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Application of Artificial Intelligence Techniques in Analysis and Assessment of Digital Competence in University Courses

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ABSTRACT: The development of digital competence has become an important part of higher education, and digital competence assessments have attracted considerable attention and concerns. Previous studies in this area mainly focused on self-reporting and manual review methods such as questionnaires, which offer limited assessment value. To solve this issue, this study uses natural language processing (NLP)—a current promising artificial intelligence (AI) technology—to analyze syllabi for assessing digital competence in universities. Analysis results show that the proposed method can achieve an average accuracy and consistency of over 80% with excellent efficiency. Moreover, the method demonstrates high consistency with manual evaluation results (kappa > 0.6) and enables automated large-scale objective assessment. In brief, the results suggest that the proposed method is efficient, effective, and reliable, making it a valuable solution for digital competence assessment. We accordingly explore the application expansion of this method in building the digital competence of universities. Furthermore, we discuss the theoretical, methodological, and applied contributions of this study.

Keywords: Digital competence, Artificial intelligence, Higher education, Text classification, Machine learning

1. Introduction

Digital applications are growing at a rapid pace and affecting people's lives, challenging the way they communicate, learn, socialize, and work. Education is an area that is most affected by this evolution, as students need to interact using digital technology (e.g., install software and work from home) in their daily life, studies, and even future careers (Olszewski & Crompton, 2020). Therefore, digital competency is important for students, and its education plays a crucial role, particularly for higher-education institutions (i.e., universities) that provide expertise in many fields. Higher education is considered a key element in digitization development (Parkes & Harris, 2002). However, there is usually a digital competence gap between university faculty and students (Chiu et al., 2021; Gonda et al., 2020). Therefore, assessing and ensuring that universities have appropriate digital competence is key to providing quality education in the present and future. Present research pertaining to digital competence in higher education is still developing and requires more attention as well as significant efforts (Müller & Mildenberger, 2021; Zhao et al., 2021).

Previous research on university digital competence assessment usually employed questionnaires and interviews as tools and showed limited results (Guo & Huang, 2021; Starkey, 2020). The limitations are due to teachers and students having different understandings of digital competence, which causes bias errors in survey results (Lucas et al., 2021). Moreover, questionnaires and interviews require considerable cooperation; consequently, implementing them regularly and continuously is difficult (Beardsley et al., 2021). Therefore, there is an urgent need for more efficient methods that ameliorate the shortcomings of the traditional assessment methods and provide more evidence of digital competence (Cabero-Almenara et al., 2021a; Weber et al., 2018). Researchers suggested that understanding how teachers integrate digital competence into teaching and curriculum content can help researchers assess digital competence (Guillén-Gámez et al., 2021). In particular, teaching methods, techniques adopted, and content taught are usually clearly described in the syllabus (Parkes & Harris, 2002). Moreover, the teaching method and course content determine the use of teaching technologies (Boss & Drabinski, 2014; Brodsky, 2017). If the syllabus describes digital competence development or requires using specific digital competence or technologies, inferring that the teacher of the course possesses the relevant digital competence and that students in the course may develop their digital competence accordingly is reasonable. Therefore, analyzing the syllabus provides objective evidence to assess the competencies that the curriculum will bring to students, including digital competencies (Boss & Drabinski, 2014; Brodsky, 2017). Syllabus analysis being an excellent solution for assessing the digital competence in universities (Çebi & Reisoğlu, 2022). However, it is a professional textual-assessment task—usually conducted manually—which is more time-consuming, labor-intensive, and difficult than questionnaire analysis (Griffith et al., 2014). Therefore, an approach to measure digital competence on a large scale is strongly needed (Hämäläinen et al., 2021).

Because of the maturity of artificial intelligence (AI) technology, it is possible to train machines to simulate human assessment methods (Ho et al., 2021) and to reinforce assessment tasks that require human expert evaluation based on textual evidence (Hong et al., 2022; Lee et al., 2023). Artificial intelligence techniques can be developed based on human guidance to assess digital competence through explainable algorithms (e.g., text classification) that analyze specific descriptions in the syllabus. The evidence is not only reliable (Kong et al., 2023); the fairness of the results generated by AI can also help reduce the bias of different university fields. This can include the diversity of the university and serve as a bridge between educational decision-makers and experts in different fields. These AI techniques allow us to leverage the role of university education to benefit students and society (Yang et al., 2021; Gillani et al., 2023). To this end, the purpose of this study is to answer the question, "What is the effectiveness of using artificial intelligence in assessing digital competencies in university courses?" By doing so, further suggestions to researchers, educational decision-makers, and other educational stakeholders can be explored to potentially further advance HAI in this field.

