THE INCREASING IMPORTANCE OF NATURAL LANGUAGE INTERACTION IN THE DESIGN OF INTELLIGENT TUTORING SYSTEMS

Kurt Englmeier
Schmalkalden University of Applied Science
Blechhammer, 98574 Schmalkalden, Germany

ABSTRACT

In the context of learning platforms for on-the-job training, we expect from an intelligent tutoring system (ITS) that it effectively brings learners to the learning program that suits their aspirations and ambitions and guides them through an individual course or even their entire course program. The better the ITS "understands" the learners' goals, behavior, misconceptions, and errors, the better it can guide the learners along their learning journey, and the more effectively learners acquire their desired knowledge. Guidance usually includes observation of learners, evaluation of their behavior, which leads to the analysis and evaluation of their input, and eventually provides helpful and useful feedback to the learners.
Digital learning platforms increasingly focus on self-paced or self-directed learning, which gives learners the freedom to learn whenever they want and at whatever learning pace that suits their personal learning preferences and attitudes. This trend fosters a shift away from predefined and rigidly wired sessions towards flexibly arranged learning nuggets and tests. There are different paradigms for the design of learner guidance or instructions in ITS. This paper draws attention to natural language (NL) as the prominent mean of communication between system and learners. The benefits of emphasizing natural language bring a number of benefits for guiding and instructing learners. The paper describes the architecture and design of an ITS in the context of a prototypical platform for self-paced learning and demonstrates the role and importance of natural language processing (NLP) as key technology for learner guidance and instruction.

KEYWORDS

Intelligent Tutoring Systems, Natural Language Processing, Digital Learning Environments, Learner Guidance and Instruction

1. INTRODUCTION

Intelligent tutoring system (ITS) have the capability to support new learning experiences by providing customized leaning paths through the learning material and individualized feedback (Guo et al., 2021; Mousavinasab et al., 2018; Paladines and Ramirez, 2020). They convey "domain knowledge in a two-way, *adaptive*, and *incremental* manner" (Yang, 2010). We can expect that ITS foster active learning, that is, the learners have much more impact on the behavior of the digital learning platform. The acquisition of sustainable knowledge, however, is a goal of outstanding importance in digital learning platforms. Their attractiveness raises if they support the learners' need for esteem and self-actualization as defined by Abraham Maslow (Maslow, 1943; Maslow 1962). This need may have many facets addressing many areas in the life of the learners, including advances in their professional life (Almotairi et al., 2019).

Consequently, the focus on ITS may comprise the formation of learners over a larger period of time covering more than just one course. Much like the adaptation of a course to the individual aspirations, requirements and capacities of the learner the curriculum (or training) planning needs to be put in the same focus. On-the-job training in the industry requires this focus on ITS in order to identify training opportunities for the continuous development of the skills of employees. The goal of curriculum planning is to determine which digital courses or further learning resources suit the actual employee's competence in combination with the skills and knowledge the learners aspire to achieve. Required skills and knowledge define the formation setting for the training. However, formation may vary among employees even if they have the same role in a company. The recommended training program, consequently, differs in the same way and evolves over time.

In the past, digital learning platforms provided their content through more or less predefined sequences of sessions and quizzes. From a modern ITS we can expect more flexibility and adaptability to the learners' individuality. Supporting self-paced learning as a leading paradigm provides well-known benefits to learning environments (Peterson, 1996). An ITS includes recommendation features (or a recommendation engine) pursuing the purpose to personalize the learner experience by suggesting learning items and steps that are most relevant and interesting to the individual learner journey. There are several types of recommendation features. In the context of learning platforms, we talk about suggestions of the next learning steps the learners should consider for their career and, later, their learning journeys.

The design of recommendation features for learning environments shall promote reliability, flexibility, and adaptability. However, these features need to be coordinated, too, along the instructional strategy of the course of the training and need to react on the learners' input.

