A Knowledge Space for the Upskilling of Management Professionals in the Domain of Artificial Intelligence

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Abstract. *The development of powerful, multimodal Artificial Intelligence foundation models brought back into the spotlight the massive transformative potential of AI for both our personal life and in business. Use of these new tools, methods and algorithms is no longer a privilege of the subject matter experts but rather a way of remaining relevant and competitive regardless of profession and domain of activity. In our research, we aim to answer to two important questions: Q1: What specific knowledge, skills, attitudes and other personal characteristics in the domain of Artificial Intelligence support the effective performance of business professionals in a managerial role? Q2: How can one use adaptive learning technologies in the process of upskilling managers in the domain of AI? The topic lies at the intersection of at least three domains that are brought together to the benefit of the business professionals: the knowledge domain of AI, competency-based managerial assessment, and use of AI in education. The use of Artificial Intelligence in education is a 50-year old endeavour but the more recent developments of powerful deep neural networks, semantic networks and large language models call for reviews of the domain, student, pedagogical and communication models of Intelligent Tutoring Systems (ITS). By analogy with the many ITSs developed for the domain of education, we propose the development of an ITS targeted at tutoring management professionals in the development of competencies in the field of AI. We thus introduce three different components of such an intelligent system: 1) a domain model of the Artificial Intelligence sphere of knowledge implemented in a Neo4j knowledge graph, 2) an AI competency framework for managers, and 3) a knowledge space to be used for tracing the knowledge of managers in the domain of Artificial Intelligence as they progress from the complete novice state to an expert level.*

Keywords: Artificial Intelligence Competency Framework, AI Knowledge Space, Competency-based management development and assessment.

Introduction

The use of Artificial Intelligence (AI) in building intelligent tutoring systems (ITS) that can personalize education was proposed in 1970's by Jaime Carbonel (Carbonell, 1970) and was soon followed by a large community of AIED - AI in education - professionals (https://iaied.org). Inteligent tutoring platforms like the Khan Academy (Khan Academy | Free Online Courses, Lessons & Practice) are now available to everyone online, thus democratising access to primary education.

While there is an extensive coverage of the scientific developments in this field for the last 50 years (Alkhatlan & Kalita, 2019), and both AIED and the ITS communities organize annual conferences (26th International Conference on Artificial Intelligence in Education), there is little focus on using these developments in the specific field of training business professionals. There are just a few intelligent platforms available in the market – like, for instance, SANA (The AI-first learning platform | Sana) - that adopted artificial intelligence in managing the learning process / training for various types of professional developments.

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We are embarked on a scientific journey of developing such an intelligent tutoring system fit for the purpose of upskilling management professionals in the domain of Artificial Intelligence (Negură & Ionescu, 2024), (Negură, 2024). In building such a system, we needed to answer to the following two research questions:

Q1: What specific knowledge, skills, attitudes and other personal characteristics in the domain of Artificial Intelligence support the effective performance of business professionals especially in a managerial role?

Q2: How can one use adaptive learning technologies in the process of upskilling managers in the domain of AI.

While answer to the first question (Q1) was introduced in an earlier paper this year (Negură, 2025), in this one we are proposing a *knowledge space* (Doignon & Falmagne, 2015) that models the professional competencies in the domain of Artificial Intelligence, tuned to the specific responsibilities of management professionals in various business functions. Together with the Neo4j knowledge graph of the various knowledge components in the domain of Artificial Intelligence – the domain model (Negură, 2025) and the AI managerial competency framework, they form the bases for a proposed solution to the research question Q2: the implementation of adaptive learning technologies for the upskilling of management professionals in the field of Artificial Intelligence.

Literature review

Use of AI in education. Development of Intelligent Tutoring Systems

The promise of AI to boost personalized education dates back to the 1970's when Jaime Carbonel spoted the opportunity to leverage the potential of AI to enhance training (Carbonell, 1970).

The domain has initially emerged as an attempt to model theories of cognition, e.g. SOAR (Newell & Simon, 1972), ACT (Anderson J. , 1993), ACT-R (Anderson & Lebiere, 1998), and test various learning theories and personalization strategies - e.g. learning from performance errors (Ohlsson, 1996) (Mitrovic, 1998) - or tutoring conversational strategies – e.g. Socratic dialogues (Collins, 1977), (Brown, Burton, & Zdyel, 1973) (Brown, Burton, & Bell, 1974) (Carbonell, 1970).