2. Related works

2.1. Digital competence and higher education

Modern digital society has witnessed a dramatic change in the way people access information, communicate, and learn. Moreover, digital competence has emerged as a new term from scientific research. It can be understood as a way of using and understanding technologies and their impacts on the digital world (Becker et al., 2017) or a set of technological capabilities that effectively optimize one's daily life (Ferrari, 2013). The European Commission defines digital competence as an ability to safely, critically, and wisely use digital technologies in work, learning, social participation, and human interactions to meet different goals (Caena & Redecker, 2019). The development of digital competence is essential for university students because they gain diverse professional knowledge. Their future work and life will inevitably involve interactions with digital technology (Burgos-Videla et al., 2021), and higher education (i.e., university) is the key to digital competence development (Olszewski & Crompton, 2020). Accordingly, considerable emphasis is placed on the prevalence and assessment of digital competencies in higher education (Spante et al., 2018; Li et al., 2021). Researchers indicated that university educators must be linked to the digital competence required by the more complex professions of the 21st century (Cabero-Almenara et al., 2021b). Moreover, instructors should integrate digital competence into their practice and professional development (Guillén-Gámez et al., 2021). Therefore, measuring the importance of digital competence in higher education has become increasingly important in educational research, particularly in curriculum design, learning activities, and teacher–student interactions (Lázaro-Cantabrana et al., 2019).

To solve the aforementioned issue, the European Commission developed DIGCOMP as a reference framework to explain the meaning of digital competence (Carretero et al., 2017). DIGCOMP defines the following areas to assess digital competence: (1) information and data literacy, (2) communication and collaboration, (3) digital-content creation (including programming), (4) safety (including digital well-being and cybersecurity related skills), and (5) problem solving (critical thinking). For example, students' use of online discussion demonstrates communication and collaboration; completing programming projects is a typical digital-content creation competency. Owing to its validity and reliability, DIGCOMP has become the most commonly used framework for assessing digital competence in higher education (Lucas et al., 2022).

Accordingly, DIGCOMP was adopted as a framework for assessing digital competence in the present study. Moreover, most studies use questionnaires to investigate digital competencies. On the one hand, questionnaires focus on the use of specific tools, such as search engines, online bulletin boards, or systems, and are limited by the number of questionnaire items, which may not cover the full range of learning activities at universities (López-Meneses et al., 2020). On the other hand, the digital competence of all surveys is based more on the perception and self-assessment of participants than on more objective conditions (Saltos-Rivas et al., 2021). Thus, a valid and objective method to measure digital competencies in universities is currently lacking (Wang et al., 2021).

2.2. Curriculum syllabus analysis

To address the aforementioned issue, researchers indicated that a syllabus includes teaching philosophies, course content, assignments, and capabilities that can be gained by the students (Johnson, 2006; Thompson, 2007). It serves as a faculty document that defines students' learning outcomes and the means by which they are achieved (Afros & Schryer, 2009; Habanek, 2005). Keyword comparison can provide effective analysis reports as a reference for educational decision makers (Jeffery et al., 2017). In brief, the digital competence in an educational environment reflects all learning activities related to digital competence in the learning process (Tomczyk et al., 2020). Even if teachers or students are unaware of their own digital competence, specific descriptions in syllabi can reveal and crystallize the existence of digital competence in the curriculum (Boss & Drabinski, 2014; Hrycaj, 2017). Typical descriptions include software instruction, digital homework grading, using digital communication media, and learning systems (König et al., 2020). Moreover, in contrast to a questionnaire, which is an instantaneous response, a syllabus is provided after careful consideration by the instructor. In most cases, instructors rely on the syllabus. Hence, reviewing these documents provides objective evidence of a teacher's or student's digital competence (Lucas et al., 2022). For example, recently, an analysis of 180 course syllabi involved the investigation of teachers' digital competence and provided libraries and teachers with appropriate recommendations to assist digital competence development (Dubicki, 2019). In another analysis, a syllabus was used to determine digital competence support opportunities for teachers and develop strategic teaching promotion, showing that syllabi are a reliable way for understanding digital competence outcomes (Beuoy & Boss, 2019).