There is no doubt, that symbols can support a very efficient interaction between learners and learning systems. However, it can be beneficial to consider the inclusion of natural language in the interaction design (Cohen, 1992; Ledgard et al., 1980). First, NL as means of communication between the ITS and learners can bring several benefits for guiding and instructing learners. These include:

- Immediate understandability: NL is an intuitive and natural form of communication for humans, making it easier for learners to understand the instructions and guidance provided by the ITS.
- Increased attractiveness: Using NL may enable that learners experience their learning environment more natural, personal, conversational, and, thus, more comfortable and convenient. This raises the system's attractiveness, which, in turn, increases learner motivation and engagement.
- Responsiveness: Natural language can be used to provide guidance that is more flexible and adaptable when allowing learners to express questions, preferences, or requirements in their language.
- Increased expressiveness: Metaphors and graphical interaction elements need to learned and not all interaction possibilities can be suitably expressed by graphical elements. Natural language steps in here to fill these communication gaps.
- Increased analytics: Tracking learners and representing their progress and performance by NL allows for more accurate and actionable insights into their learning experience.

This paper focuses also on the design of ITS that supports the individual layout of training programs for employees in the industry. Furthermore, it also fosters adaptive learner guidance and instruction in order to enable self-paced learning within a digital course. Completing a course does not compellingly and automatically lead to sustainable acquisition of knowledge, even when completed successfully. If newly acquired knowledge falls to oblivion too soon, the course failed to achieve its mission. The course shall encourage the learners to adopt the knowledge provided by the course and not just completing the course successfully. The goal shall be the self-contained learner's adoption of the knowledge domain. The ITS as described here is part of the research project eduplex that aims to develop a more adaptive learning environment for on-the-job training in the industry.

Based on these design principles, the second chapter outlines the architecture our ITS is acting upon and references to related work. Chapter 3 describes in more detail the recommendation features of our ITS. Chapter 4 shifts the focus towards natural language as key ingredient in the design and implementation of our ITS.

2. ARCHITECTURE AND RELATED WORK

Recommendation features of an ITS as discussed in this paper prominently focus on two areas:

1. The setting for coaching employees in the broader context of helping them to find and compose a suitable training program to satisfy their professional goals and aspirations in order to improve their skills and knowledge.
2. Guidance of trainees within a particular course that supports self-paced learning.

It is important to understand the layout of our digital courses in order to better understand the design and implementation of our ITS for self-paced learning. The architecture and design of the digital course is built upon a couple of key principles:

- The entire content of a course is split up into a small number of chapters.
- Each chapter comprises thematically related *learning nuggets*.
- *Learn controls* are provided adjacent to each subset of learning nuggets.