The term Intelligent Tutoring Systems (ITS) was introduced by D. Sleeman and J.S. Brown in 1982 (Sleeman & Brown, 1982). In their collection of scientific papers in the domain of AI in education (AIED), published under the name "Intelligent Tutoring Systems", the authors review a few systems that are grouped into four categories: 1) problem solvers, 2) coaches, 3) lab instructions and 4) consultants (Sleeman & Brown, 1982, p. 2).

A reference architecture of the Intelligent Tutoring Systems has been defined since the 1980s (Wenger, 1987) and although in practice a wide range of architectures for ITS systems are encountered (Nwana, December 1990) (Woolf, 2009) (Nkambou, Bourdeau, & Mizoguchi, 2010), this architecture that is based on four functional blocks is useful for analyzing and clarifying conceptual aspects regarding the development of adaptive ITSs.

Knowledge tracing

An important component of an adaptive learning technology is related to understanding the specific context of each learner, both cognitive and affective states at the time of taking the learning session. This is the objective of the *Learner Model*, more specifically, the knowledge tracing part of it.

Several conceptually different knowledge tracing classes of models have been proposed since the introduction of teaching machines by Pressey in 1926 (Pavlik, Browner, Olney, & Mitrovic, 2015):

- Porgrammed student models: *Linear Programming* (Lumsdain & Glaser, 1960), *Branching* (Crowder, 1959);
- Overaly & probabilistic models: *Markov Models* (Atkinson & Crothers, 1964; Calfee & Atkinson, 1965; Groen & Atkinson, 1966), *Bayesian Knowledge Tracing* (Corbett & Anderson, 1995), *Constraint-Based Modeling / Tracing* (Ohlsson & Mitrovic, 1991), Logistic Regression Models - *Item Response Theory* (Hambleton et al., 1991), *Performance Factor Analysis (Pavlik Jr et al., 2009);*
- Knowledge Space Models: *Knowledge Space Theory* (Doignon & Falmagne, 1985), *Partial Order Knowledge Structures* (Desmarais et al., 1996);
- Deep Knowledge Models: *Deep Knowledge Tracing* (Piech, et al., 2015), (Zhang, Shi, King, & Yeung, 2017). With the advancement of more powerful AI models like the LLMs the challenge of knowledge tracing has also been addressed more recently with advance deep neural models.

Knowledge Space Theory (KST). Learning Space Theory (LST)

The knowledge space theory was introduced by Jean-Paul Doignon and Jean-Claude Falmagne in 1985 in a paper called *"Spaces for the assessment of knowledge"* (Doignon & Falmagne, 1985). The paper presented the application of mathematical combinatorial concepts in building knowledge spaces to be used in the assement of knowledge.

In the following years, the two authors have extended their theory significantly (1987, 1988, 1989, 1990, Doignon -1994, 1999, 2006, 2011, 2013, 2015) – e.g. by the introduction of *Learning Spaces* - and many more authors have also contributed to the development of the theory in a practical tool for assessment:

- Cosyn E and Uzun H.B. (2009)
- Cornelia Dowling, Jurgen Heller and Reihard Suck in Germany;
- Dietrich Albert and Cord Hockemeyer (1997, 1998) in Austria;
- Mathieu Koppen in Netherlands;
- Luca Stefanutti in Italy.

Few commercial applications were also developed based on the theoretical grounds of the knowledge/learning space theories: ALEKS, RATH.

An alternative, more restrictive knowledge space theory was also proposed by Desmarais in the form of *Partial Order Knowledge Structures* (Desmarais, Maluf, & Liu, 1996).

AI managerial competency frameworks

In training a business management professional to become more knowledgeable within the AI knowledge domain one first need to identify the type and level of competencies the manager needs to develop such as to attain high performance in the job as defined by Prof. David McClelland (Spencer & Spencer, 1993).

According to the European Commission's Joint Research Centre (JRC) JRC121897 Technical Report on labour, education and technology competence is defined as "*a general ability to do well in a particular task domain*" (Rodrigues, Fernández-Macías, & Sostero, 2021/02). This level of task domain competence is attained by learning and developing a mix of knowledge, skills, and attitudes specifically relevant to each business role.

It is just recently that researchers have started to analyze these specific knowledge, skills, attitudes and other personal characteristics in the domain of Artificial Intelligence that support the effective performance of business professionals in managerial roles.

