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# Artificial Intuition for Automated Decision-Making

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**ABSTRACT**

Automated decision-making techniques play a crucial role in data science, AI, and general machine learning. However, such techniques need to balance accuracy with computational complexity, as their solution requirements are likely to need exhaustive analysis of the potentially numerous events combinations, which constitute the corresponding scenarios. Intuition is an essential tool in the identification of solutions to problems. More specifically, it can be used to identify, combine and discover knowledge in a "parallel" manner, and therefore more efficiently. As a consequence, the embedding of artificial intuition within data science is likely to provide novel ways to identify and process information. There is extensive research on this topic mainly based on qualitative approaches. However, due to the complexity of this field, limited quantitative models and implementations are available. In this article, the authors have extended the evaluation to include a real-world, multi-disciplinary area in order to provide a more comprehensive assessment. The results demonstrate the value of artificial intuition, when embedded in decision-making and information extraction models and frameworks. In fact, the output produced by the approach discussed in their article was compared with a similar task carried out by a group of experts in the field. This demonstrates comparable results further showing the potential of this framework, as well as artificial intuition as a tool for decision-making and information extraction.

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## Introduction

Problem-solving skills have enabled the human race to thrive throughout the centuries. Despite clear evidence that animals exhibit such skills, only humans have managed to perfect them, which have led to the establishment of several sciences. Rational thinking is one of the main components of science, as logical and methodical approaches have identified new solutions in a replicable and rigorous manner. However, not all discoveries have been solely guided by

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rationality. Intuitive thinking allows us to find novel ideas, which would not be possible to achieve by using rational approaches.

The ability of identifying alternative paths to new solutions is an important aspect that have been often demonstrated to be crucial in several scientific endeavors Xiaolong et al. (2019), Ray et al. (2018)

As a consequence, artificial intuition is drawing increasing attention from the computational sciences communities, as it is likely to lead to efficient decision-making approaches (Johnny, Trovati, and Ray 2020, Shao et al. 2017, Trovati et al. 2019). Loosely speaking, artificial intuition can be defined as the ability to evaluate a problem within a specific context and discover new connections to enable the automation of decision-making processes (Trovati, Johnny, and Polatidis 2022). Moreover, intuition depends on prior knowledge and experiences, which can be used to identify solutions otherwise difficult to discover via ordinary logical process (Dundas and Chik 2011).

Artificial intuition and artificial creativity are usually associated with different, but overlapping research areas, where the former aims to discover novel solutions related to specific problems. The objective of the latter, on the other hand, is to achieve "artistic" beauty. Artificial creativity tends to utilize specific machine learning methods by identifying data patterns which constitute beautiful and appealing products. Alternatively, artificial intuition focuses on pinpointing innovative problem-solving solutions. Since the context of the corresponding problems needs to be taken into consideration, their semantic properties must be investigated and assessed.

This article aims to expand and further discuss the approach to artificial intuition introduced in Trovati, Johnny, and Polatidis (2022). In particular, a more comprehensive evaluation will be introduced to demonstrate its applicability and efficiency, based on multi-disciplinary research on how to optimize innovation in organizations (Cullen and De Angelis 2021); Bolton, Green, and Kothari (2016) More specifically, the evaluation consists of a real-world case scenario focusing on business innovation. Companies capitalize on new ideas and technologies via different business models. While there are specific channels for exploring and assessing new ideas and technologies, they tend to have limited ability to identify innovative processes to discover new knowledge related to their business models (Chesbrough 2010).

In Thomas and Autio (2019), the concept of "innovation ecosystem" is introduced to define the complexity related to the different components of business innovation. More specifically, the authors emphasize that the dynamics of such ecosystem poses challenges in the full understanding and prediction of the most relevant parameters and trends. A a consequence, many information identification steps and decision-making processes are influenced by individual knowledge, as well as intuitive thinking, which is also defined as the *gut feeling*.