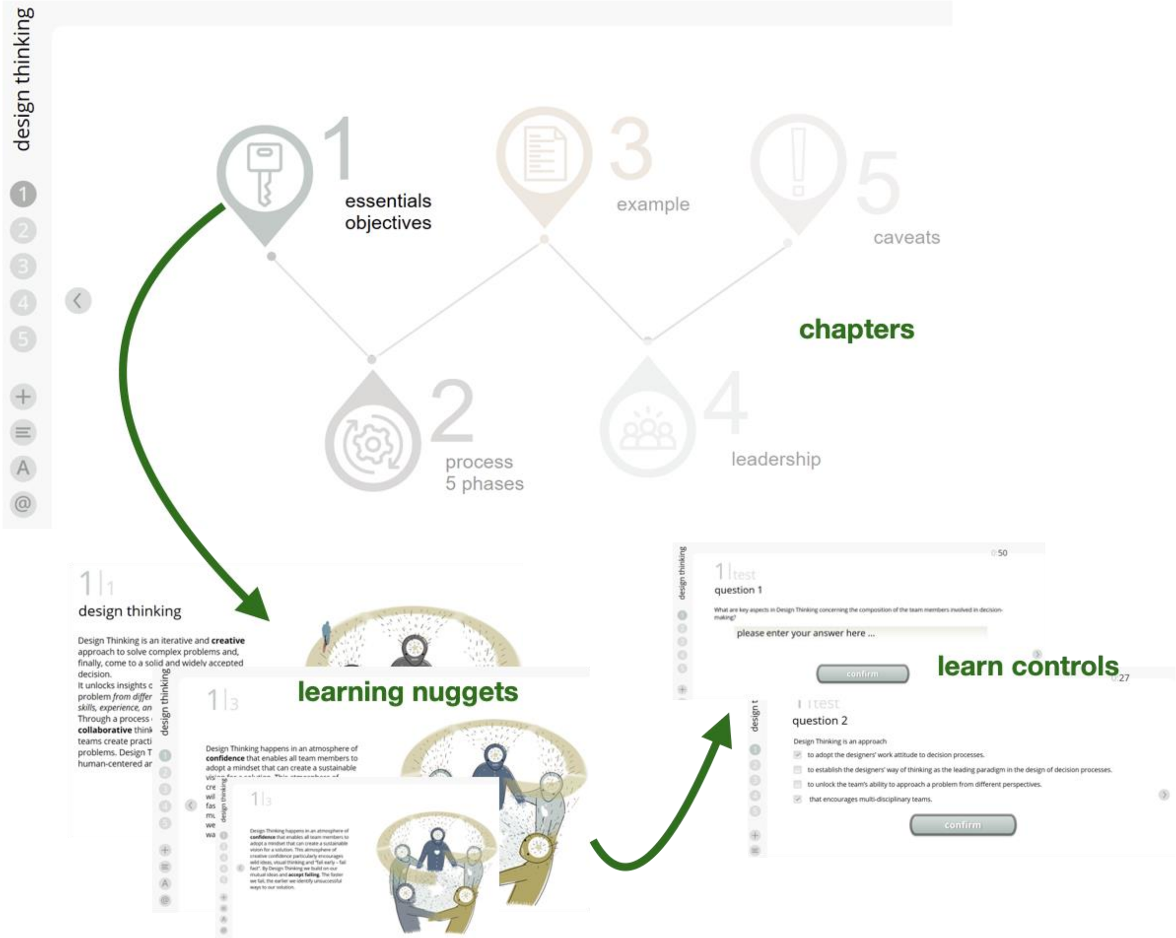

Figure 1. Example of the composition of a self-paced learning course (for Design Thinking) along chapters, learning nuggets, and learn controls

The *functionality of ITS* can be achieved through the collaboration of a number of system components addressing learners, instruction, adaptive training, the domain knowledge, and the interaction (inclined to Yang, 2010). The prominent role of NL suggests the consideration of an explicit language model.

The *domain knowledge* represents in a structured way knowledge and concepts within the *business* domain of the respective organization. It comprises all topics that are important in the training context of this organization. The annotation of the content related to this knowledge area is the first skeleton for the operationalization of NL for the purposes of learner guidance and instruction. The structure of annotation terms summarizes in an operational way the meaning of text in the knowledge base.

The *learner profile* is an operational summary of learner characteristics, preferences, and needs. It is essential when it comes to adapt the learners' journal according to their learning experience and progress. Adaptive instructions reflect the specific needs and abilities of the learners. A learner profile can include information such as:

- Prior knowledge and experience: what the learner already know and what they need or want to learn.
- Learning pace and results from the learn controls: what the learner has learned and in which time.
- Learning paths: the individual sequences of the course sections and quizzes visited along the learner journey.
- Statements reflecting further aspects of the individual learner journeys.

It is the learner profile that helps trainers and course designers to create more adaptive and engaging learning experiences by putting more emphasis on the unique characteristics and needs of each learner.

The *adaptive training model* is the overarching model reflecting the learners' formation over a larger period of time and over a range of courses. (Nkambou & Kabanza, 2001) It depicts, for example, the learner journey towards a new job or specialization within the existing job. The implement of adaptive training models can be considered as a meta model orchestrating the individual formation of an employee. It may reference digital courses, static learning material, class room events, or even individual appointments with a trainer. Usually, the model's parameters are updated in accordance with the learner's progress or new available learning resources. The adaptiveness of the training model emerges from the fact that the initial situation of the formation is not completely known at the beginning of the training.

