Machine Learning and Artificial Intelligence in Higher Education: A State-of-the-Art Report on the German University Landscape

Birte Keller[1], Janine Baleis[1], Christopher Starke[1], Frank Marcinkowski[1]

[1] Heinrich-Heine-Universität Düsseldorf
Universitätsstraße 1
40225 Düsseldorf

birte.keller@hhu.de | janine.baleis@hhu.de
christopher.starke@hhu.de | frank.marcinkowski@hhu.de

Abstract. This report provides an overview of some promising applications of artificial intelligence (AI) in German universities. Although the AI sector is booming, the higher education sector seems to have benefited little from this boom thus far. In any case, schools and universities are relatively low-priority targets in the development of new AI-based systems than, for example, medical diagnostics or individual transport. This report aims to provide initial insights into the relevant applications that are currently being developed at and for universities in Germany in this opaque scenario. To this end, the report was prepared based on a methodological triangulation. In the first step, relevant literature on AI in the university sector and existing state-of-the-art reports of other countries were evaluated. In the second step, an analysis of the official documents of German universities pertaining to AI and digitization strategies was carried out, as far as such papers were available. In the third step, 13 guideline-based expert interviews were conducted to confirm and extend the impressions gained from the relevant literature and from the document analysis. On this empirical basis, a few of the AI systems currently in use at tertiary education institutions are presented, the opportunities and risks associated with their use are discussed, and the future of such systems is discussed. Even if we cannot claim that this report provides a complete picture of the domain, it does highlight important fields of application and lines of development related to AI.

Keywords: Higher Education, Artificial Intelligence, Learning Analytics, Big Data, Predictive Analytics

1 Introductory remarks

The explicit goal of the government of the Federal Republic of Germany is “to make Germany and Europe leading locations for AI and thus [contribute] toward securing Germany's future competitiveness” (Federal Government, 2018, p. 8 – translated by authors). Until a few years ago, the "Internet of things" was the expression for a comprehensive vision of the changes in work and private lives over the course of digitalization. In the present day, the discussion revolves around the use of artificial intelligence (AI) in all areas of life in modern societies. The potential attributed to AI is enormous. To leverage it, large technology companies are already deploying systems such as Alexa and Siri, which are intended to make everyday life easier for users. In addition to companies, governments are striving for technological and social progress through the use of AI.

AI systems that employ machine learning methods and are used to process large numbers of tasks benefit from the growing flood of data (Big Data) and increased computing power (Wischmann & Rohde, 2019, p. 100). Big Data is already penetrating many areas of life, including the education sector (Dede, Ho, & Mitros, 2016, p. 1). Experts have assumed that annual data growth in the education sector is 35% (Liebowitz, 2017, p. 7). One of the reasons for this growth is that an increasing number of learning processes are taking place through online learning platforms, and users leave their data traces on various such learning platforms (Daniel, 2015, p. 912). Thus, when using learning management systems such as Moodle or Ilias, users create data traces that allow one to determine the frequency and intensity with which they access and process the learning materials. In addition, information on examinations, grades, and courses are stored digitally in the form of study history data. The data generated in this manner can support both learning and teaching with the help of AI and within the framework of Big Data analysis. Therefore, concepts such as learning analytics have great potential for use in the optimization and acceleration of learning processes (Büching et al., 2019, p. 142).

Despite the great potential for the use of AI applications and Big Data, thus far, they have rarely been used in practice (Attaran, Stark, & Stotler, 2018, p. 169; Büching et al., 2019, p. 142). Nevertheless, in some countries, the education sector is already supported by AI applications, albeit not yet to the extent that one would expect given the potential of these technologies. In some countries such as the United States, Australia, and the UK, institutions have already started to rely on various systems that support adaptive learning or facilitate individual performance feedback. The US deserves a special mention here because the use of AI applications in universities is already a subject of scientific analysis in that country, and relevant inventories are available (Ekowo & Palmer, 2016). In the German research landscape, this topic has only been discussed sporadically thus far (cf. e.g., Berens et al., 2018), but a systematic overview of the implementation of AI is not available. In this scenario, we aim to present the first evaluation of promising avenues for AI application in the German higher education sector. This report is a part of the preparation for an extensive research project on the use of AI in teaching, research, and administration in German universities, which will focus on the "fairness, accountability, and transparency (FAT)" of machine learning [Link]. To this end, the present report aims to answer the following research question:

> Which technologies and AI systems are already being used in German universities or will play a role in this area in the future?