Such an example is the work of Philip Jorzik (Jorzik, Yigit, Kanbach, Kraus, & Dabic', 2024) that took an inductive qualitative approach (Gioia, Corley, & Hamilton, 2013) - 47 semistructured interviews between Oct 2021 to June 2022 – to explore "*How can Top Management encourage and facilitate AI-enabled Business Model Innovation*". Their research outcome is a 2-levels competencies frame composed of first-order concepts aggregated into five second order competency themes - *Knowledge*, *Mindset*, *Leadership*, *Navigability* and *Decision-making Ability* - that are linked to eight overarching roles of top management in AI-enabled business model innovation.

A second relevant example of an AI competency Framework is the outcome of a collaborative project of Concordia University and Dawson College financed by *Pôle montréalais d'enseignement supérieur en intelligence artificielle* (PIA) (Concordia University and Dawson College, 2021). The framework defines a comprehensive list of competencies grouped in 13 themes: *Data, Mathematics and Statistics, Programming, Machine Learning, Deep Learning, Infrastructure, Libraries and Frameworks, AI Initiative and Project Planning, AI Initiative and Project Scaling, AI Technologies, Innovation, Teamwork, Professionalism*. These are further split into three major categories: technical, business, and human competencies.

Another relevant example is the work of Yannick Peifer and Sebastian Terstegen called "*Artificial Intelligence - Qualification and Competence Development Requirements for Executives*" (Peifer & Terstegen, 2024). They introduce the concept of qualification as developed and tested within the en[AI]ble project funded by the German Federal Ministry of Labour and Social Affairs (BMAS). The paper also introduces the learning modules proposed by the en[AI]ble project, namely: 1. What is AI – a module laying the foundations for identifying and evaluating AI, 2. Explainability of AI, 3. AI solutions in mid-sized companies.

The topic of AI Literacy (Long Duri, 2020) (Chiu, Ahmad, Ismailov, & Sanusi, 2024) is also touching on the topic of AI competencies but rather generally applicable competencies, and not necessarily focused on the competencies that contribute to business management professionals effective performance in their roles.

Methodology

We briefly introduce below the research methods used in the development of the relevant components of the proposed solution, with a more detailed presentation of the approach taken in the development of the knowledge space of managerial competencies in the domain of Artificial Intelligence.

An ontology of knowledge components in the domain of Artificial Intelligence

The *expert module* (a.k.a. *domain module*) of an ITS is reponsible with the implementation and management of the knowledge domain model (Nkambou, Bourdeau, & Mizoguchi, 2010).

One potential approach to building portable domain models is to organize them in domain *ontologies* written in standardized formats (OWL/RDF). Such approaches have been applied in the development of pedagogical/learning ontologies - see SMARTIES Project (Mizoguchi & Bourdeau, 2000), (Hayashi, Bourdeau, & Mizoguchi, 2009), and in building an ontology of AI Innovation – see InnoGraph AI (Alexiev, Bechev, & Ositsyn, 2023) (Massri, 2023).

Given our specific objective, namely upskilling management professionals in the domain of Artificial Intelligence, we have analyzed the *factual, conceptual, procedural and meta-cognitive knowledge* (Bloom, 1982) in the AI sphere of knowledge and identified the atomic *knowledge components* (Dai, Hung, Tang, & Li, 2021) relevant for our enterprise. We then assigned them to a corresponding entity *class*. The objective of the ontology was to describe the various classes of knowledge components and the types of relationships among these entities, thus aiming for domain fidelity rather than operational effectiveness.

The ontology was manually implemented in a Neo4j knowledge graph – see Fig. 1 for a partial image of this knowledge graph, for exemplification purposes. The detailed results have been presented in the paper called "*An ontology of knowledge components in the domain of Artificial Intelligence*" (Negură, 2025).