The intrinsic complexity in the identification and analysis of the main parameters which define business innovation demonstrates that this is

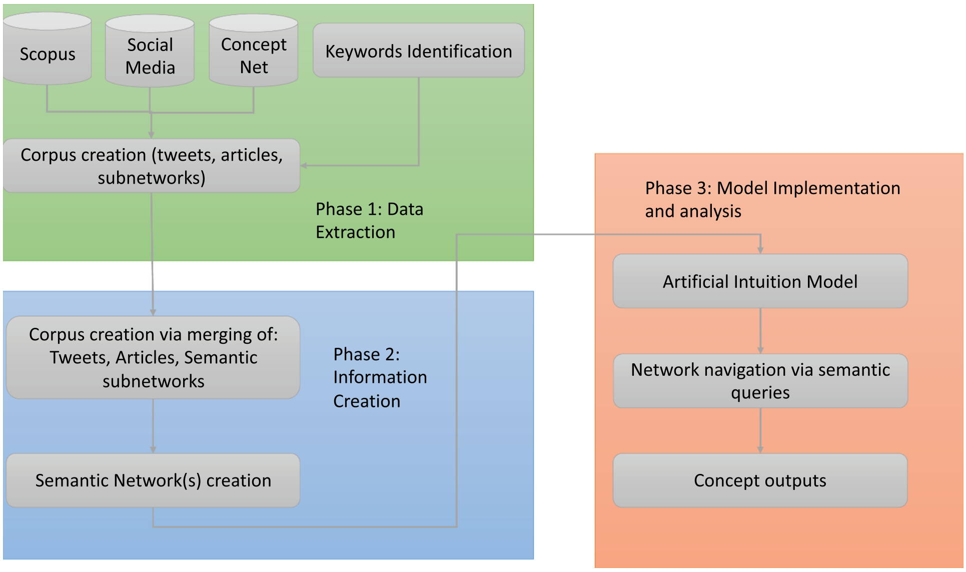


**Figure 1.** The overall architecture of this approach. All steps and phases are detailed in Sections 4, 5 and 6.

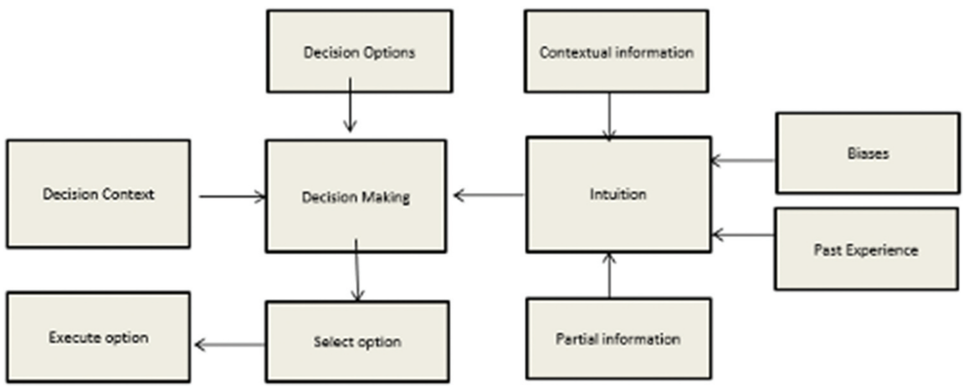


**Figure 2.** Overview of entrepreneur decision-making process.

a valuable and non trivial area to investigate to demonstrate the potential of the approach discussed in this article.

This work is structured as follows: in Section 2, the relevant background is discussed, and Section 3 introduced the core concepts of this work. Sections 4, 5 and 6 discuss the main components of the approach, and their implementation. The evaluation is discussed in Section 7, and finally, Section 8 concludes this work and prompts future research directions.

## Background

The computational and application aspects of intuition have been the focus of extensive multi-disciplinary research.

In Johnny, Trovati, and Ray (2020), the authors introduce a computational model of artificial intuition based on the assumption that specific data patterns can be extracted form prior knowledge related to the domain of the problem. One of the applications of such framework has been identified by Bolton and Cullen (2022) to extract information related to small-medium enterprises (SMEs). SMEs play a crucial global economic role, and in particular the UK economy heavily relies on a healthy ecosystem created by the wealth, opportunities and knowledge generated, shared and augmented by SMEs.

In Simon (1987), the authors discuss managerial decision-making approaches which focus on how intuition is used. In particular, real-time information integrated with intuition can lead to proactive behaviors with respect to the environment, as depicted in Figure 2.

In Kahneman and Frederick (2002), two fundamental and distinct intuition modes are introduced. These are defined as *System 1* (intuition) and *System 2* (logic-based reasoning) (Stanovich and West 2000). More specifically, System 1 is related to (automatic) thought processes, which require limited attention and is based on prior knowledge. System 2 is a strenuous and controlled type of thinking. Despite System 1 is usually defined by pattern recognition approaches, System 2 requires rational analysis to exhaustively select the most suitable choice.