The present study employs the following methodological triangulation: The first step involves evaluating the relevant literature. In this step, the terms AI, Big Data, and Learning Analytics are introduced briefly. Subsequently, the attributed potentials and challenges are sounded out by deploying AI systems in universities. This is followed by a description of the systems that are in use in other countries. To empirically answer the research question, the documents describing the official digitization strategies of German universities are analyzed, and this analysis is supplemented by conducting expert interviews. The presentation of the methodology is followed by an evaluation of the interviews, discussion of the development of AI at German universities, and our conclusions.

2 University of the future

AI generally deals with the "attempt to develop a system that can independently work on complex problems"[1] (Kirste & Schürholz, 2019, p. 21). A distinction can be made among different levels of AI: Weak AI, Strong AI, and Super Intelligence. While super intelligence surpasses human intelligence and capabilities, strong AI is roughly comparable to human capabilities. Weak AI, by contrast, is focused on solving the problems associated with a certain phenomenon (Kirste & Schürholz, 2019, p. 21). In the current lexicon, the term "AI" almost always refers to weak AI systems.

In addition to the term AI, terms such as machine learning or deep learning appear repeatedly in the literature. The concept of AI was coined in the 1950s, and at that time, it was concerned with "logical representation systems with the help of which simple conclusions could be drawn" (Kirste & Schürholz, 2019, p. 23). In the 1980s, this definition was extended and a subcategory of AI called machine learning was created. Machine learning systems can independently learn from data without being explicitly programmed for it (Adams Becker et al., 2017, p. 46). About 10 years ago, deep learning developed as another branch that led to a renewed and sustained interest in AI. Deep learning involves the use of neural networks that "emulate the network structures of nerve cells" (Kirste & Schürholz, 2019, p. 29) and, thus, facilitate human–machine interaction, for example, in the form of speech recognition (Adams Becker et al., 2017, p. 46).

The application of these methods is made possible, among other things, by the growing availability of databases (Wischmann & Rohde, 2019, p. 100), which creates the scope for far-reaching Big Data[2] analysis. "(…) [A]nalytics generally refers to a set of software tools, machine-learning techniques and algorithms used for capturing, processing, indexing, storing, analysing and visualising data" (Daniel, 2017, p. 1). Within

[1] This and the following quotations from Kirste and Schürholz have been translated from German by the authors.

[2] A number of attributes are generally defined under the term Big Data: "huge in *volume* (…); high in *velocity* (…); diverse in *variety* (…); *exhaustive* in scope (…); fine-grained in *resolution* and uniquely *indexical* in identification; *relational* in nature (…); *flexible*, holding the traits of *extensionality* (…) and *scalability* (…)" (Kitchin, 2014, S. 1f.). For more information, see Kitchin (2014).

the domain of Big Data analysis, three categories can be distinguished: Descriptive, predictive, and prescriptive analytics. Descriptive analytics provides information about the underlying data, visualizes them, and highlight trends, for instance, year-on-year trend in the number of graduates enrolled in a university. Predictive analytics predicts what will happen based on projections made using the current conditions or historical trends. Multiple future scenarios can be drawn depending on the actions of the decision-makers. Prescriptive analytics go one step further and forecasts what should be done to achieve a certain result and why (Attaran, Stark, & Stotler, 2018, p. 171f; Daniel, 2017, p. 3; Daniel, 2015, p. 913ff). Various data can be included in the analysis, such as student data, company data from operative systems, website sample data (e.g., from learning management systems), transaction data, information from social media accounts, or data from mobile devices (Stackowiak, Mantha, & Licht, 2015, p. 1).

AI is already being used in many industries to expand the portfolios of companies, as well as to automate work processes and, thus, increase efficiency (Gabriel, 2019, p. 95ff.). However, such moves are often viewed critically by employees. A recurring concern is that human resources could become redundant. For example, 73% of Americans fear that with the implementation of AI, although some new jobs will be created, a greater number of existing jobs will be lost (Gallup Inc., 2018, p. 13).