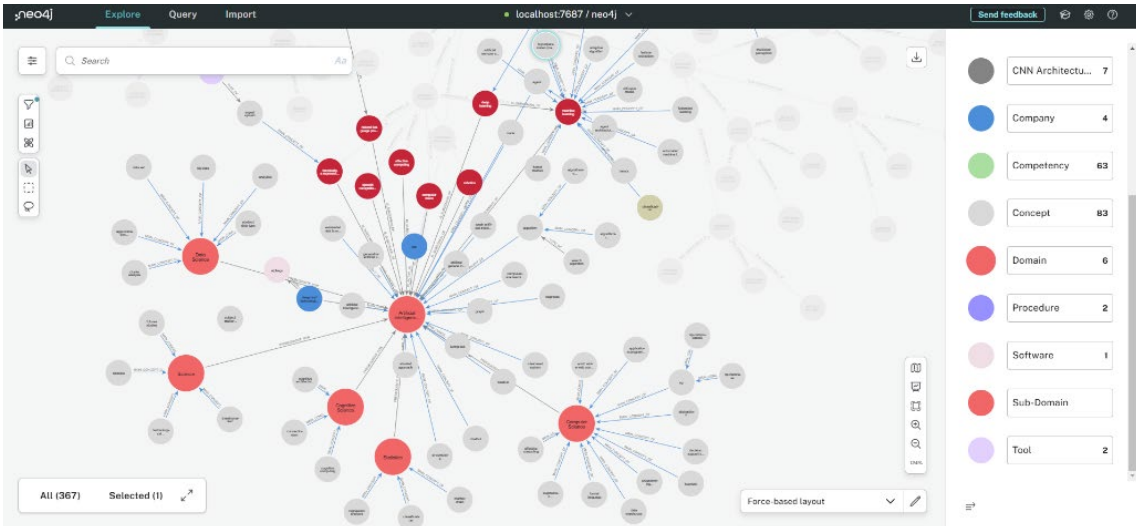

Fig.1 A knowledge graph of the Artificial Intelligence domain of knowledge

Source: Author's contribution.

The knowledge graph will serve as the domain model of the Artificial Intelligence sphere of knowledge in the targeted ITS.

A managerial competencies framework in the domain of Artificial Intelligence

We mentioned in the introduction that we have also developed an AI-competency model fit for the purpose of upskilling management professionals. The model contains both *AI Foundation Competencies* as well as higher order AI competencies specific to the planning, organizing, leading and controlling functions at various management levels (Negură, 2025)

For exemplification purposes we present in Figure 2 a high-level overview of the AI Foundation Competencies. This will serve us in proposing the methodology for building the knowledge space of managerial competencies in the domain of AI.

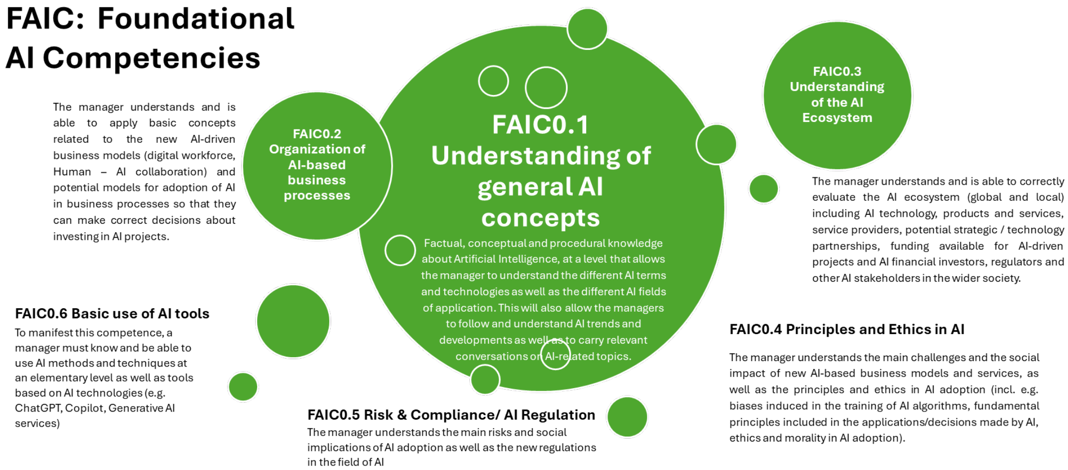

Fig.2 Foundation competencies in the domain of Artificial Intelligence

Source: Author's contribution.

A knowledge space for managerial competencies in the domain of Artificial Intelligence

In this section we are presenting the approach we took in modelling the above managerial professional competencies in the domain of Artificial Intelligence into a *knowledge space* based on the *Theory of Learning Spaces* (Doignon & Falmagne, 2015). While this theory is an application of the mathematical set theory in the field of knowledge and learning, the structure we introduce is a directed, acyclic knowledge graph (DAG) that is appropriate for knowledge tracing.