However, a comprehensive review of all courses in a school is difficult. Previous studies indicate that analyzing 1000 courses' syllabi requires at least 480 hours of team review time, not accounting for time spent on training, compiling, and analyzing data (McGowan et al., 2016). Moreover, with constantly changing syllabi, manual analysis is neither effective nor efficient. Therefore, more efficient analysis methods must be developed.

2.3. Human-centered Artificial Intelligence in Education

To address these problems, researchers have noted that there are clear distinctions in activities and their descriptions related to digital competence in the syllabus, such as utilizing software. Because of such characteristics, AI technologies (e.g., natural language processing (NLP)) can complete tasks in an accurate and efficient manner based on human recognition and domain expertise (Yang et al., 2021). In particular, AI can automatically process complex algorithms and large databases under human control. This leverages the strengths of both humans and machines, enabling them to collaborate in a way that mutually reduces blind spots and delivers high-performance applications and real creative improvements, also known as human-centered artificial intelligence (HAI) (Shneiderman, 2020). Currently, approaching AI from an educational stakeholders' (students, teachers, and leaders) perspective by considering human conditions and contexts in educational settings has gained considerable focus in HAI applications (Renz & Vladova, 2021).

Typical HAI in educational settings can be divided into several categories, including intelligent tutoring systems (e.g., personalized learning), NLP (e.g., language education and text analysis), educational robots, educational data mining (performance prediction), and affective computing (learner emotion detection) (Wang, 2021). While most HAIs in education focus on teaching and learning outcomes, researchers have noted that the manner in which education providers and institutes use AI to reinforce their functions will be an important issue in the future (Yang, 2021). NLP is considered a key area leading the AI trend because it not only mimics human understanding but also helps educational institutes and educators make interpretable and evidence-based decisions (Chang et al., 2021; Chen et al., 2022). For example, Sun and Ni (2022) used AI to analyze and identify students' text comments on an educational video resource service system, thereby significantly reducing the manual review workload. Another study by Mohammed and Omar (2020) adopted the term frequency-inverse document frequency (TF-IDF) algorithm to automatically map test questions to the appropriate bloom taxonomy cognitively and assess students' learning outcomes. Further, Yang et al. (2021a) used bidirectional encoder representations from transformers (BERT) to replace manual work to automatically assess students' text notation skills and explore the relationship with learning outcomes.

The use of AI (e.g., NLP) to facilitate syllabus analysis has been recognized as a promising approach, and there have been some research attempts recently. For example, a study by Fréchet et al. (2020) extracted various types of software used in teaching from syllabi to provide curriculum design suggestions. In another study by (Yasukawa et al., 2020), AI was used to analyze the syllabus to determine information that must be included in the syllabus and concluded that such an approach is not only credible and efficient but can also produce systematic and objective results. Accordingly, the present study uses AI to assist in syllabus analysis for assessing the digital competencies in universities.

3. Methods

The AI method used in this study involves a text-classification technique based on NLP to analyze syllabi. It includes the TF-IDF + machine learning (ML) classifier and BERT. TF-IDF + ML is the classical text-classification method that uses word frequency as a feature to distinguish articles and is a context-independent method. Meanwhile, BERT is the most advanced text-classification technique that has been preprocessed to consider the context of words. The former has the ability to provide interpretable classification rules, while the latter can achieve excellent performance. Based on HAI perception (Riedl, 2019), both methods are used and discussed using the results herein.

3.1. Data collection and labeling

Web crawler programs were used to collect course information offered by the authors' university in the previous year. A total of 7880 syllabi (70.6% were written in Chinese and 29.4% in English) were collected. To assess digital competence, DIGCOMP 2.1—a framework proposed by the European Commission and considered a key document in assessing digital competence—was used. It has been adopted by many countries and researchers (Hernández-Martín et al., 2021). Noting that the activities in a university may not completely reflect on the DIGCOMP framework, we focused on identifying the five areas of digital competence as suggested by previous studies (López-Meneses et al., 2020; Mattar et al., 2022) rather than examining subitems in each area.