Thus far, AI has had only a few points of contact with domains such as education or public administration in Germany, despite good conditions, although there plans and efforts are underway to introduce AI in German universities (e.g., Berens et al., 2018). The slow progress can be ascribed to a lack of resources required to perform Big Data analysis. This applies to the public sector in general and the higher education sector in particular. Especially, the required technical infrastructure has not been expanded, and there is a lack of skilled personnel (Dede, Ho, & Mitros, 2016, p. 1f.; McGuirt, Gagnon, & Meyer, 2015, p. 10; Wirtz, Weyerer & Geyer, 2018). However, these sectors exhibit tremendous potential for process automation and digital learning support (Gabriel, 2019, p. 97). Therefore, the opportunities for and risks of the use of AI at universities are presented in the following section.

2.1 Potential and challenges of Big Data analysis in the higher education sector

In the context of universities, the following goal is pursued through the use of Big Data analysis: "(…) [A] wide range of administrative and operational data gathering processes aimed at assessing institutional performance and progress in order to predict future performance and identif[y] potential issues related to academic programming, research, teaching and learning" (Daniel, 2015, p. 911). AI-based data analysis can be applied in two different areas: Learning analytics and academic analytics.[3] Academic

[3] Daniel, by contrast, differentiates among four possible areas of application for Big Data analysis at universities. In addition to learning and academic analyses, he distinguishes between *institutional* and *information technology analytics* at universities. While *information technology analytics* aims to integrate data from different systems, *institutional analytics* aims to analyze the operational data of universities to help make well-founded decisions at the institutional level (Daniel, 2015, p. 911f.).

analytics supports decision making at the administrative level in terms of research, resource allocation, or management (Daniel, 2015, p. 911f.). However, universities especially see great potential for deploying learning analytics as a part of predictive analytics. Learning analytics is generally thought to refer to the measurement, collection, and analysis of data about learners and their contexts to improve the quality of learning processes and environments (Daniel, 2015, p. 913; Long & Siemen, 2011, p. 34).

This creates potential in various aspects at both the institutional and individual levels. For instance, the use of learning analytics can help one to provide students with performance feedback and learning recommendations by uncovering patterns in their individual learning behaviors. Such individually tailored learning proposals could help optimize learning experiences and the learning process (Daniel, 2015, p. 913; Daniel, 2017, p. 2; Dede, Ho, & Mitros, 2016, p. 3f; Pistilli & Arnold, 2010, p. 23f). In this way, inequalities in learning progress and outcomes can be counteracted, and weak-performing students can be identified and provided the required assistance (Muñoz, Smith, & Patil, 2016, p. 17).

Furthermore, it is possible to identify and support at an early stage the students who are likely to drop out of a course. Meanwhile, information about students' learning behaviors and progress can be fed back to the lecturers so that they can evaluate and adapt the curricula or teaching methods accordingly. This not only creates opportunities to provide feedback about student performance but also about the performance of the institution itself (Arnold & Pistilli, 2010; Attaran, Stark, & Stotler, 2018, p. 173ff; Büching et al., 2019, p. 142ff; Daniel, 2017, p. 2). In this way, analytics should serve to improve student performance and increase graduation rates (Attaran, Stark, & Stotler, 2018, p. 175; Daniel, 2015, p. 913; Yanosky and Arroway, 2015, p. 9).

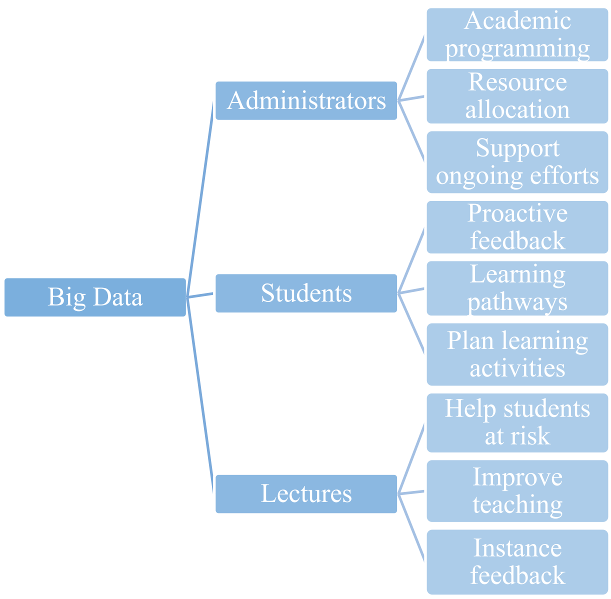

Fig. 1. Key Big Data opportunities for three end-users in higher education (Own illustration adapted from Daniel, 2015, p. 914).