The approach we introduce is a manual one, fit for the purpose of exemplifying the basic concepts behind the proposed knowledge space. For a more detailed process, one that considers the huge complexity of a real-life application see the QUERY routine introduced by Koppen (Koppen, 1993) based on Müller (Müller, 1989), and further improved by Downling (Dowling, 1994) and J-P Falmagne (Doignon & Falmagne, 2015).

The process we followed consisted in series of steps that organized the knowledge components in the domain of Artificial Intelligence arround the competencies introduced in the managerial competencies framework:

STEP1: Each competency in the proposed framework was broken down into its constituent knowledge components - or smaller groups of components - and the corresponding cognitive precedence relationships were identified. For example, in the case of *AI Foundation Competencies*, the basic terms and concepts must be learned and understood before a manager is able to understand more complex topics like the deeper conceptual and procedural knowledge specific to each of the sub-domains of AI, or the global structure of the AI products and services market – see Figure 3.

Nevertheless, the knowledge space theory factors in that, in reality, each student follows his/her own approach to learning particular topics and thus allows that alternative paths to reaching a specific knowledge state may exist. We will come back to this aspect in Step 4.

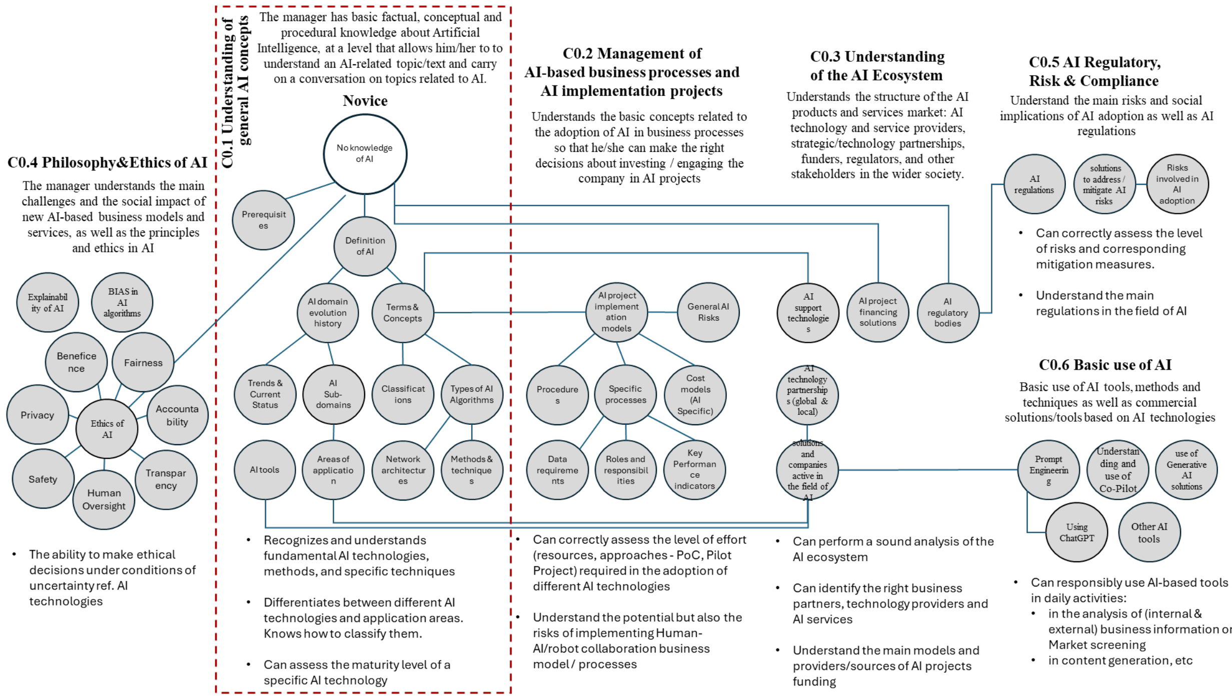

Fig.3 Knowledge components of foundation competencies in the domain of AI

Source: Author's contribution.

STEP2: For each knowledge component/group of components we defined a corresponding list of *questions* (a.k.a. *problems* or *items*) that would serve as test units to validate the level of understanding of the concept(s) by a particular learner - See Figure 4. These questions form the *domain* of the proposed knowledge space (Doignon & Falmagne, 1985) (Falmagne & Doignon, 2011).