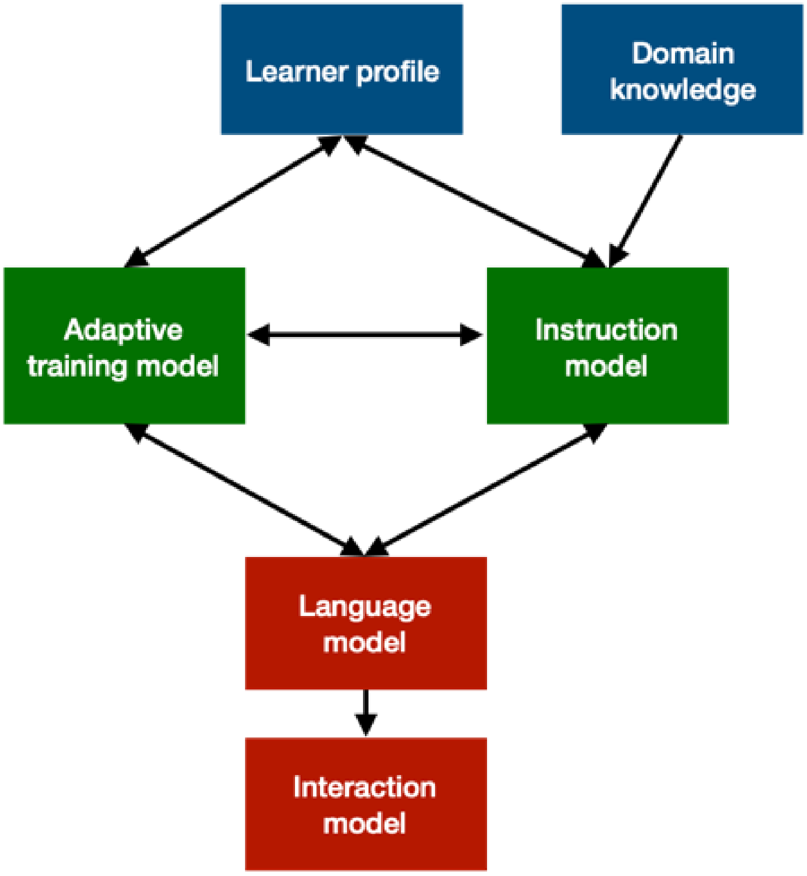

Figure 2. Architecture schema of an intelligent tutoring system (inclined to Yang, 2010)

The instruction model outlines patterns of learner guidance in order to successfully complete a course and to sustainably acquire knowledge. The instruction model describes the learning steps and the content of the learn controls including evaluation algorithms that express the learners' level of progress. Instruction models contain many references from learning nuggets to questions as part of the learning control. These references help, to provide proper feedback to the learners that help them understand their errors and misconceptions (Benbunan-Fich, 2002). In summary, the instruction model describes how learning nuggets are interconnected and how they are related to the learning controls. It also defines the reporting of the learner's achievements that are recorded in the learner's profile.

The interaction model defines the way in which the learning system with the learners. This includes the way it responds to inputs, actions, and the way it communicates. In the context of our ITS we apply a rule-based system that enables or disables navigation and interaction possibilities. They also include natural language processing and dialogue management for the interactions with the learners. Therefore, the language model is an integral part of the interaction model that supports the analysis of natural language instructions and learner statements in order to generate or trigger adequate actions of the learning system. The language model maintains the semantic context the recommendation features of the ITS are acting upon.

3. RECOMMENDATION IN THE CONTEXT OF ON-THE-JOB TRAINING

Recommendation for the professional or personal development on the job has a clear focus on the formation of employees in a certain work context. Recommendations shall answer the question “What to do next?”. On the formation level, these recommendations emerge from the employee’s goals and career aspirations. From this goal horizon, more specific goals can be derived that reflect development and improvement of skills, competences, and job-related knowledge. Usually with a person from the human resources department or functional management (or a training coach) the employee (or trainee) discusses her or his strengths and areas for improvement. Coaching an employee typically addresses specific areas of expertise, such as management, sales, production, technical skills, or soft skills like efficient and effective communication, emotional intelligence, leadership and the like. It may work in a variety of settings, including businesses, government agencies, and educational institutions.