In addition, there are opportunities at the institutional level, in that, appropriate systems can be deployed to optimize resource usage and processes (Yanosky & Arroway, 2015, p. 9). Especially, diagnostics and predictive analytics can help strengthen the bond between students and the university (Sclater, Peasgood, & Mullan, 2016, p. 8) and, in the process, increase graduation rates and strengthen the social commitment of students to the university. This would create economic advantages because it is expensive to train young academics, and the financial resources spent on a student in the event of termination do not yield the desired return. For US universities, the loss of a student means a decrease in income in the form of tuition fees (Ekowo & Palmer, 2016, p. 6). To achieve these objectives, predictive systems should ultimately be seen as a part of a more comprehensive care system:

> *"A predictive model should be part of a prediction-and-response system that (1) makes predictions that would be accurate in the absence of a response and (2) enables a response that renders the prediction incorrect (e.g., to accurately predict that, given a specific intervention, the student will succeed)"* (Dede, Ho, & Mitros, 2016, S. 10).

Nevertheless—and not surprisingly—, the use of Big Data analysis entails some risks as well. The first and foremost is the problem of data protection and data quality (Büching et al., 2019, p. 151; Daniel, 2015, p. 916f.). Digital learning generates large amounts of data. Moreover, students are often mandated to use digital learning platforms, which means that they are required to disclose personal data, regardless of their desire to do so. In addition, students leave their digital footprints in many areas of life, and companies and universities collect and use these data without the students necessarily being aware of such use (boyd & Crawford, 2012, p. 671f.).

Moreover, it is likely that the algorithms themselves generate stereotypes and thus have a discriminatory effect or that the data inherently contain a bias (Attaran, Stark, & Stotler, 2018, p. 176; Büching et al. 2019, p. 152; Ekowo & Palmer, 2017, p. 10f; Muñoz, Smith, & Patil, 2016, p. 6ff). A bias causes distortion within the data, which can be transferred to the outcome. The use of such data can reflect the existing discrimination against individual groups (boyd & Crawford, 2012, p. 668; Muñoz, Smith, & Patil, 2016, p. 8). An example of this is the disadvantage faced by prospective students in an automated admission procedure for admissions because they belong to a population group that is statistically less likely to graduate (Muñoz, Smith, & Patil, 2016, p. 18).

In addition, the available data may not necessary be representative of the entire population. This means, for example, that the success of older students cannot be predicted with a certain level of accuracy because of unavailability of adequate amounts of data (Muñoz, Smith, & Patil, 2016, p. 19). Moreover, it is problematic when input data is considered a valid measurement of a complex issue without first validating the measurement. An example of this pertains to the supplementary factors in the prognosis of study success, such as the external attractiveness of students (Dunkake et al., 2012).

Therefore, in addition to data quality, data interpretation, privacy, and security must always be considered (Ekowo & Palmer, 2017, p. 7ff.). These considerations create the need for transparency and accountability and call for clarification of the intention with which the available data are evaluated (Daniel, 2015, p. 904, 916). In this context, security precautions with regard to data protection and norms and standards for the use of learning analytics at universities are required (Attaran, Stark, & Stotler, 2018, p. 176; Büching et al., 2019, p. 152). This is particularly important in view of the challenge outlined by Daniel:

> *"However, the biggest challenge is no longer whether or not institutions use data but how data is captured, processed, stored, presented and used to make better decisions and how decisions made today are likely to affect tomorrow's outcomes."* (Daniel, 2017, S. 2)

