An intelligent tutoring System for developing AI competency in business management professionals

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Abstract: *The need for rapid development of AI competency at all levels of management, regardless of the industry and type of organization the management professionals lead, calls for intelligent tools that can customize their development journey and adapt it to the specific needs of each learner. While the concern of building AI-based intelligent tutoring systems (ITS) is not at all new, the rapid pace of advances in the field of AI allows for further improvement of existing solutions. Moreover, in this paper we are proposing the development of an ITS that is targeted at business management professionals, a group of users that has not been typically addressed by previous ITS research. We will propose an ITS system architecture, and discuss specific challenges related to the AI knowledge domain modelling and competency-based development of management professionals.*

Keywords: Intelligent Tutoring System (ITS), Artificial Intelligence (AI), AI-Competency Framework, Competency-based management development.

1. Introduction

The use of artificial intelligence (AI) in building tutoring systems that can personalize education was proposed in 1970's by Jaime Carbonell (Carbonell, 1970) and soon followed by a large community of AIED (AI in Education) professionals.

The term "Intelligent Tutoring Systems" (ITS) was introduced by D. Sleeman and J. S. Brown in 1982 in their publication of a collection of articles in the domain of AIED (Sleeman & Brown, 1982). The authors review a few of the early intelligent systems and group them in four categories: 1) problem solvers, 2) coaches, 3) lab instructions and 4) consultants.

While the architecture of intelligent tutoring systems has not changed much since the early developments of ITSs in the fields of Algebra (Brown, 1983) (Koedinger, 1998), Geometry (Aleven & Koedinger, 2002), and many more, significant room for improvement exists today in developing e-learning tools that can accelerate the learning curve of both students and adult professionals through increased personalization.

As we will briefly present in the findings of a market research we ran in the third quarter of 2024 on business management professionals from major companies in Romania, managers are concerned about the development of AI competencies and expect smart, AI-enabled tools that can accelerate their development in this domain.

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As such, we propose a fit-for-purpose intelligent tutoring/training system, including the modeling of the knowledge domain and the competency framework tuned to the specific management roles and responsibilities of management professionals in various business functions, and their limited technical knowledge.

2. Development of AI competency today

For many of the non-tech business management professionals, new technologies like Artificial Intelligence and their transformative potential are hard to be understood despite their ubiquitous presence and impact in their specific domain of activity (e.g. marketing, finance or human resources) across all industries.

The cost of management not being properly equipped with the minimum level of understanding of these technologies is huge, even devastating for some companies (see the former bankruptcies of Kodak, Nokia, and the likes that have either bet on the wrong technologies or have ignored to see the potential of emergent ones).

A quick look at the number of courses available on MOOC platforms like Coursera (+500 AI courses), Pluralsight (~1000 course and several other resouces) or Udemy (+10.000 courses in AI domain) confirms the sheer availability of content in the domain of artificial intelligence. Yet, the abundance of courses and information sources (videos, blogs, market reports, leadership programs, etc) makes it very difficult for a non-technical manager to choose the most effective type and channel of professional development, one that meets his/her specific needs and level of understanding.

Nevertheless, the timely development of AI competencies is today a matter of survival rather than an option. This allows managers to maintain business competitiveness and reach operational efficiency regardless of functional area of responsibility.

As such, between June and August 2024, we ran a market survey aimed at understanding how managers in large companies of Romania (+ 50 employees) organize their professional development in the field of AI today and how they use the wide mix of tools and channels available to them. The survey was based on an online questionnaire with 9 questions addressing both the current practices in developing general managerial competencies and the more specific domain of AI managerial competencies.

The respondents were senior HR professionals or seasoned trainers with longstanding experience and deep understanding of the local corporate training market from 40 companies having a national presence in major industries of Romania.

In Figure 1 we present the responses to the question “What tools would you prefer/recommend using for the development of AI competency?”