Clinical decisions are another example of a System 1 approach that consist of the inductive reasoning experiences (Payne 2015). However, System 1 approaches might be subject to bias-induced errors when unusual data patterns might occur. According to Liu and Ping (2019), suitable environments and experiences are significant to the learning process, suggesting that past experiences play a crucial role.

In Roger (2003), intuition is defined as the subconscious pattern recognition process where prior knowledge and experience are crucial for the accuracy of any intuition based decision-making process. In Dundas and Chik (2011), the authors present an implementation of human-like intuition where relational relationships connecting experience with associated attributes are implemented. In Srdanov et al. (2017), the authors present an artificial intuition approach via random based optimal path searches. According to Diaz-Hernandez and Gonzalez-Villela (2017), intuition consists of three stages: inputs, processing, and outputs. The authors implement such steps via data collection extracted from human abilities facilitate by intuition; implicit intuitive performance analysis; integration and simulation of intuitive action/reaction steps.

### Applications of Artificial Intuition

In this section, an overview of applications of artificial intuition is presented.

#### Intuition in Clinical Settings

Intuition in clinical practice enables the rapid identification of links between collected information and pattern recognition to unconsciously assess data trends (Billay et al. 2007). In Lyneham, Parkinson, and Denholm (2008), the authors argue that intuitive decision-making process within clinical settings exhibit three stages: cognitive, transitional, and embodied intuition. The cognitive stage stems from the integration of experience with clinical knowledge and experience. The transitional intuition stage is the result of cognitive and embodied intuition, and finally the embodied intuition stage is the effect of clinical practitioners' confidence on their experience and knowledge.

#### Intuition and Business Decision

There is strong evidence from research that intuition has significant applications in strategic business decision making (Simon 1987). In Miller and Ireland (2005), the authors present a study based on behavioral decision-making approaches, and business modeling. The authors argue that executives extensively and consistently employ intuition in their decision making. However, they also argue that intuition can lead to the erroneous conclusions, if not properly utilized and interpreted.

#### Player's Intuition in Games

Remembering prior data patterns and quickly superimposing them to relevant scenarios is a crucial feature of artificial intuition. For example, subsequent to completing a game, the most relevant moves tend to be remembered and captured as mental models and represented as semantic networks to capture the mutual (semantic) relationships. In Silver et al. (2016), the authors suggest that the experience of intuitive thinking based on prior knowledge is a likely candidate to a successful model representation.

## General Definitions

Intuition involves the identification of new semantic paths, during the process of discovering potential solutions related to a specific problem. Such problems, or *queries*, consist of mutually connected semantic entities, as defined below.

**Definition 3.1** (Definition of Query (Trovati, Johnny, and Polatidis 2022).) A *query* is a group of semantically equivalent concepts, which describes a problem objectives. The *solution of a query* is defined as the paths joining the query with specific concepts.

The concepts related to a query are defined as the *query leaf nodes*.

As introduced in Trovati, Johnny, and Polatidis (2022), in this work we shall consider three types of knowledge.

- *Existing knowledge* which is the information related to prior knowledge
- *Intuitive knowledge*, which is linked with general (intuitive) knowledge, and finally
- *Contextualized knowledge*, which is related to individual experience.

**Definition 3.2.** We define three types of knowledge:

### *Network Theory*

Let $G = G(V, E)$ be an undirected network, where $V = \{v_i\}_{i=1}^n$ is the set of *nodes* and $E = \{e_{w_{i,j}}(v_i, v_j)\}_{v_i v_j \in V}$ is the set of *edges*. Many real-world systems are modeled by networks and in particular, by *weighted networks*, that is networks where each edge $e_{w_{i,j}}(v_i, v_j)$ has a weight $w_{i,j} \in (0, 1]$. Two nodes are said to be *adjacent* if they have a common edge and *incident* edges have a common node. We define a *path* $P(v_a, v_b)$ between $v_a$ and $v_b$ as a sequences of incident edges

$$e_{w_{a,k_1}}(v_a, v_{k_1}), e_{w_{k_1,k_2}}(v_{k_1}, v_{k_2}), \ldots, e_{w_{k_{n-1},k_n}}(v_{k_{n-1}}, v_{k_n}), e_{w_{k_n,b}}(v_{k_n}, v_b)$$

joining the two nodes. A network is said to be cyclic if more than a single path can occur between any two nodes.

Semantic networks are specific networks where nodes are defined by concepts, and their mutual edges, as directed binary relations (Brasethvik and Gulla 2001). Semantic networks have been widely applied within artificial intelligence, machine learning and natural language processing techniques, as they provide a declarative graphical representation that can be utilized to model and reason about knowledge.