Due to the high complexity of the AI domain, the "a" to "w" items presented in Figure 4 actually represent collection of *notions* that include several different knowledge components, sharing the same cognitive sub-area of the knowledge space (e.g. *definition of the AI domain*, or *terms and concepts* of AI).

For each of these items a more granular knowledge space (sub-space) must be built and its constituent knowledge components tested in an "*inner loop*".

Question/Item Id	Category	Class	Question definition (notion)	Level (non-tech mgr)	Competency	Cognitive Process
a	Metacognitive	Concepts.Techinques	Know what one needs to know, expectations, how to learn AI	Novice	C0.1 Understanding of general AI concepts	Remember. Understand. Apply
b	Prerequisites	Concepts	Basic concepts from math, statistics, neuro-biology, data science, computer science etc required to understand AI basic concepts	Novice	C0.1 Understanding of general AI concepts	Remember. Understand
c	Factual & Conceptual	Facts.Concepts.Classific	Definition of the AI domain. Historical evolution. Trends	Novice	C0.1 Understanding of general AI concepts	Remember. Understand
d	Conceptual	Concepts.Classifications	Terms & Concepts. Classifications. Types of AI	Beginner	C0.1 Understanding of general AI concepts	Remember. Understand
e	Factual & Conceptual	Facts.Concepts.Classific	Areas of Application. Solutions/Tools. Case Studies	Intermediate	C0.1 Understanding of general AI concepts	Remember. Understand. Apply. Analyze
f	Conceptual & Procedural	Concepts. Methods. Tec	AI Sub-Domains: Concepts. Methods, techniques and procedures. Architectures	Advanced	C0.1 Understanding of general AI concepts	Remember. Understand. Apply. Analyze. Evaluate
g	Factual	Facts. Organizations. Pr	Solutions and Companies active in the filed of AI. Supporting technologies	Beginner	C0.3 Understanding of the AI Ecosystem	Remember. Understand
h	Factual	Facts. Organizations	AI Technology Partnerships (local & global)	Beginner	C0.3 Understanding of the AI Ecosystem	Remember. Understand
i	Factual & Conceptual	Facts. Organizations	Financing Solutions	Beginner	C0.3 Understanding of the AI Ecosystem	Remember. Understand. Apply. Analyze
j	Factual	Facts. Organizations	Regulatory bodies	Novice	C0.3 Understanding of the AI Ecosystem	Remember. Understand
k	Conceptual & Procedural	Concepts	AI adoption models. Roles and responsibilities. Expected timelines.	Beginner	C0.2 Management of AI-based business processes and AI implementation projects	Remember. Understand. Apply
l	Conceptual & Procedural	Concepts. Classification	AI Risks.	Intermediate	C0.2 Management of AI-based business processes and AI implementation projects	Remember. Understand. Apply. Analyze. Evaluate
m	Conceptual & Procedural	Concepts. Classification	AI Costs.	Advanced	C0.2 Management of AI-based business processes and AI implementation projects	Remember. Understand. Apply. Analyze. Evaluate
n	Conceptual & Procedural	Concepts	Data requirements.	Intermediate	C0.2 Management of AI-based business processes and AI implementation projects	Remember. Understand. Apply. Analyze. Evaluate
o	Conceptual & Procedural	Concepts. Case Studies	AI-driven business models. Human-AI collaboration processes. KPIs	Advanced	C0.2 Management of AI-based business processes and AI implementation projects	Remember. Understand. Apply. Analyze. Evaluate
p	Conceptual & Procedural	Concepts. Case Studies	Ethics of AI. Definition. Principles	Beginner	C0.4 Philosophy & Ethics of AI	Remember. Understand. Apply. Analyze. Evaluate
q	Conceptual	Facts. Concepts	Explainability in AI. BIAS in AI algorithms	Intermediate	C0.4 Philosophy & Ethics of AI	Remember. Understand. Apply. Analyze. Evaluate
r	Factual & Conceptual	Facts. Organizations	AI Regulations	Novice	C0.5 AI Regulatory, Risk & Compliance	Remember. Understand
s	Conceptual	Concepts	Risks in AI adoption.	Beginner	C0.5 AI Regulatory, Risk & Compliance	Remember. Understand
t	Conceptual & Procedural	Concepts	Potential mitigation measures	Intermediate	C0.5 AI Regulatory, Risk & Compliance	Remember. Understand. Apply. Analyze. Evaluate
u	Conceptual & Procedural	Solutions. Procedures	Use of LLM-based solutions. Prompt engineering	Beginner	C0.6 Basic use of AI	Remember. Understand. Apply. Analyze. Evaluate
v	Conceptual & Procedural	Solutions. Procedures	Use of generative AI solutions	Beginner	C0.6 Basic use of AI	Remember. Understand. Apply. Analyze. Evaluate
w	Conceptual & Procedural	Solutions. Procedures	Understanding and Use of AI Agents (e.g. Co-Pilot)	Intermediate	C0.6 Basic use of AI	Remember. Understand. Apply. Analyze. Evaluate