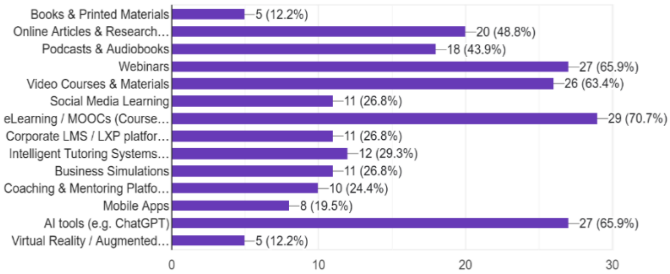

Figure 1. Preferred tools for AI competency development

We notice that almost 30% of respondents would prefer using Intelligent Tutoring Systems along with other digital tools and channels like AI-tools - ChatGPT (66%) and eLearning MOOC platforms (70.7%).

A lower interest is registered though for the use of mobile applications - only 19% of respondents declaring they prefer and would recommend these tools for AI competency development. This is somehow counter-intutive given the extremely large penetration of mobile devices in the Romanian business universe.

A full report of the findings of the survey is presented by the author in the ICECO Conference organized by the Doctoral School of Economics II, Bucharest University of Economic Studies in October 2024.

3. Proposed system architecture

We are proposing in Figure 2 the architecture of an Intelligent Training System dedicated to the upskilling of business professionals.

While the architecture follows the generally accepted 4-module approach introduced as early as 1980s by several authors (Wenger, 1987), (Self, 1990), (Nwana, 1990) we propose a solution that is optimised to the specific needs of the target segment. The system is based on independent microservices that implement specific functionalities within the platform. This architecture allows future adoption of emerging, more powerful AI/ML technologies, methods and models.

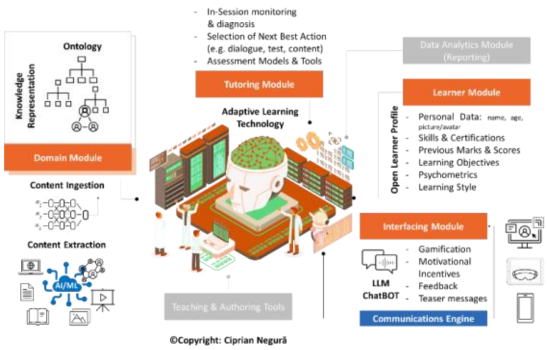

Figure 2. Proposed system architecture for an ITS targeted at Business Management Professionals

The high-level form of the architecture was introduced by the author in an earlier article published in FAIMA Business & Management journal (Negura & Ionescu, 2024).

3.1 AI domain knowledge modelling

The **Domain Module** (also known as Expert Module) is reponsible with the implementation and management of the knowledge domain model.

Today's powerful foundation models/LLMs can be used to extract information and knowledge components from existing corpus of knowledge available in the public space (e.g. from open sources like Wikipedia); most of the public content is expected to have been already made available to the model through the pre-training phase anyhow. Yet, more importantly, proprietary materials and other specific documents can also be used in training the model through *Retrieval Augmented Generation* (RAG) techniques, such as to further customize model's output.

In 2023 alone, 149 foundation models were released (Maslej et al., 2024). Some of them are fully closed, accessible by subscription, but many are fully open, accessible either via APIs and/or downloadable from open sources like Hugging Face or GitHub (Solaiman, 2023).

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).

Yet we are proposing an approach of modeling the AI domain of knowledge based on the *Theory of Learning Spaces* (Doignon & Falmagne, 2015). We thus organize the factual, conceptual, procedural and meta-cognitve knowledge (Bloom, 1982) in atomic knowledge components (Dai, Hung, Tang, & Li, 2021) and structure them in a learning space that allows the identification of the inner and outer fringes corresponding to the specific knowledge state reached by each individual learner.