Concepts are associated with other concepts so that prior knowledge can be connected with new one.

In this article, as per Definition 3.2, we define a network defined by the union of three following (typically overlapping) networks

$$G = G_k \cup G_i \cup G_c \tag{1}$$

where $G_k, G_i$ and $G_c$ are related to existing, intuitive and contextualized knowledge, respectively.

Each node is defined by a concept and the network topology of the network $G$ controls how information is shared.

## Phase 1: Data Extraction

As discussed above, in this article we will focus on a specific context, namely innovation in business ecosystems. Innovation is, by definition, the process that allows to discover new and impactful solutions, concepts and their mutual connections Figure 1 depicts the overall architecture of the framework proposed in this article. Usually, it involves "thinking outside the box," which is based on more than objective and quantifiable knowledge. The *gut feeling* some individuals might exhibit with respect to specific areas, can lead to novel solutions and ideas. The motivation of using innovation as a test case, also originates from its intrinsic multi-disciplinary definition, which makes it difficult to pinpoint it in a very quantitative manner. In particular, intuitive thinking has been demonstrated to successfully understand and address inconsistent growth in SMEs (Bolton and Cullen 2022). This work is also motivated by the attempt to automate such insights.

In this section, the main data extraction process is introduced and discussed. In Trovati, Johnny, and Polatidis (2022), an initial evaluation was described, which suggested the model suggested by the authors could provide an effective approach to a systematic implementation of artificial intuition. In this work, a more comprehensive analysis is introduced based on various large textual datasets, whose integration generates large fragments of semantic networks.

### *ConceptNet Dataset*

The first dataset considered in this article is ConceptNet, which consists of common sense knowledge encompassing various aspects of everyday life. Information used to created ConceptNet has been extracted from multiple sources, such as expert created resources as well as the Open Mind Common Sense corpus, which is a crowd-sourced knowledge project (Liu 2004).

In this work, ConceptNet is utilized to find semantic networks as per the following steps:

(1) Identify query concepts
(2) Establish the appropriate network
(3) Integrate it with any other one previously created

(4) Assess the network(s) to enable knowledge discovery pertaining to the query.

An important point to consider, when defining a knowledge graph from ConceptNet, is which (semantic) nodes should be represented, due to the related implications on the network and its use. Furthermore, this has also significant effects on any other resources which might be linked, as well as any corresponding representation (Liu 2004a). Furthermore, statements contain (semantic) concepts, which are connected by a positive or negative weight, where higher (positive) values suggest more reliable corresponding assertions, and negative weights may imply unreliable assertions (Liu 2004a).

### *Wikipedia, Scopus and Twitter Datasets*

ConceptNet still has limited data capture and semantic information and relationships. To augment and complement ConceptNet, Wikipedia was also used, which is a multilingual online encyclopedia (McNeill 1994). It is widely utilized in numerous AI and machine learning tasks due to its extensive and free content. To further extend the (textual) dataset used in this work, Scopus (https://www.scopus.com/home.uri) was queried to identify academic articles via based on the following keywords:

- Business innovation
- Risk
- Revenue
- Opportunity
- Margin

All the above keywords were combined and permuted, and the corresponding synonyms and lexical variants were also considered. This allowed to extract over 500 abstracts, which were subsequently analyzed to extract relevant concepts and dependence relations as described in Trovati et al. (2017).

Text analysis was carried out via SpaCy (https://spacy.io), which included tokenization, lemmatization, POS tagging, Named Entity Recognition (NER) and subsequent syntactic relation extraction. See Trovati et al. (2017) for more details used in this article. Once the textual analysis identified the different concepts and mutual relationships, this naturally defined a graph representation of knowledge (Choi, Tetreault, and Stent 2015).

Finally, the same keywords were utilized to extract data from Twitter, which created approximately 600 tweets, via the Twitter Developer API (https://developer.twitter.com/en), which was accessed on 20/12/2023. The authors are aware that Twitter only offers limited data from social networks. In fact, a free account was utilized, restricted capabilities. Furthermore, tweets usually include partial information that could be used to extract precise temporal information to identify a definite timeline. Finally, an in-depth analysis based on social networks should also incorporate information from other platforms, such as LinkedIn, Facebook, as well as general blogs. However, the motivation to use Twitter was to initialize and partially simulate intuitive knowledge, which, by definition, may not have a framework as rigorous and well- developed as other types of knowledge (??).