Fig.4 Knowledge Domain: group of questions/items in the domain of AI

Source: Author's contribution

STEP3: At this step we identified the list of *knowledge states*, namely sets of questions that a manager should be able to answer at a given time, as it progresses from the state of complete *novice* (no knowledge of AI) to the status of *beginner*, *intermediate*, *advanced* and ultimately *expert* in the domain of Artificial Intelligence.

Note that the total number of states that could be theoretically built given a number *n* of questions/items in a domain is 2^n. In our case, even with the proposed level of aggregation of knowledge components in sub-domains we would still have a potential total number of knowledge states of $2^{23} = 8,388,608$ making such a knowledge space intractable.

In practice though, not all knowledge states are feasible because of the constraints imposed by the precedence conditions in the cognitive structure of the domain. Moreover, some of the states have a low statistical probability to appear in the real life distribution among the target group, but this probability can only be measured after implementation, from the actual population of learners (Falmagne, Doignon, Koppen, Vilano, & Johannesen, 1990).

STEP4: We then defined the *knowledge structure* of the domain of AI managerial competencies as a directed-acyclic graph containing the feasible knowledge states. Transition from one knowledge state to another in the knowledge structure happens when the manager learns/acquires a new knowledge component – either factual, conceptual or procedural. Yet each learner may have its own order of acquiring new knowledge, thus having alternative learning paths to reach a specific knowledge state. This factual knowledge about learning was factored in the *Knowledge Space Theory* by relaxing the formation of the knowledge spaces on *U-Closure* conditions: the essential condition for a knowledge structure to constitute a knowledge space is closure under union but not necessarily under intersection.

The authors of the KST theory have proven that, given certain conditions that the knowledge space meets – namely the knowledge structure is closed under union and wellgraded - the entire knowledge space can be represented by its *base* and each state can also be represented by its *inner* and *outer fringes*. These properties facilitate the practical aspects of operating with the huge size of the resulting knowledge spaces – see section Results and Discussions.

The *knowledge space* we have thus built allow us to trace the knowledge state of each management professional during his/her learning process and thus adapt the instructional strategy to his/her particular cognitive context.

Results and discussions

In Figure 5 we present - for exemplification purposes - a partial view of the resulting knowledge space. This view only includes a part of the potential knowledge states and possible transitions, and allows one to understand the complexity of different learning paths that one learner could take in his/her particular learning journey. Even the complet view at this stage is only an intermediary step towards an optimized knowledge space as explained below.

Following proper procedures - e.g. QUERY (Doignon & Falmagne, Knowledge Spaces and Learning Spaces, 2015) - the expert(s) view of the knowledge space can be used to reduce the number of states in the structure. By consequently answering questions of the form below, several (hundreds of) states can be eliminated from the knowledge space:

[Q] = "Given that a manager does not know/can't answer the items $\{a, b, \ldots q_i\}$ would he also most probably not be able to answer the question/item q_{i+1} ?"

