Kadhimi et al. [110] proposed MIAKDD, a multi-intelligent agent for knowledge discovery in databases in cooperation with human experts. The MIAKDD agent integrates a combined rule generation-classification component which uses classification based on association. The output of rule generation and classification process is stored in a knowledge-based component which is accessed and reviewed by domain experts. The modified rules update the knowledge base, which is further accessed by the MIAKDD agent for refining the results.

In [72], the authors proposed an agent that integrates a genetic programming method for acquiring the knowledge underpinning tactical behaviours of both own and opponent forces in military and game simulations. The objective of the study was to learn the tactical behaviours of observed humans and create a tactical agent able to emulate those behaviours in a plausible manner. The genetic programming method was used in conjunction with context-based reasoning for evolving tactical agents using data acquired from humans performing missions on simulators. The agent proposed by Fernlund and colleagues was able to adopt the behaviour of the observed entity only from interpretation of the data collected through observation. A similar approach was used in [15] where the authors proposed an integrated framework for knowledge discovery from electromyography (EMG) data. They used artefactual data from 1000 medical cases and over 25,000 neurological tests for extracting pertinent medical information for diagnosis. Their miner agent framework uses a the EMG data module that ensures storage and update of raw data, a data-mining module that uses classic threshold-based association rule engine to gain knowledge about the medical domain, a knowledge-base module that stores the discovered knowledge, and a dissemination module that further refines the results in order to provide accurate individually customised feedback to users.

Fuzzy systems were also used in integrated mining agents. In [145] the authors propose a framework for capturing, storing, disseminating and utilising marketing knowledge, in which agent technology is combined with a fuzzy Analytical Hierarchy Process (fAHP) and fuzzy logic. The resultant fAHP miner agent uses the fuzzy AHP for allocating the weight of determinant criteria for the

fuzzy rules, and the fuzzy logic refines the final decision for three situations: pessimistic, moderate and optimistic.

In [42] the authors integrate a Bayesian network in a miner agent capable to discover causal relations between data objects in heterogeneous data sets. The proposed integrated agent environment embeds a data warehousing module, an on-line analytical processing (OLAP) module, and a knowledge discovery module for supporting the knowledge modelling tasks. The warehousing and OLAP modules implement the gathering, organising and storing information from various data resources. The knowledge discovery module uses a cross-reference technique for performing an informed search, and a Bayesian network for representing the association rules and knowledge patterns extracted from data. The authors note that the Bayesian network representation facilitates a non-monotonic reasoning process which, through integration with the other modules, facilitates data analysis (1) in a multidimensional data space and (2) at different levels of abstractions. A Bayesian approach was also used in [194], where Secretan et al. propose an agent architecture for private and high-performance integrated data mining. The authors describe a miner agent that uses a Naive Bayes classifier for data classification and a data perturbation method—SMC (the secure multi-party computation), for privacy preserving in order to implement the knowledge discovery module, which in their study is called the privacy preserving data mining module.

7.3. Summary of machine agents

We included in this section those methods which suited the perspective depicted earlier in the paper in Fig. 2. In Table 2 we summarise this section in a tabular manner and through this, we emphasise the contribution of this class of methods to the creation of the roadmap that facilitates the KA process, and we show how each of the methods can fill an appropriate branch in the decision tree, corresponding to machine agency. Thus, overall, this section contributes to demonstrating the decision support role of the machine agent class of methods in the KA exercises.

8. Discussion

8.1. The proposed perspective on KA

The review provided in this paper captures the existing work on KA in human activity systems from an agent perspective, motivated by the continuous evolution of human activity over time. The section where we presented the historical view on KA and human activity showed how this evolution changed significantly the amount

and the type of activity on one side, and the amount and availability of the SMEs and/or data that were subject to KA exercises. In these conditions, the KA exercise becomes subject to choosing not only the techniques, but in the first place the type of elicitor that will make use of those techniques. Thus, it becomes useful and pertinent to discuss the literature taking into consideration how the eliciting agency will be able to cope with the amount of activity to be analysed, given a certain level of analysis detail required by the goals of the KA exercise. We believe that having in place a classification that appropriately places the existing KA techniques into the portfolio of one or more of the human, human-inspired or machine agents, will allow one to decide the amount and the type of eliciting entities to be employed by the KA exercise, depending on the availability and size of the source of knowledge.