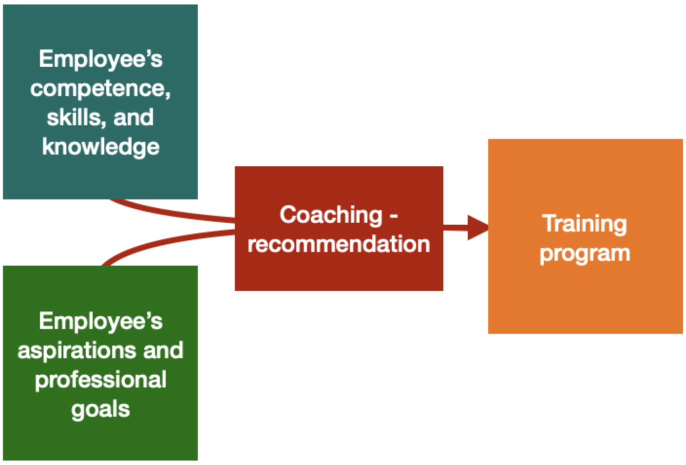

Figure 3. Schema for recommendation in the context of professional and personal formation

Formation-related recommendation comprise suggestions or endorsements considering the competences, skills and knowledge of the employees and the goals of their further development. Additionally, it would be beneficial if the recommendation also includes the expectations on the trainee's progress and how the acquired knowledge will form their job and career. An individual's career aspirations and goals greatly impact the types of training programs they need to choose to participate in. By understanding career aspirations and goals of their employees, organizations can tailor their training programs to better align with the needs and goals of their workforce. This ensures that the *recommended* training program are meeting the needs of the employees and are helping them to progress towards their career aspirations and professional goals. Recommendation on the formation level addresses the selection of the training resources (or courses) that help the employee to achieve personal and professional goals and career aspirations. It is important that the goals of the individual parts of the training program sum up to the overall goals as defined on the meta level. With this selection of training resources, the overall formation goal is broken down into more detailed goals reflecting the expectations connected with the training program.

Recommendations on the course level address the trainee's performance during the training period. They are used to assess the trainees’ progress at the individual stages of each course and their readiness for further stages within the same course or advancement to the next consecutive course.

In a self-paced learning course, the automatic recommendations provided by the ITS are based on the following data:

- Points achieved as result from the learn control
- Time spent on studying a single learning nugget, subset of nuggets, or chapter
- Learning nuggets as marked by the trainees, because they are of special interest for them
- Notes left on the page of a learning nugget

From this information the ITS generates recommendations for the next step of the trainee, such as

- repeat one or more learn controls
- repeat one or more learning nuggets
- repeat an entire chapter and re-taking the associate learn controls
- proceed to the next chapter/learning nugget

It is important to note that the recommendation also consider the time elapsed between studying the different chapters of a course in order to take into account the fact, the humans can forget what they have learned. There are, thus, reminders that automatically appear after a certain number of weeks or months has been passed. The time span depends also on the results the trainee has achieved in the respective learn control of the chapter or learning nugget.

4. THE SPECIFIC ROLE OF NATURAL LANGUAGE

4.1 Matching Learning Resources with Learning Goals

There are some very prominent application areas for Natural language processing (NLP) in the context of the ITS as described in this paper. When coaching employees to find the best set of training program for their professional goals and aspirations, NLP helps to analyze and highlight the trainees' actual skills, competences, and knowledge and the ones they want to achieve through the training program. Learner profiles result from this NLP-based analytic step. NLP has a prominent position in this process, because required information is mostly contained in job descriptions, curricula vitae, and personal statements that sketch the aspired competence, knowledge or skills. This future perspective on the individual formation can also be achieved from job or skill descriptions. NLP identifies and extracts from the descriptions the *essential information* that *summarizes the actual and future stage in the formation of the employee*. This information constitutes the profile of the employee in the context of her or his training. In the end, it reflects the objectives of the training.

Courses, course chapters, and learning nuggets are part of the *knowledge base* among other learning resources. We can assume that each learning resource comes with a brief description summarizing its content and learning objectives. Applying NLP on these items extracts the essential information here, too. By matching the essential information on the learner's side and on the course's side NLP can identify all courses that are useful concerning the training goals for the employee.