Table 1. Examples of labelled syllabi

Dc area	Course title	Syllabus digest
NA	Music and Other: On Arts and Differences	This music appreciation course explores music and the issue of differences, better known as *Other* in social science and cultural studies. In music, portraying something foreign (or *Other*) involves various complex aesthetic and technical concerns.…
Area 1	Social Media and Communication Research	Social media have been deeply integrated into the lives of millions of people for a wide variety of purposes. … In particular, in this course, you will learn important concepts, terms, and theories related to social media; *explore different social media sites; critically analyze possible social, political, and psychological impacts of social media us***e**; and come up with ideas to....
Area 2	Digital Technology and Language Learning	This course aims to explore various types of popular and/or cutting-edge digital technologies and their application and influence in a second and foreign language (L2/FL) teaching and learning. …. By the end of this course, you will be able to do the following: *name the most commonly used and cutting-edge technologies for L2/FL teaching and learning, elaborate the fundamental principle of implementing technologies for L2/FL teaching and learning, demonstrate how to use selected digital technologies L2/FL teaching and learning,…*
Area 3	Data Structures and Object-oriented Programming	There are three major themes in this course: *1) Understand object-oriented programming, 2) implement C++ programs to solve problems, and 3) learn and use Standard Template Library. After completing this course*, you should learn the following skills: 1) design a system using classes based on system specifications…
Area 4	Network Attacks & Defenses	The popularity of the computer and Internet has a rapid and enormous impact on the life of human beings. Therefore, understanding how the network functions and help improve the security and efficiency of communication is important. This course introduces network security, network defense, and network management. *It enables students to learn about network security systems, detection and defense algorithms, and management knowledge and skills.*
Area 5	High-tech Facility Design	The purpose of this course is to provide.... High-tech includes (but is not limited to) the advanced technologies applied in the fields of microelectronics,…Students will gain skills needed to meet everchanging … *Use the basic theories and principles to design systems for heating, ventilation, and air conditioning (HVAC), water/air treatment, noise, and vibration mitigation. …Establish contamination control programs for constructing, operating, and maintaining high-tech facilities. Address the issues in automatically managing the emergency, safety, and security systems.* Link to the information sources for further studies in nano/micro fabrication and research.

The syllabi were labeled according to these five areas. If a syllabus clearly indicates that the teacher will use or the student must use one or more of these five areas in the course, it is labeled according to the corresponding highest area of digital competence (i.e., both Area1 and Area2 are labeled as Area2). However, if the syllabus does not describe any activities related to these five areas, it is labeled “NA,” meaning not incorporating digital competence. According to the labeling results based on the preceding criteria, of the 7880 courses, 479 were labeled as Area 1, 395 as Area 2, 1541 as Area 3, 78 as Area 4, and 112 as Area 5. There were 5275 files labeled as “NA.” In addition, each syllabus was labeled by an undergraduate student and two master’s students, and their overall labeling consistency was reflected by kappa = 0.86, indicating excellent consistency. Finally, a professor with information education expertise reviewed and corrected the syllabi that were marked inconsistently. Table 1 provides examples of labeled syllabi.

3.2. Pre-processing

In the feature-extraction stage and before the classification process, the datasets were preprocessed to reduce unnecessary, repetitive, irrelevant, and noisy raw data. We wrote a python program and used jieba, NLTK, and scikit-learn to process text segmentation, stop word removal, and for feature extraction. Moreover, unnecessary data such as punctuation marks, numbers, and non-Chinese or non-English characters were also removed and all words were converted into lowercase. Words such as “the,” “a,” “an,” and “in” in English, and “是,” “因為,” and “我們” in Chinese were removed. Although English words may also exist in Chinese syllabi, these are mostly specific terms or tool names (e.g., Circuit Simulator, Music Making), and the same is true for the English syllabi. Therefore, this study does not specifically address English in the Chinese syllabus or vice versa but rather separates the training of Chinese and English syllabi.