The tweets were downloaded as a CSV file and subsequently, they were manually pre-processed to remove any inconsistent or redundant tweet, as well as any duplicated one. Furthermore, any non-ASCII characters were removed to allow the creation of a new CSV text file, suitable for the subsequent text analysis. A similar textual analysis as per above was conducted. The different knowledge graphs created a single (overlapping) network, whose nodes and connections were labeled depending on their source, that is ConceptNet, Scopus, Wikipedia and Twitter, respectively.

The rationale behind the choice of the above data sources was to simulate the three types of knowledge introduced in Definition 3.2. Namely, Twitter data was associated with intuitive knowledge, Wikipedia and ConceptNet with existing knowledge, and academic articles (extracted via Scopus) with contextualized knowledge. The authors acknowledge that other (perhaps, even better) datasets could have been selected. However, based on their availability, suitability and wide usage within the AI and machine learning research community, the above data sources were deemed to be sufficiently justified and appropriate.

The above steps generated a large of amount of textual data, which had to be pre-processed and analyzed to ensure the format is fully compatible and integrated. This is discussed in the following section.

## Phase 2: Information Creation

As discussed above, the data identified in Section 4, consists of fragments of texts, pairs of concepts linked by semantic relationships, as well as further keywords. In order to generate a navigable network, the different concepts had to be linked by suitable semantic relations which, if not explicitly defined, had to be identified from the different textual fragments.

A group of keywords (and corresponding synonyms) related to semantic relations was manually identified, which include (but not limited to):

- Cause
- Depend (on)
- Based (on)

- Influence
- Impact
- Induce
- Stimulate
- Count (on)
- Act (on)
- Regulate
- Affect

The identified text fragments (containing relevant concepts and/or relational links) were pre-processed and lemmatized to ensure they were uniform and spurious words and punctuation were removed. The concepts identified were coupled, which naturally define edges, based on whether they were linked by a relational link or whether they occurred in the same sentence. More details can be found in Trovati et al. (2017).

The presence of any of the above relations linking paris of concepts (nodes) would entail a stronger relation type (being explicitly linked by a dependency relation) compared to the latter, which only depends on co-occurrence properties. The strength of each edge also depends on how many times such couples occur in the texts. As mentioned above, the different networks from the datasets described in this section had their nodes and edges labeled accordingly to identify their origin for the algorithm implementation as per Section 6. The resulting network had 9634 edges and 675 nodes and a single connected components. Figure 3 depicts its degree distribution. In particular,

- Average Degree: 26.161
- Diameter: 4
- Average Path length: 2.1068
- Density: 0.075, which suggests a sparse graph

In the next section, the model initially introduced in Trovati, Johnny, and Polatidis (2022) is implemented to analyze and assess the approach discussed in this work.

## Phase 3: Model Implementation and Analysis

The model initially introduced in Trovati, Johnny, and Polatidis (2022) is based on some definitions and results which will be discussed in this section. First of all, edges have an activation value $\alpha(x, y) \in (0, 1]$, measuring the influence between $x$ and $y \in V$. Every node $x \in V$ has a probability of occurrence $p(x) \in (0, 1]$. This is combined with the information propagation to define the post node probability of $x$ with respect to its neighbor $w$ as