4.2 Supporting the Interaction for Self-Paced Learning

It is important to note that many systems supporting self-paced learning do not really support NL input, in particular, when it comes to the design of learn control features. Because of their limited text analysis features, they support mostly single choice questions, multiple choice questions or similarly schematic question types that bypass types that enable free-text answers in natural language. For a more ambitious design of a learn control environment the eduplex project considered it important to provide learn control questions that require free text input. In this setting, NLP helps to identify the meaning of the correct answer and of the trainee's answer. The comparison of the two respective statements and, thus, the correct evaluation of the trainee's answer can only be achieved through a series of NL processes such as automatic correction of misspellings and estimating to what extend the learner's statement lies within the meaning of the correct answer.

In the same way, NLP identifies and extracts essential information from learning nuggets and learn controls as well as statements the learners left with a nugget or learn control. These statements can have the form of reminders ("Check this section again in a week"), questions ("How shall I compute the entries in the risk matrix?") or the like.

NLP helps to annotate all learning nuggets, learn control, and trainee statements with standardized terms. In the next step, NLP can relate these annotations forming a semantic net over these learning components and comments. This, in turn, is the source for the automatic and dynamic identification of navigation paths or to recommend the trainee what to do next.

4.3 Standardized Annotation

We use a variety of natural language processing (NLP) techniques to analyze all kind of textual information in the context of our ITS. This includes machine-learning based text analysis with a particular emphasis on named entity recognition. In our approach, we develop annotation features using domain-specific BERT transformers (Devlin et al., 2019) modelled on the European Skills, Competences and Occupations classification (ESCO) system. The models help to produce standardized semantic networks for each profile type (learner, knowledge, learning resource). Recursive text summarization produces hierarchically structured annotation sets from the descriptions that we link with the semantic networks. It is important to note that named-entity recognition (NER) is applied in this process to improve the expressiveness of the semantic profiles (Fort et al., 2009). They complete the definition of the ontologies that represent the different profiles (Hernandez, 2005). NER is useful when it comes to identifying time-related or quantity-related characteristics in job descriptions, such as the number of years a person practices in a particular field, for instance. The same holds for trainee statements like "I want to come back in one week". Beside NER, we also apply n-gram identification in order to increase the precision of our NLP features. The larger the value of n, the more context is taken into account, but also the sparser the data becomes. For our analysis features we restrict to 2-, 3- and 4-grams. By using all of these techniques together, we improve the accuracy and efficiency of our annotation tasks.

The use of a standardized vocabulary increases the correctness of the matching processes, in particular when it comes to compare the meaning in the annotations to be matched. For this purpose, we first expand all terms in both annotations by their synonyms. Before expansion, however, we restrict the set synonym terms to those terms that are part of the respective knowledge domain. If the course addresses Agile Computing, for instance, we take the vocabulary of the entire learning material of this course as controlled vocabulary where the synonyms for the text analysis are recruited from.

These techniques mentioned here can be used to extract insights from learner data and to describe the learners' movements along their journey. Once the data has been analyzed, results are going to be interpreted and draw conclusions about the learner's journey. This can include things such as identifying areas where learners struggled, determining which stages of the journey were successful, and understanding the overall their performance throughout the journey. The semantic network enables the learning platform to perform or propose actions suitable for the learners' journey.

In summary, in our ITS, the learner journey (including all the related profiles) is predominantly expressed in NL. The semantics of each stage of the journey, that is, of the learning nuggets and learn controls are mainly expressed in NL. They show:

1. Key stages and milestones that the learner will go through. These stages include studying learning nuggets, progress tracking, and learn control results.
2. Representations on the learner's interactions and statements.
3. The learner's competence and knowledge and the objectives the learner aspires to achieve.