3.3. Feature extraction and classification

After preprocessing, the TF-IDF algorithm extracted features and conducted text classification. TF-IDF is a common weighting technique for information retrieval and text mining that evaluates the importance of a word to one file set or a corpus (Dalianis, 2018). The importance of a word increases with the number of times it appears in a given file but decreases with the increasing occurrence frequency in the corpus. In addition, BERT has become a popular deep-learning method in recent years. BERT first completes model pretraining with a wide range of thematic data and many data files; then it fine-tunes the pretraining model with specific data according to various situations to achieve excellent results (Devlin et al., 2019). Therefore, TF-IDF was used in conjunction with three common ML classifiers: support vector machines (SVM), k-nearest neighbors (KNN), and naive Bayes (NB). BERT served as a classification method.

3.4. Evaluation metrics

Accuracy, precision, recall, F1-score, and kappa value were used to evaluate the effectiveness of the abovementioned classification methods. Accuracy reflects the percentage of correctly classified syllabi from the total number of syllabus files and is the most basic classification evaluation index. F1-score, or the harmonic average of sensitivity and accuracy, provides another general indicator of model effectiveness. The kappa value evaluates the consistency of the classifications performed. All the abovementioned indicators are scored between zero and one, where zero indicates poor performance and one indicates good performance. To measure the proposed model’s effectiveness, 20% of the data not included in the training set were evaluated as a test set. We also divided all the data into 10 equal parts; for each group, we took it as test data and the remaining nine groups as training data. Thus, the 10-fold cross-validation method could be used to evaluate classifier effectiveness for preventing model overfitting (Kohavi, 1995).

4. Results and discussion

4.1. Effectiveness evaluation of syllabus analysis

Results show that when 20% of the data were used as the test set, the SVM, KNN, NB, and BERT classification accuracies ranged from 0.57 to 0.83, the F1-scores ranged from 0.59 to 0.84, and the kappa values ranged from 0.20 to 0.64 (Table 2). When the TF-IDF and ML methods were used, the SVM, F1-score, and kappa value were the highest with the test dataset or 10-fold cross-validation. Therefore, SVM exhibited the best performance in syllabus analysis and BERT had the best overall classification effectiveness. When 10-fold cross-validation was used, the accuracy of the TF-IDF + ML models ranged from 0.68 to 0.83, which was slightly greater than that of the F1-score and kappa value. Similarly, SVM afforded the highest accuracy (0.83) among different ML methods. Although KNN was slightly less accurate than SVM, it still showed good consistency (0.59). This result shows that there was no significant difference between the two ML models. The F1-score indicates that the TF-IDF + SVM models can achieve good performance. Further, the TF-IDF + NB models performed poorly among ML models. This finding is consistent with past results because the stability of NB effectiveness is often used as the basis for text classification, and there was no outstanding effectiveness in the text classification (Xu, 2018). Nevertheless, we suggest that NB can be used as the basis for model comparison.

Table 2. Evaluation of classification models

		20% test set validation					10-fold cross-validation				
		ACC	Precision	Recall	F1	Kappa	ACC	Precision	Recall	F1	Kappa
TF-IDF+	SVM	0.65	0.63	0.65	0.64	0.47	0.83	0.55	0.60	0.57	0.50
	KNN	0.57	0.59	0.55	0.59	0.20	0.80	0.42	0.50	0.46	0.59
	NB	0.59	0.65	0.61	0.62	0.32	0.68	0.51	0.53	0.52	0.43
BERT		0.83	0.83	0.86	0.84	0.64	0.80	0.61	0.74	0.67	0.56

Table 3. Examples of syllabus files classified by AI with different digital competence areas