Early in the paper, before proceeding with the core review of the techniques for each agency, we provided in Fig. 2 a summary of this assumption and discussed how the proposed classification can be used as decision support for the KA exercise by facilitating the generation of a roadmap, in the form of a decision tree, associated to the KA process model. After reviewing the relevant techniques for each category of agents and summarising their role and scope in Tables 2–4, we are able to refine the assumption presented in Fig. 2. Arguably, apart from providing decision support in the KA exercise, the proposed classification can describe the performances that can be achieved by each type of agent, taking into account the trade-off between the size of the knowledge source and the level of detail for analysis and representation. Fig. 7 summarises this idea visually, depicting a trade-off curve for each agency.

The human agency has the lowest performance curve, due to obvious limitations in both analysis detail and knowledge source size. At one extreme, techniques like observations or unstructured interviews allow human elicitors to analyse SMEs and represent knowledge at high level of detail, however the amount of activity (i.e. number of SMEs) is drastically limited. For example, a human elicitor cannot handle large numbers of experts, such as hundreds of thousands, due to time and effort limitations. At the other extreme techniques like questionnaires or surveys can handle large numbers of subjects, eliminating much of the face-to-face elicitation time and effort; however, their contents cannot be excessively long or detailed. Thus, only low levels of detail for analysis and resultant representation can be achieved. Human-inspired agents can obtain a better trade-off curve, but only on the amount of activity (data) direction. In the activity/data direction, the number of questionnaires that can be analysed by an automated computer program is virtually unlimited compared to human analyst case. On the level of analysis direction though, due to the fact the human-inspired agents are mainly computer-based automated

Table 4
Summary of machine agent methods: agent perspective roadmap and KA process.

KA approach	Agent perspective roadmap		KA process model			References
	Amount of activity	Richness of analysis	Elicitation	Analysis	Representation	
Interaction-based Collaborative agents	Very high	Rich	Partial	Partial	Yes	[39,90,131,175,192]
Interaction-based Cooperative agents	Very high	Rich	Partial	Partial	Yes	[6,60]
Interaction-based Negotiative agents	Very high	Rich	Partial	Partial	Yes	[43,127]
Integration-based Miner Intelligent Agents	Very high	Very rich	Yes	Yes	Yes	[15,40,72,110]
Integration-based Fuzzy Miner Agents	Very high	Very rich	Yes	Yes	Yes	[145]
Integration-based Bayesian Miner Agents	Very high	Very rich	Yes	Yes	Yes	[42,194]

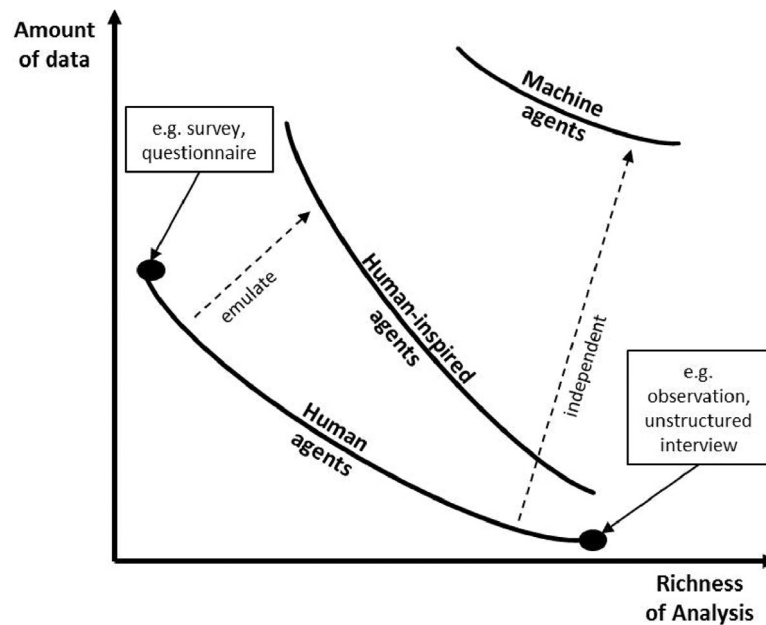


Fig. 7. The proposed agent perspective: a data size—analysis/representation trade-off.