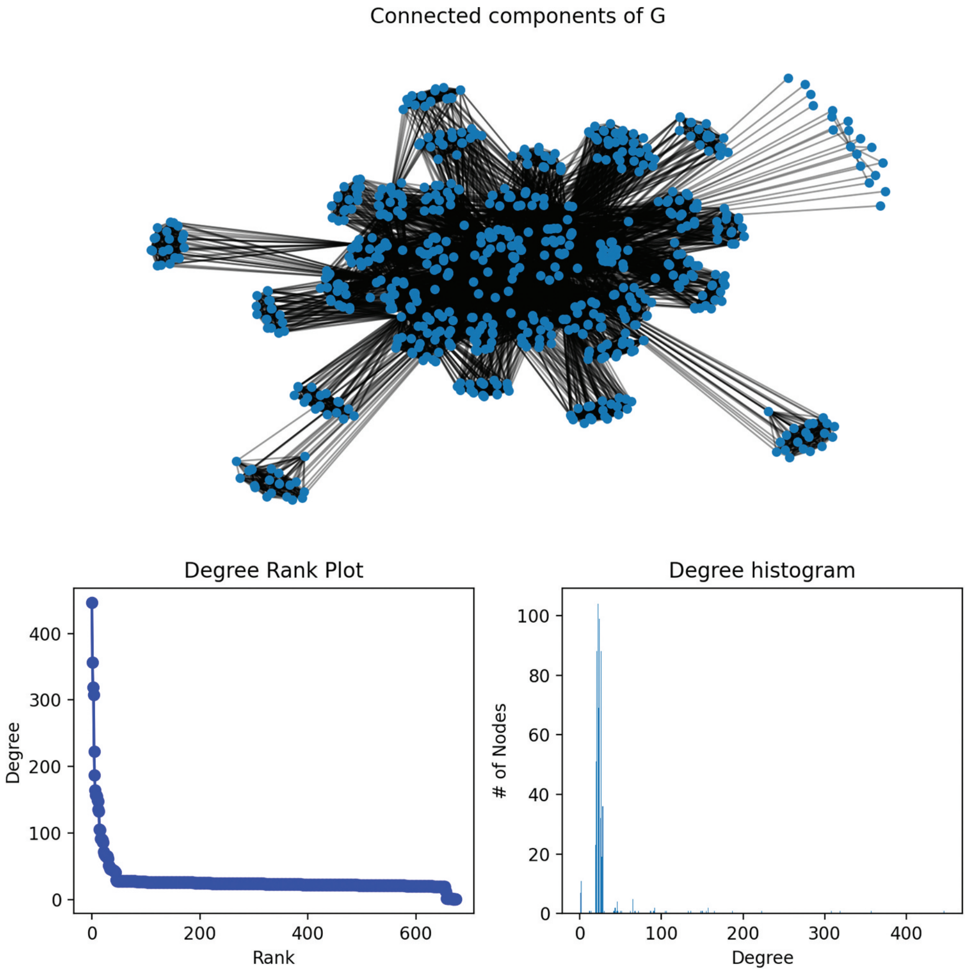


**Figure 3.** The network and degree distribution of the network defined in Section 5.

$$\tilde{p}(x) = \min\{I(w,x), p(x)\}. \tag{2}$$

The topology of the network can be assessed by algebraically combine the edge attributes via the disjoint, joint and information independence relationships (Trovati, Johnny, and Polatidis 2022). More specifically, for $x, y, z \in V$, $x \odot y(\rightarrow z)$ is defined as

$$x \odot y = p(x)p(y)W_{x,y}W_{y,z}, \tag{3}$$

where

$$W_{x,y} = \tanh(2\alpha(x,y)), \tag{4}$$

Similarly, $x \oplus y \rightarrow z$ is defined as

$$x \oplus y = \begin{cases} p(x)W_{x,z} + p(y)W_{y,z}, & \text{if } p(x)W_{x,z} + p(y)W_{y,z} \leq 1 \\ 1, & \text{otherwise.} \end{cases} \tag{5}$$

A path $P(x_1, x_n) = \odot_{i=1}^{n} x_i$ can be written as $\underline{x} = [x_1, \ldots, x_n]$. Definition 5 in Trovati, Johnny, and Polatidis (2022), introduces the innovation index between $x_s$ and $x_e \in V$ linked by the path $\underline{x}$ is defined as

$$i(\underline{x}) = \frac{|E(G \backslash G_k)(\underline{x})|}{|E_p(G)(\underline{x})|}, \tag{6}$$

where $E_p(G \backslash G_k)(\underline{x})$ and $E(G)(\underline{x})$ refer to the sets of edges in $G \backslash G_k$ the edges in $G$ for a path $\underline{x}$, respectively. The overall innovation index between $x_s$ and $x_e$, based on the assumption that there are $n$ paths linking them is

$$i(x_s, x_e) = \frac{1}{n} \sum_{j=1}^{n} i_{\underline{x}_j} \tag{7}$$

**Algorithm 1.** Solution Assessment Algorithm

Let $t = 1$ and $D \leq 1$ be the threshold for the maximum entropy  
Let $\underline{x}_t$ be a path connecting a query concept with one of its leaves leaf$(\underline{x})$  
**for** path $\underline{x}$ **do**  
    **if** $\alpha(\underline{x}_t) \geq 1/(te)$ **and** $H(\underline{x}_t) \leq D$ **then**  
        Continue  
    **else**  
        Stop  
    **end if**  
    **if** $\underline{x}_t ! =$ leaf$(\underline{x})$ **then**  
        $t = t + 1$ Stop  
    **else**  
        stop  
    **end if**  
**end for**  
**return** path $\underline{x}_t, H(\underline{x}_t)$

Algorithm 1 is subsequently used to identify suitable solutions to a specific query, where

$$\alpha(\underline{x}) \prod_{x_i \in \underline{x}} \alpha(x_i) \tag{8}$$

is the propagation index, and the (overall) entropy from $x_s$ is defined as

$$H(x_s) = -\sum_{j=1}^{k} \alpha\left(\underline{x}_t^j\right) \log \alpha\left(\underline{x}_t^j\right), \tag{9}$$

for all the paths $\underline{x}_t^1, \ldots, \underline{x}_t^k$ from $x_s$.