Dc area	Course title	Syllabus digest
NA	Experiments in Physical Chemistry	Implement the physical chemistry experiment course. Teach undergraduate students basic concepts and theories of physical chemistry. Help students understand experimental methods and skills to validate theories and experiments. Help students further understand experimental processes and principles.
Area 1	Anthropology	Introduce course description, course material use, academic performance evaluation, cultural anthropology *online resources*, and other anthropology library resources.
Area 2	Media Psychology	Media technologies are inextricably intertwined with everyone’s life. They affect the ways people learn, think, interact with others, feel, and act. Understand contemporary media use, its underlying causes and mechanisms, and possible impacts. *Guide students to observe and think about the relationships among media technologies, people, and the social environment with mutual impacts.* Mid-term and final assessment reports by teams are required.
Area 3	Introduction to Computers and Programming	Fundamentals are introduced. The objective is to *enable students to possess the following capabilities: (1) understanding concepts and skills of C programming and (2) proficiency in solving computing tasks by programming.*
Area 4	Enterprise Cybersecurity	This course explores current security challenges in enterprise operation and analyzes new generations of corporate security measures, including *(1) status of security threats, (2) forward-looking defensive strategies, (3) security maturity assessment and defensive strategies,* and (4) building a strong security-management team. Case studies are included. Capital security risk assessment criteria are briefly introduced. *Automated tool usage is introduced to facilitate hands-on practice for students.*
Area 5	Computer Networks	This course introduces innovation and application capabilities of information technologies and mathematics knowledge. The following knowledge and capabilities are taught/trained: information technology tools’ applications; *design and evaluation of computerized systems, programs, and components; identifying, analyzing, and solving problems; learning current issues; understanding the impacts of information technologies on the environment, society, and world; continuous learning; understanding professional ethics and social responsibility.*

Moreover, compared with the TF-IDF + ML method, the BERT model achieved the highest efficiency in almost all the criteria when the 20% nonrepeating test dataset and 10-fold cross-validation were used. The BERT model’s accuracy in the 10-fold cross-validation was slightly less than that of SVM, suggesting the superiority of BERT to traditional ML classifiers in syllabus classification. In particular, the BERT accuracy was 0.83 for nonrepeating datasets, almost 1.4 times the ML model accuracy. The consistency of the BERT model was 0.64, 1.74 times higher than the best ML model (SVM). These results highlight BERT’s excellent capability in syllabus analysis. Unsurprisingly, as BERT has pretrained universal language models using a cross-domain text corpus, BookCorpus, and Wikipedia, it demonstrates excellent performance in NLP tasks (Yu et al., 2019).

However, there is no large difference in the performance of classical (TF-IDF + ML) and advanced (BERT) NLP methods in classifying syllabi. A possible reason is that while TF-IDF extracts features from word frequencies, the terms/words associated with digital competence are often unique and—to a certain extent—reflect the digital competence area to which a syllabus relates. Thus, although TF-IDF does not consider the context, it still performs well compared to BERT. For example, “Python” has two different meanings: a programming language or a snake genus), but if a syllabus mentions both “Python” and “syntax” we can obviously identify that it is related to digital competence (programming language). We also found that such a finding is revealed when classifying articles in many subject domains (Kim et al., 2022).

In short, the above discussion indicates that using AI (i.e., TF-IDF + ML, BERT) to analyze syllabi can provide an average accuracy of over 80% and a consistency score greater than 0.6, which are satisfactory. Moreover, after the four models used in this study were trained, the longest time to perform a classification task was only seven minutes (using Google Colab Pro, GPU: Tesla P100, Memeory:16 GB). By contrast, manual analysis takes from a few days to more than a week. Therefore, AI methods can achieve good results similar to those of manual analysis in considerably less time and with acceptable consistency, demonstrating efficient and effective syllabus analysis capability. Table 3 lists the syllabus files classified by AI. Each classified syllabus file has a clear description corresponding to labeled digital competence areas. Nonetheless, one should be aware of the possible implications and treatment of imbalanced data, for example, by involving experts to determine which of these rare instances may be the most efficient solution to the current categorical imbalance classification model (Haixiang et al., 2017).

4.2. Digital competence assessment in universities

According to previous literature, AI methods can provide accurate, consistent, and verifiable assessment for educational data analysis (Guan et al., 2020). The presented results confirm this point and allow researchers to further explore the utilization of AI methods to assess digital competence in universities. In this study, digital competence levels of different courses were compared, e.g., differences between school levels (undergraduate/graduate schools) and among different colleges within a university. Table 4 reveals that 34% of the courses assessed contain some degree of digital competence. This is not considered low and is reasonable because the university is known for electrical engineering, electronics, and information technologies, which inevitably require digital tools.