3.2 The knowledge tracing

A **Learner Module** manages the knowledge about learners and their specific characteristics. This model stores both profile data about the professional learner but is also responsible for tracking his/her specific level of knowledge in the domain of competence required by the managerial role, namely the *learner model***.**

The learner model has been traditionally limited to understanding the level of knowledge in a specific domain like algebra, geometry, specific programming languages and so on, and addressed by the use of probabilistic methods like *Bayesian knowledge tracing* (Corbett & Anderson, 1995). This was mainly attributed to the limitations of the processing power of computers during the early times of ITS domain development, that did restrict the number of variables that could be operationally tracked in the learner model, namely engineering concerns. (Nkambou, Bourdeau, & Mizoguchi, 2010). With the advancement of more powerful AI models like deep networks and LLMs the challenge of knowledge tracing has also been addressed more recently with *deep knowledge learning* models (Piech et al., 2015), (Zhang et al., 2017).

Another challenge in modeling the learner is to identify and track the psychological aspects, namely motivational drivers and inhibitors, preferred learning style or specific emotional context of the learner, that can vary from one training session to another. This has been studied lately from various perspectives (Woolf, 2009) and was embedded into *Emotionally Intelligent Tutoring Systems* (Ochs & Frasson, 2004).

Today though neither processing power nor the capacity of AI models to handle huge amounts of data are any longer an engineering barrier. Since learner's knowledge varies both in time and along consequent learning sessions, we recommend the use of deep neural networks like LSTM that seem to be most appropriate for this task. This type of networks can model and track in time the evolution of multiple skills in domain and learner-specific competency matrices, at the same time tracking the emotional state of the learner and/or other learner profile features.

3.2 Tutoring module

The **Tutoring Module** implements the tutoring strategies (the *tutoring model*). It defines the system's reaction to learner's observed behaviour and/or inferred state.

In the proposed platform architecture, the tutoring module tracks the management professional's progress toward the achievement of the personal learning & development objective stipulated in the initial setup of his/her development journey.

The model tracks the specific AI competencies linked to management roles and responsibilities and embeds adult learning principles (Knowles, Holton III, & Swanson, 2015)

Each tutoring module decision triggers a call to a specific microservice that delivers the proper intervention.

3.2 Interfacing module

Interfacing and communication modules of the ITSs developed to date have evolved from the simplistic text-oriented conversations and Socratic dialogues to the media-rich graphical environments of the 1990s-2000s and to the current multimodal environments.

Today's tutoring systems can implement powerful conversational egines based on the advanced capabilites of LLMs and can also present information in several human-friendly formats: e.g. virtual avatars (soulmachines.com, deepbrain.io), virtual worlds (VRChat.com, secondlife.com) and/or augmented reality.

4. AI competency framework for business management professionals

In training a business management professional to become more knowledgeable within the AI knowledge domain we will first need to identify the type and level of competencies he/she 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). 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.

As such, we developed an AI-competency model fit for the purpose of upskilling management professionals, that contains both AI Fundamental competencies (e.g. understanding of general AI concepts and the AI ecosystem, organizing AI-based business processes, principles and ethics in AI, Ai regulation and basic use of AI tools) as well as higher order AI competencies specific to the planning, organizing, leading and controlling functions at various management levels.

A more detailed introduction of the proposed AI management competency framework is presented by the author in the paper submited to the 2024 ICECO Conference.

5. Conclusions

We proposed the introduction of an Intelligent Tutoring System fit for the upskilling of business management professionals in the knowledge domain of AI and discussed several considerations specific to this architecture and specific target group.

The system is specialized in addressing the specific needs and challenges of less technical managers and is built on a knowledge structure and AI competency framework aimed at optimizing these particular development journeys.

A such, one of the key strengths of the proposed ITS is paradoxically also a key limitation of the system: the over-engineering (overfit) of the solution to meet the specific needs of management professionals limits its efficient use in addressing other target groups: e.g. more technical professionals like tech managers and/or the developers of AI-enabled business applications.

For instance, the design and implementation of a domain knowledge structure optimised to address the development of AI managerial competencies puts 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.

While the introduction of an adaptive ITS tool that assists managers in developing such in-demand competencies may significantly increase the effectiveness of the learning & development process, the solution also requires further validation such as to statistically confirm the fit and efficiency in increasing managerial performance through the adoption of AI tools and methodologies both at individual and organizational levels.

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