5. CONCLUSION

The paper prominently describes the role of NLP in the design of analytical features for ITS. First, NLP first supports the adequate matching of employees with learning opportunities that meet their aspirations and career goals. NLP is probably the only instrument to produce digital profiles of the competences, skills, and knowledge of employees on a broad scale. Almost all information on these qualities is available in texts only. The same holds for all kind of learning resources that are usually described in texts, too. With the presentation of the employees' professionals in textual form, all three types of key sources of information for our ITS are candidates for NLP. Machine-learning tools like BERT are powerful instruments for the annotation of texts. However, our research shows, that for the proper annotation of text related to occupations and training the integration of features handling named entities and n-grams are indispensable. The use of nomenclatures like ESCO are also useful. However, their items cannot cover the details of the texts. Too many information is not addressed by ESCO. That, in turn, requires the application of automatic summarization techniques on the texts and the proper linking of the hierarchical structure of the summaries with ESCO.

The support of NL also significantly enriches the interaction in our prototypical course system for self-paced learning. Even though we haven't conducted yet a comprehensive evaluation of our platform for self-paced learning, from the feedback of our first users we can assume that our approach and, in particular, the natural language interaction will be appreciated.

Beside a profound evaluation of our approach, we will also extend the automatic production of references between learning nuggets. NLP can construct a coherent semantic network across learning nuggets and related learn controls. The expansion of this network towards learning entities that are part of other courses, for instance, appears appealing. It gives the learners the possibility to easily explore into knowledge areas akin to the one of the courses at hand but reaching beyond its content limits.

ACKNOWLEDGEMENT

Research as outlined here is part of the eduplex project under the research framework INVITE of the Federal Institute for Vocational Education and Training (BIBB) funded by the German Federal Ministry of Education and Research.

REFERENCES

Almotairi, M. et al., 2019. Enhance employees' competences through customized learning. *Proceedings of the 10th International Conference on E-Education, E-Business, E-Management and E-Learnings.* Tokyo, Japan, pp. 42-47.

Benbunan-Fich, R., 2002. Improving education and training with IT. *Communications of the ACM*. Vol. 45, No. 6, pp. 94-99.

Devlin, J. et al., 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies.* Minneapolis, USA, pp. 4171-4186.

Fort, K. et al., 2009. Towards a methodology for named entities annotation. *Proceedings of the Third Linguistic Annotation Workshop.* Suntec, Singapore, pp. 142-149.

Guo, L., Wang, D., Gu, F., Li, Y., Wang, Y., & Zhou, R., 2021. Evolution and trends in intelligent tutoring systems research: a multidisciplinary and scientometric view. *Asia Pacific Education Review*, Vol. 22, 441-461.

Hernandez, N., 2005. Ontologies pour l'aide à l'exploration d'une collection de documents. *Ingénierie des systèmes d'information, RSTI série ISI, Recherche, extraction et exploration d'information*, Vol. 10, No. 1, pp. 11-31.

Ledgard, H. et al., 1980. The natural language of interactive systems. *Communications of the ACM*. Vol. 23, No. 10, pp. 556-563.

Maslow, A. H., 1943. A theory of human motivation. *Psychological Review*, Vol. 4, No. 50, pp. 370-396.

Maslow, A. H., 1962. *Toward a psychology of being*. D. Van Nostrand Company, Princeton, USA.

Mousavinasab, E., Zarifsanaiey, N., Kalhori, S.R., Rakhshan, M., Keikha, L., & Saeedi, M.G., 2018. Intelligent tutoring systems: a systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, Vol. 29, pp. 142-163.

Nkambou, R. and Kabanza, F., 2001. Designing Intelligent Tutoring Systems: A Multiagent Planning Approach. *ACM SIGCUE Outlook*, Vol. 27, No. 2, pp. 46-60.

Paladines, J. and Ramirez, J., 2020. A Systematic Literature Review of Intelligent Tutoring Systems With Dialogue in Natural Language. *IEEE Access*, Vol. 8, pp. 164246-164267,

Peterson, P. L., 1996. Self-paced training expanding educational opportunities. *Proceedings of the 24th annual ACM SIGUCCS conference on User services.* Chigago, USA, pp. 127-131.

Yang, F.J., 2010. The Ideology of Intelligent Tutoring Systems. *In acm Inroads*, Vol. 1, No. 4, pp. 63-65.