The undergraduate courses offering digital competence are classified as Area 1, 2, and 3. The percentage of graduate courses offering digital competence is higher than that at the undergraduate level, and 25% of the courses are categorized as Area 3 (digital-content creation). This aligns with the university’s graduate school training that emphasizes independent thinking with innovative ideas. More than 80% of the courses offered by the College of Intelligent Sciences and Green Energy and more than 85% of the courses offered by the College of Information Technology require use of digital competence. By contrast, less than 20% the College of Science courses and less than 12% of the College of Dentistry courses require use of digital competence. The College of Information Technology naturally requires extensive use of digital competence, which was clearly stated in the syllabi. By contrast, digital competence is not so widely applied in the medical and health fields, explaining the lack of digital competence displayed by the College of Dentistry and confirming results from previous studies (Golz et al., 2021; Lázaro-Cantabrana et al., 2019).

The results of this study demonstrated an HAI application that universities can use this approach to periodically review the status of digital competencies on campus. By doing so, in addition to providing evidence beyond the questionnaire response, further identification of programs for improving the digital competencies of faculty, staff, and students based on objective evidence (i.e., syllabus) is possible. This result also indicates that different universities are often organized with similar domains of expertise and provide the same courses (e.g., Microelectromechanical Systems and calculus), and that the syllabi of these courses usually have common specific terms. Accordingly, the approach adopted in this study reveals an opportunity for other higher-education institutions to demonstrate generalizability.

Although there has been some research on syllabus analysis, the expert-based approach is limited by human resources and the technique-based approach may lack involved domain knowledge. This study uses both classical (i.e., TF-IDF + ML) and advanced NLP techniques (i.e., BERT) to complete the same task. The former may provide easy-to-interpret classification rules based on word frequencies, while the latter can provide higher accuracy through repeated validation, both providing significant improvements in efficiency and consistency. This means that human experts can themselves decide the level of AI intervention to maximize their own capabilities (Shneiderman, 2020) either by leaving the analysis of the syllabus entirely to the machine or by determining the level of automation to provide explorable results or evidence for educational decisions (e.g., looking at the proportion of digital competence and essential learning/teaching activities in each domain offered by different colleges). To the best of our knowledge, this study is the first to use HAI to assess digital competencies, which adds to the usefulness and value of HAI in the educational domain.

Table 4. Courses with digital competence in the entire university at different school levels and in different colleges

	Area1		Area2		Area3		Area4		Area5		NA	
	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*
Campus	6.08%	479	5.01%	395	19.56%	1541	0.99%	78	1.42%	112	66.94%	5275
School												
Graduate	3.30%	137	4.39%	182	25.14%	1043	1.21%	50	1.21%	50	64.76%	2687
Undergraduate	9.20%	342	5.73%	213	13.31%	495	0.75%	28	1.67%	62	69.35%	2579
College												
Humanities and Social Science	6.25%	30	11.88%	57	13.13%	63	0.42%	2	1.04%	5	67.29%	323
Engineering	4.09%	28	5.55%	38	13.87%	12	0.00%		1.46%	10	75.04%	514
Dentistry	1.69%	3	2.81%	5	6.74%	29	0.00%		0.00%		88.76%	158
College of Life Sciences	2.24%	8	3.08%	11	8.12%	103	0.00%		0.00%		86.55%	309
Biological Science and Technology	4.42%	24	2.95%	16	18.97%	104	0.18%	1	0.00%		73.48%	399
Biomedical Science and Engineering	3.62%	23	1.57%	10	16.35%	32	0.16%	1	0.16%	1	78.14%	497
Photonics	5.76%	11	7.85%	15	16.75%	51	0.00%		1.05%	2	68.59%	131
Industry Academic Innovation School	9.31%	39	0.48%	2	12.17%	15	0.00%		1.91%	8	76.13%	319
Hakka Studies	12.18%	24	9.14%	18	7.61%	2	1.52%	3	3.55%	7	65.99%	130
Law	9.30%	4	4.65%	2	4.65%	3	0.00%		0.00%		81.40%	35
Semiconductor Technology	2.50%	1	7.50%	3	7.50%	38	0.00%		0.00%		82.50%	33
Sciences	5.89%	31	5.32%	28	7.22%	80	0.57%	3	0.00%		80.99%	426
Artificial Intelligence	0.00%		0.00%		74.77%	420	2.80%	3	0.00%		22.43%	24
Computer Science	2.59%	16	2.10%	13	67.96%	208	6.96%	43	6.31%	39	14.08%	87
Electrical and Computer Engineering	16.77%	139	10.98%	91	25.09%	123	0.97%	8	4.22%	35	41.98%	348
Management	8.06%	66	7.33%	60	15.02%	102	1.59%	13	0.49%	4	67.52%	553
Medicine	2.70%	21	1.80%	14	13.13%	8	0.13%	1	0.13%	1	82.11%	638
Pharmaceutical Sciences	0.00%		1.16%	2	4.65%	45	0.00%		0.00%		94.19%	162
Nursing	3.65%	7	3.13%	6	23.44%	8	0.00%		0.00%		69.79%	134
Other	5.63%	4	4.23%	3	11.27%		0.00%		0.00%		77.46%	55