versions of the human elicitors, the highest level of analysis or representation detail cannot exceed that of human agents (i.e. automated interviews compared to human elicitor interviews). Machine agent curve is, arguably, the one providing highest performances due to the ability of human-independent methods to analyse large amounts of data at high levels of detail. We consider that in this case both extremes of the curve can exceed their human and human-inspired counterparts through their very nature, generating better KA outputs in situations where the other types of agents have severe limitations (either technical or cognitive).

The trade-off view on the proposed classification completes the position we have regarding agents and the KA in human activity systems. Apart from summarising the contribution of the proposed classification as a model of choice in support for the KA exercise, the trade-off view also includes implicitly the historical evolution of the field and the KA process model. It includes the historical evolution through that it shows how the increase in the amount of activity (and resultant data) and the increasing level of analysis details created the need of new techniques, which moved the focus from human agents to human-inspired and then further to machine agents. It includes the KA process through that we discuss the trade-off using the elements of the three stage process model: elicitation (amount of activity/data direction), and analysis and representation (richness of analysis direction).

8.2. Future potential perspectives on KA

The literature presented in this study suggests that the process of migrating from the classic human agent CTA methods to the human-independent machine agents is not only still open, but is far from being ended and has not yet reached its peak. We expect a significant increase in the conversion and application of the classical human agent methods to the new challenges raised by the broad concept of “human activity”, in the conditions of higher and higher dynamics of change in this respect. Thus, we speculate on two possible directions of research that are candidates for inclusion in future reviews on “human activity”-related KA, provided our expectation of growth materialises: the co-evolutionary KA, and the challenge-based KA.

We note that the categories we considered in this study, and the subsequent methods, do not take into account the change in the knowledge acquiring entity as a result of the interaction with the knowledge sourcing entity. While these methods may describe acquirer entities that can handle dynamic knowledge sources, they do not include mechanisms for treating the change in their own level of knowledge, that is, the way their perception about the acquired knowledge changes throughout the acquisition process, with an impact on the way they generate the ontological construct for representing the knowledge. We consider that the acquisition process is essentially a co-evolution process in which both parties evolve and gradually improve their understanding of the domain through interaction. Few very recent studies that relate co-evolutionary learning to knowledge acquisition exist [135,204], however, reviews and explicit classification of the work are not yet in place. We expect a growth of the amount of work in this direction, which will lead in the future to significant advances in the knowledge acquisition.

Another aspect that we note in relation to the KA field is that the methods usually describe the “extraction” of knowledge from a knowledge sourcing entity. While certain degrees of interaction are described by the methods, this interaction does not reach the level where the knowledge acquiring entity challenges the knowledge sourcing entity (the SME) towards knowledge improvement, in order to be able to acquire better knowledge as a result of SME’s improvement. A scenario explaining this concept is an elicitor that seeks knowledge about a domain but the available SME is not knowledgeable enough to satisfy elicitors’ needs. Thus, the elicitor must first challenge the SME towards learning about the domain, in order to eventually acquire knowledge of a better quality. This approach was recently described as part of the computational red teaming (CRT) paradigm [1,5,165], however the amount of work explicitly positioned as contribution to the KA field is still low. We expect that the future will bring an increased interest in this direction and we foresee a growth in the amount of published work.

Overall, we consider that the two research directions mentioned above, coevolution-based KA and CRT-based KA, can add in the future to the proposed agent view on KA by generating a complementary agent-based classification which captures two aspects of KA less present in the KA literature so far: (1) the amount of