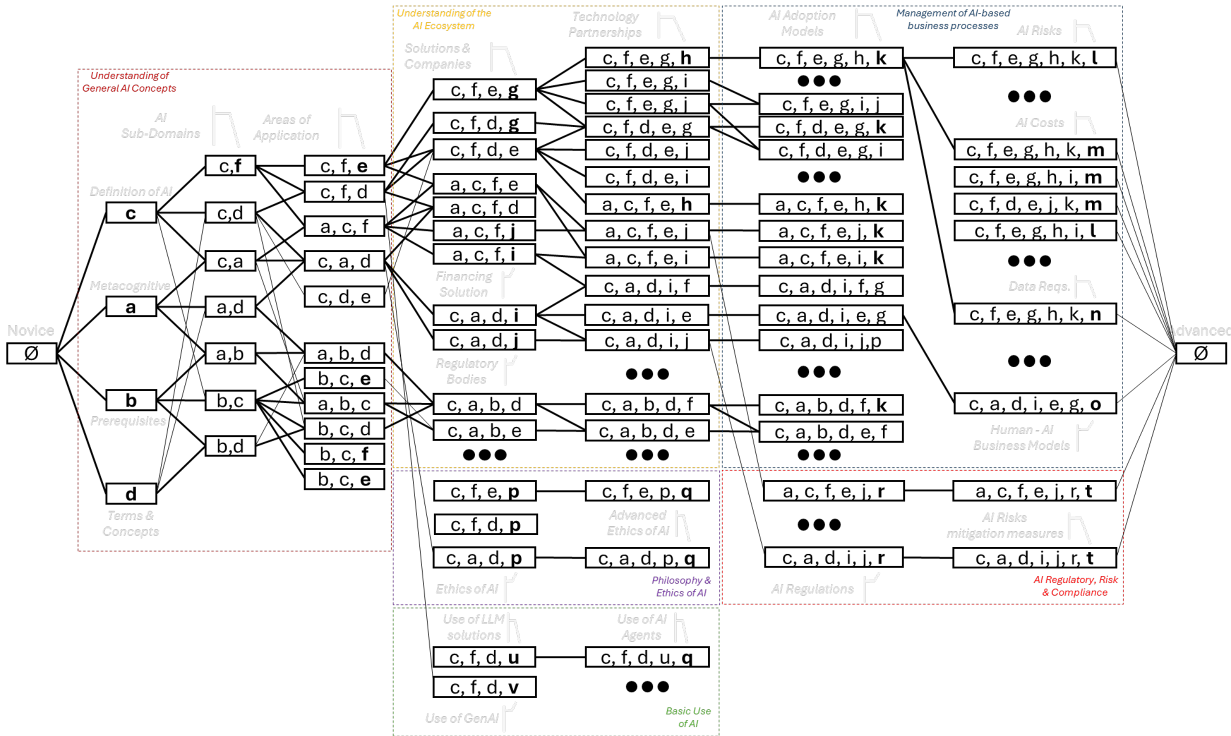

Fig.5 Knowledge Space for managerial competencies in the domain of AI – partial view

Source: Author's contribution.

Due to the *Closure Under Union* condition of the knowledge space theory, the knowledge space can be reduced to the collection of minimal sets of questions called *atoms*, where we call "atom at question *q*" the minimal state that contains question q out of the total collection of knowledge states containing question "q".

For instance, items "a", "b", "c" and "d" have atoms made of one single element, namely {a}, {b}, {c} and {d} while item "f" has an atom made of the minimal collection of items {c,f}. This means that before introducing the several *subdomains* within the sphere of Artificial Intelligence knowledge one should first understand *what is the definition of AI* - what it deals with and how it evolved form the symbolic AI to the foundational / deep AI neural network models of today.

The collection of all the atoms at each of the 23 question q Є {a, b, …w} domain forms the *base* of our knowledge space. All knowledge states in the knowledge space are unions (sub-sets) of these atoms (Falmagne, Doignon, Koppen, Vilano, & Johannesen, 1990).

While this is still in an early stage, the proposed knowledge space is – to our knowledge – the first attempt to build a model of the AI domain of knowledge targeted at building managerial competencies in this domain.

A proper implementation of this space as part of an ITS application would allow managers to develop missing AI competencies by acquiring specific factual, conceptual, procedural and metacognitive knowledge that complement the actual knowledge state of each learner.

Conclusion

We proposed the introduction of *knowledge space* that models the professional competencies in the domain of Artificial Intelligence, We then discussed several considerations specific to this structure and specific target group.

The knowledge space we introduced will serve in the development of an Intelligent Tutoring System (ITS) targeted at the upskilling of business management professionals in the knowledge domain of AI. However, the knowledge space should be further validated with a group of subject matter experts in the field of Artificial Intelligence for optimisation (size reduction) before implementing it in an ITS.

Also an obvious limitation is that the proposed design and implementation of this knowledge structure was optimised to address the development of AI managerial competencies. As such it was tuned to the specific responsibilities of management professionals in various business functions. The proposal put less emphasis on the more detailed procedural and applied technical aspects required by the specialisation of technical professionals in AI sub-domains like ML models and techniques, knowledge representation and search optimisation, AI agents and robotics, and so on.

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