Against this background, Prinsloo and Slade (2017, p. 118) emphasized the need for an ethic of justice and care. The former refers to objective decisions and universal rules for fair and equitable treatment of all participants. The latter refers to reciprocal consideration and consideration of the needs of others in decision making (Botes, 2000, p. 1072). To these ends, they proposed four principles: First, student data must always be viewed in context. Second, there is a need for transparent presentation of practices and a rapid, sensitive, and dynamic response to multidimensional contexts of students, that is, consideration of individual characteristics and social backgrounds of students. Third, with regard to the cost and scalability of applications, one must always ask how moral choices can be made when resources are limited. Fourth, care must be distinguished from pity because the former refers to careful consideration of costs, scalability, and appropriateness of measures, while pity do not recognize the student's autonomy (Prinsloo & Slade, 2017, p. 118ff.).

2.2 Applications of AI systems at universities

Empirical evidence indicates that graduation rates can be increased through the use of early-warning systems (Attaran, Stark, & Stotler, 2018, p. 178; Muñoz, Smith, & Patil, 2016, p. 17). Although the use of learning analytics has a demonstrably positive effect on the success of studies (Sclater & Mullan, 2017, p. 7), in Germany—in contrast to the US, Australia, and Great Britain—learning analytics has rarely been used (Büching et al., 2019, p. 143). Büching et al. presented three concrete perspectives for the use of learning analytics at universities: (1) Personalized learning, (2) automated feedback and counselling, and (3) humanoid robots as assistants in university teaching (Büching et al., 2019, p. 153ff.).

In the area of automated feedback and advice, early-warning systems, also called dropout systems, play a particularly important role in identifying risk students. These systems use study history data to predict which students are at the risk of not successfully completing an examination or even an entire course. These students can then be warned and provided opportunities to work through their deficits. In this way, the success of studies can be improved, and students can be protected from failure (Arnold & Pistilli, 2012; Attaran, Stark, & Stotler, 2018, p. 173, 178). Such systems are increasingly being used in the US (Attaran, Stark, & Stotler, 2018, p. 178; Aulck et al., 2016), for instance, Georgia State University (Ekowo & Palmer, 2016, p. 8ff.) and Purdue University (Arnold & Pistilli, 2012). In Germany, too, such systems are being used in a few cases (e.g., Berens et al., 2018; Wigger, Kemper, & Vorhoff, forthcoming). The early-warning systems developed in Karlsruhe and Wuppertal have prediction accuracy values of up to 85% after the first semester and up to 95% after the third (Wigger, Kemper, & Vorhoff, forthcoming) or the fourth semester (Berens et al., 2018).

Predictive analytics can support personalized learning by supporting not only risk students but also their fellow students with adaptive and individually tailored learning offerings. In this way, the learning process is optimized and accelerated (Attaran, Stark, & Stotler, 2018, p. 175ff; Ekowo & Palmer, 2016, p. 5). Recommendation systems, which propose, for example, enrollment in certain courses by considering personal and academic obligations are among the advisory services offered by universities (Vialardi et al., 2009, 2011). For example, a corresponding system at Open University Australia can identify the learning paths of students and provide performance assessments and learning suggestions in terms of content, as well as predict course results (Adams Becker et al., 2017, p. 39; Sclater, Peasgood, & Mullan, 2016, p. 37).

Virtual tutors in the form of chatbots can be used in various areas, for example, to support learning and to convey and query content (Adams Becker et al., 2017, p. 46f.). Abbasi and Kazi demonstrated in an experimental study that the use of virtual tutoring systems positively influences both content retention and learning outcomes (Abbasi & Kazi, 2014, p. 65).

In the US, for example, administrative processes are already supported by AI systems. Such applications can shape the management of the enrolment process at universities by forecasting the development of student numbers, supporting student retention, or improving financial support programs (Adams Becker et al., 2017, p. 47; Ekowo & Palmer, 2016, p. 6; Sclater, Peasgood, & Mullan, 2016, p. 8). Moreover, it is possible to automate admission procedures by using algorithms (Attaran, Stark, & Stotler, 2018, p. 173; Muñoz, Smith, & Patil, 2016, p. 16), as is already being done in the New York school system (Herold, 2013).