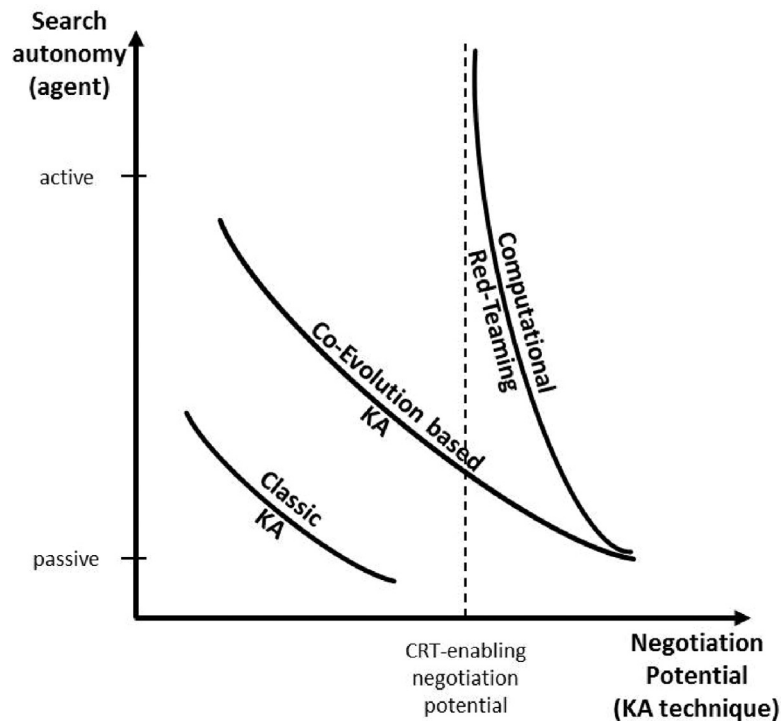


Fig. 8. A future perspective on KA: the Autonomy-Negotiation trade-off.

autonomy involved in the interaction between knowledge sourcing and knowledge acquiring entities and (2) the potential of the existing KA techniques to offer support for this interaction.

The first aspect refers to the ability of the agent to actively and autonomously seek for and fill the agreed ontological construct with the necessary and sufficient component elements. At one extreme passive agents can only receive the data that are made available to them, and thus can only fill the agreed ontological construct using those data. An example can be an automated interview in which a computer-based emulator of a human elicitor performs an interview with an SME. The emulator follows a fixed sequence of questions and receives answers from the SME, and is incapable of seeking clarifications if SME's answers do not fit in the agreed ontological construct. As a result, the knowledge representation will contain gaps corresponding to those parts of the ontological construct that were not filled due to incomplete or incorrect answers. At the other extreme, an active agent can seek autonomously for data that contribute to filling the gaps in the ontological construct, such as in the case of a human agent that performs an interview with an SME. In this case the human elicitor can actively seek for clarifications whenever SME's answers are not filling the ontological construct as required.

The second aspect refers to the potential offered by KA techniques to negotiate the ontological construct in order to achieve the agreed goals of KA exercise. An example can be acquisition of knowledge about diagnosing heart conditions in patients. If the only KA technique used for this purpose is a questionnaire using as an ontological construct the height and weight of the patient, then there is no chance of representing the knowledge about patients in a more detailed manner. However, if an unstructured interview is used for this purpose, then there is the potential of unveiling extra details due to the interaction between the elicitor and the patient, during which a set of elements that are essential for diagnosing the correct condition (i.e. the ontological construct) is gradually established. Thus, in this case the ontological construct is not fixed, being the result of a negotiation between the agents.

We further consider that these two aspects are subject to a trade-off that generates a potential three-tier classification using co-evolution and computational red-teaming. In Fig. 8 we display this potential classification in the form of three trade-off curves: the lowest performance curve corresponds to what we could call the classic (or existent to date) views on KA, while the other two are the co-evolutionary and CRT-based views in increasing order of performance, respectively.

9. Conclusions

In this paper we provided a multi-disciplinary review which investigated from an agent perspective the knowledge acquisition in human activity systems, where knowledge acquisition is seen as the process of acquiring understanding about the underpinnings of human activity with the fundamental purpose of improving this activity. We proposed a classification of the methods based on the type of agency involved in the KA process, with a focus on the degree of involvement of human element. The motivation for this classification stays in the continuous change over time of the concept of human activity, as the factor that fuelled researchers' and practitioners' efforts for more than a century. Thus, we discussed the concept of knowledge acquisition under three categories—the human agents, the human-inspired agents, and the machine agents—and we showed how this classification can play a decision-support role in relation to the KA exercises.

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