In particular, $H(x_s)$ can be utilized to explore the query space by allowing to identify:

- Whether, from a given network, it is possible to identify one or more solutions based on a query, and
- The depth of the network (in terms of the number and lengths of paths originating from the query/concepts) required to reach a feasible solution.

## Evaluation of the Model

The evaluation aimed to compare the results of our approach with Bolton and Cullen (2022) to assess whether the same "intuition" could have been replicated using the method discussed in this work. Artificial intuition is a new research area, and as a consequence there are very limited evaluation benchmarks or comparison tests. Furthermore, the multidisciplinary nature of artificial intelligence does not easily allow the use of existing (or new) datasets. Therefore, in this work the experimental evaluation has been independently assessed by a group of experts to understand whether the method introduced in this article yields comparable results with respect to manual assessment.

It is, however, not suggested that this method *replicates* intuition as such a claim would need to be substantiated by a series of large scale experiments, capturing different concepts and spanning across different topics and contexts. Such endeavor would, in fact, require the creation of large and more sophisticated semantic networks and corresponding models. The discussion included in this article is hopefully leading the general effort in that direction.

Computational intuition can also be viewed as the discovery of new knowledge, which cannot be *directly* extracted from given data. In other words, the semantic network defined above needs to be assessed based on the algorithm defined in Section 6, to discover semantic connections linking specific concepts. It is important to emphasize that such discovery process needs to identify novel information, which is not trivially identified from the given data. Table 1 depicts some concepts that have been recently identified in Bolton and Cullen (2022) as important factors linked to business productivity. It is important to point out that the mutual relationships have either not been published, or not included in the articles used in Section 4. As a consequence, any relation discovered via the method introduced in this work is not immediately discoverable.

As a consequence, the concepts in Table 1 were used to assess the method introduced in this article with respect to business productivity. More specifically, the concepts which are non trivially related to it include *clear objectives and priorities; data collection; technology adoption; business age; performance assessment* and *reactive strategic innovation*, as shown in Table 2.

All these concepts were normalized and grouped into semantically equivalent nodes to ensure they were captured by the network created. For example, *clear objectives and priorities* were simplified as *objective* and *priority*. This query pre-processing was carried out automatically and subsequently

**Table 1.** Research Variables Detailed as per (Bolton and Cullen 2022), which were used to inform the creation, query and analysis of the data introduction and discussed in Sections 4, 6 and 5.

| Variable | Unit | Value |
|---|---|---|
| Turnover | £ | Numerical |
| Profit | £ | Numerical |
| Productivity | £ | Numerical |
| Increase in employment | Number of Employees | Numerical |
| Product and Service Development | New to market product or service developed | Binary |
| Technology Adoption | New to firm product and service developed | Binary |
| Reactive Strategic Innovation | Innovation initiated within the past 3 years | Binary |
| Ability to identify and define problems | Manually assessed | Categorical |
| Ability to establish clear objectives and priorities | Manually assessed | Categorical |
| Collecting data and evidence evidence and identifying insights | Manually assessed | Categorical |
| Ability to evaluate options for alternative solutions | Manually assessed | Categorical |
| Ability to develop optimal solutions and action plans for implementation | Manually assessed | Categorical |
| Ability to monitor and evaluate performance against objectives | Manually assessed | Categorical |
| Business Age | Years | Numerical |
| Size | Number of Employees | Numerical |

manually verified to ensure that the identified nodes were semantically and lexically as close to the original concept as possible.