Another potential application of predictive analytics at universities is automated evaluation of examination performance by using so-called robo graders (Adams, 2014; Attaran, Stark, & Stotler, 2018, p. 174). In addition, hybrids of robo graders and detection systems that can predict student performance in the form of grades are being pursued (Kotsiantis, 2012). In teaching, there is the possibility of analyzing which methods are the most effective (Attaran, Stark, & Stotler, 2018, p. 175). Furthermore, research processes can be optimized, for example, by automatically evaluating datasets (Stackowiak, Mantha, & Licht, 2015, p. 6). Finally, research on the (further) development of humanoid robots to support teaching is being conducted (Adams Becker et al., 2017, p. 47). At the Philipps University Marburg, the robot "Pepper" directly interacts with students. Such robots can support teaching by asking quiz questions or by answering questions (Büching et al., 2019, p. 155).

In terms of the future of this domain, the NMC Horizon Report presents key short-, medium-, and long-term trends of technological development at universities identified by an expert panel. One long-term goal is the establishment of an innovative university culture and the expansion of deep learning approaches. Within the next three to five years, the methods for measuring and evaluating learning progress and educational needs will be expanded. This would call for the restructuring of learning spaces by considering mobility and flexibility. In the short term, the expansion or development of blended learning formats, as well as collaborative learning in groups, is in the foreground. In blended learning, the learning environment of the online room is opened. This simplifies access to learning content and improves flexibility. Simultaneously, opportunities are created for the use of multimedia and various other technology offerings (Adams Becker et al., 2017, p. 8ff.).

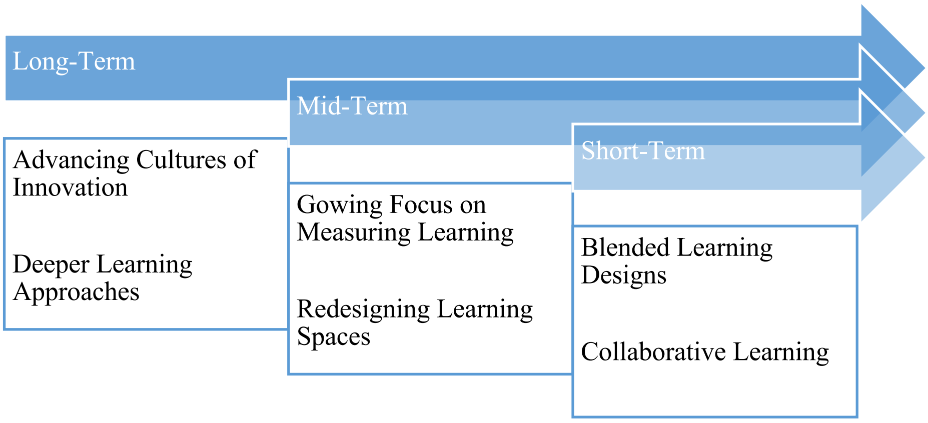

Fig. 2. Key trends for accelerating technology adoption in higher education (Own illustration adapted from Adams Becker et al., 2017, p. 3).

Although various surveys on the use of AI systems in universities have been conducted, especially in the US, as well as in Australia and the UK (Adams Becker et al., 2017; Ekowo & Palmer, 2016; Sclater, Peasgood, & Mullan, 2016), there is no corresponding overview of the German landscape. Therefore, the present study aims to generate an overview of the use of AI systems at German universities and to sound out the opportunities and risks thereof through the use of concrete applications to assess the digital future of German universities.

3 Method

A methodological triangulation was employed to answer the question of which AI systems are in use at German universities or the use of which systems is in the planning stage. The term triangulation refers to the parallel use of different types of data or "the combination of methodologies in the study of the same phenomena" (Denzin, 1970, p. 297). In the present case, official documents outlining the AI and digitization strategies of German universities were first analyzed, and the results were deepened and supplemented with the findings of expert interviews. From the viewpoint of planned replication of the survey, its methodology is described in detail below.