5. Conclusions

Assessment of digital competency in higher education is still a nascent topic. To address the limitations of the use of self-reporting and the inefficiencies of manual analysis. This study explored the following question: “What is the effectiveness of using artificial intelligence in assessing digital competencies in university courses?” from an HAI perspective. Our results point to a high degree of consistency in human analyses conducted using AI. Our results show that universities can use this approach to proactively and efficiently assess all university courses with minimal human effort. There will be an opportunity to provide equitable digital competency education to students from diverse backgrounds, resulting in greater benefits for individuals, educational institutions, and society. Based on the result, we summarized the findings and contributions of this study from three perspectives:

Regarding theory, from an educational research perspective, a syllabus represents the contract between teacher and student and reflects the activities that occur in the curriculum, and it can be an objective method of assessing specific competencies. This study uses HAIs to practicalize this perspective. To the best of our knowledge, this is the first study to adopt HAI to assess digital competencies through syllabus analysis, which may provide inspiration for practicing HAI in the education field. Regarding methods, we used both classical (TF-IDF) and advanced (BERT) AI (i.e., NLP) techniques, showing that advanced AI achieves higher accuracy rates, but the classical one may provide interpretable results with acceptable accuracies. Both classical and advanced AIs significantly reduce the task time and produce reliable results. Therefore, educators can decide which AI technique to use and achieve their goals. As mentioned by Shneideman (2020) HAI retains manual control where appropriate, thereby increasing performance and enabling creative improvements. Regarding application, this study provides an opportunity to fill the diversity and inclusion gap by establishing a joint dialogue on digital competency education among departments of different professional backgrounds in the university from the HAI perspective. We show that this approach is explainable and trustworthy in universities, and it can proactively and efficiently evaluate programs across the university with a minimal workload. Such an approach may help universities provide equitable digital competency education to students from different backgrounds, creating greater benefits and societal interests in higher education (Yang et al., 2021b). Universities will also have more opportunities to promote quality education, as emphasized in the Sustainable Development Goals (SDGs).

6. Limitations and future works

Although the results of this study are promising, the proposed has method limitations. First, this study focused on the syllabus' textual description, but the contextual relevance, semantics, and implied intention between sentences were not considered in the model. Future research could improve the performance of the classifier using other algorithms. In addition, this study assesses digital competence using a syllabus, and verifying the consistency of this method with student/instructor's perceptions of digital competence and its applicability to other universities as well as exploring the existence of overfitting effects in future research is useful. Second, this study presents a method to investigate the digital competencies in universities, although it can be used to identify solutions that facilitate the development of digital competencies for universities. However, the development of teachers' and students' digital competence may be related to individual differences such as age and gender (Gnambs, 2021). We need to clarify these relationships in future research to create effective digital-competency training programs. Finally, development of machines to understand human socio-cultural norms and theories of the mind is in its nascency, and we agree that AI cannot replace humans but rather reinforces human capabilities. Thus, this study does not address some problems (unbalanced data) but leaves the final judgment to experts to accommodate the two-dimensional framework of HAI (Shneiderman, 2020).

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