Despite a relatively small set of relations described in Table 2, the overall process was based on extensive textual analysis and investigation, which was manually assessed and evaluated by a group of approximately 25 experts, including business practitioners, researchers and analysts (including the authors of (Bolton and Cullen 2022), who routinely complement their practical and academic research with intuitive thinking to identify data trends and insights, which are often hidden in the data. These individuals are part of the Edge Hill University Productivity Innovation Research Center (https://www.edgehill.ac.uk/departments/support/e3i/supporting-business/pic/), which aims to identify, assess, and facilitate business innovation across UK SMEs. The members of this center (who include some of the authors, as well as business practitioners

**Table 2.** The experimental results as discussed in Section 7.

| | Path length | Propagation Index | Innovation Index |
|---|---|---|---|
| Clear objectives and priorities | 6 | .71 | 0.51 |
| Data collection | 4 | .49 | 0.45 |
| Technology adoption | 9 | .24 | 0.53 |
| Business age | 17 | .82 | 0.81 |
| Performance assessment | 9 | .51 | 0.34 |
| Reactive strategic innovation | 14 | .27 | 0.56 |

and academics in various disciplines) collect and digitalize data produced by the center's activities.

The results were also manually evaluated by experts to assess whether they were aligned with the findings inBolton and Cullen (2022). A notable instance is *business age*, as it is not a trivial association with *business productivity*. This was reflected by a relatively high innovation index, suggesting an "intuitive solution" with respect to the overall knowledge.

The experimental evaluation, based on a much more comprehensive data from various sources compared to Trovati, Johnny, and Polatidis (2022) has again demonstrated the potential of this method. The evaluation was also performed on innovative research, which has been carried out within business productivity. The aim was to enable a scientifically sound and academically justified evaluation, which was independently confirmed by experts.

## Discussion and Conclusions

Artificial intuition has been demonstrated to have significant potential in automated decision-making approaches. However, the development, implementation and ultimately the evaluation of artificial intuition frameworks have several challenges due to the novelty and multidisciplinary nature of this area. This work has been motivated by Trovati, Johnny, and Polatidis (2022), which is supported by the experimental evaluation discussed in this article and it

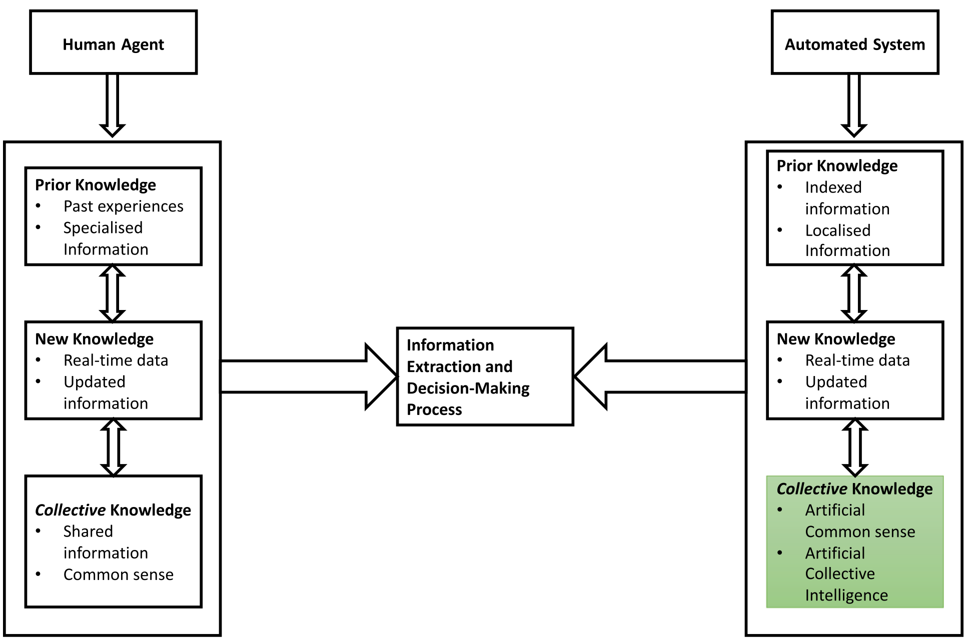


**Figure 4.** The research motivation.

further motivates more research in this area. Figure 4 depicts how the proposed intuition framework can be mapped to current and future research. In particular, subsequent research efforts will focus on the creation and analysis of suitable dynamic semantic knowledge network. This will be only partially manually maintained and augmented as novel “data-evolutionary” algorithms would model the natural data stages, via suitable dynamical changes. These would enable an efficient and agile data creation system to create a knowledge system mimicking a “collective intelligence” system. Furthermore, there is scientific evidence that collective intelligence (e.g. created by an ant colony) is used by the individual components (e.g. individual ants) to self-organize and regulate their common maintenance and survival.

This will enable an agile, adaptive and accurate data structure model that not only would it enhance artificial intuition but it would also improve the state-of-the-art technology in data science and AI.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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