3.1 Document analysis

To obtain an initial overview of the concrete applications of AI at German universities, their official digitization and AI strategies were researched preliminarily. In this step, all 87 German public universities were identified using “Hochschulkompass” (an information portal of German Rectors' Conference, HRK). Subsequently, a comprehensive web research of currently valid strategies was carried out. To this end, first, a search query was executed on the official homepage of the universities with the search string “*AI Strategy*.” In addition, a supplementary web search consisting of the name of the university and the search term mentioned was added. The results suggested that there official AI strategies of universities are not publicly available. Then, the research was supplemented in the second step by searching for the following terms: *Digitization strategy, development plan, IT strategy, and eLearning strategy*. With regard to development plans, these are not agreements in terms of objectives between universities and state governments but independently formulated university development plans or structural and developmental plans of institutions. In addition, some constraints were imposed on the search. These included official, documented, and currently valid strategies with a minimum validity up to and including August 2019. In addition, only freely available documents were considered; internal university papers were not analyzed, and strategies of individual departments were neglected. Thereafter, all relevant documents were archived for subsequent analysis. A total of N = 79 documents originating from 57 universities were archived.

Coding. A quantitative content analysis of the archived documents was performed. The formally coded categories were a consecutive number, number assigned to the university, university name, and document type. A full text search of the relevant terms was carried out to obtain information on the strategies of the universities with regard to the use of AI systems. All 79 documents were scanned for the search terms *artificial*, AI, auto*, robo*, machine*, machine learning*, and *algorithm**. During identification of one or more of the terms, the relevant text passage was read to open up the context of the term. For example, the term “auto*” may include “autonomy” and may refer, for example, to the competencies of the university. However, the term is only relevant for analysis in the sense of automation of processes or in the sense of autonomous systems. The occurrence of a term was therefore only coded if a technical reference or a reference to AI was recognizable. If no connection to the research interest defined by the research question was identified, the use of the term was ignored. Given the different scopes of the archived documents, only the occurrence of a term was coded as 1 or its absence as 0. The occurrence frequency was not considered. In addition, examples of the use of terms in the context of an embedded sentence were recorded in a further variable.

Evaluation. Within the scope of the quantitative content analysis, the different document types were first examined. No AI strategies were found that explicitly referred to themselves as such. Unlike the German Federal Government (Federal Government, 2018) and a few Federal States such as Hesse (Pfannes et al., 2018), Schleswig-Holstein

(Prime Minister of Schleswig-Holstein, 2019), Baden-Württemberg (2019), and Bremen (2019), universities have not yet started to consider the importance of AI for their own field of action from a strategic viewpoint. At the very least, however, relevant considerations have not yet led to a result that could be laid down in a programmatic paper. However, 10 digitization strategies, 14 IT strategies, 7 eLearning strategies, and 48 university development plans or structural plans from a total of 57 universities were identified and collected. All documents were included in the subsequent keyword search. In half of the 79 documents, at least one of the search terms was found (49.4%). Most frequently, that is, in 28 documents, the terms automation and autonomous systems were the subject. "Artificial intelligence", however, was specifically mentioned only in 10 articles, among which two used the term "AI" (see Table 1).

Table 1. Term count in document analysis.[4]

	artificial*	AI	auto*	Robo*	Maschinell*	machine learning	algorithm*
Number of contributions in which the term occurs	10	2	28	14	10	3	8
N = 79							

With reference to the document types, if the development plans are neglected, which never deal exclusively with the digitization of higher education institutions but usually treat the digitization rather marginally, only 16 of the 57 German universities have officially adopted currently valid strategies that explicitly deal with the technical development of higher education institutions and are included in the analysis. Moreover, it is clear that the use of AI has rarely been addressed directly. If the terms are mentioned, they are usually contained in teaching content related to AI or AI research papers but not in plans for concrete application of the corresponding systems in everyday university life.

Based on the documents analyzed in this study, it can be assumed that the topic of AI at higher education institutions is not yet a subject of strategic planning at German universities. Rather, one can assume that the majority of universities continue to be occupied with the digitization of internal processes, meaning a large part of their data remains available in analog form. For this reason alone, the idea of using Big Data Analytics and Machine Learning at many locations is not immediately obvious. Insofar

[4] The search term "maschinell*" is the German translation of the term "machine", and it was included in the analysis in the context of machine learning.

as such technologies are introduced at German universities, it would be a result of strategic decisions at the management level (top down) or on the behest of individual entrepreneurs, chairs, or institutes (bottom up). Moreover, it can be assumed that the pioneers of AI usage in German universities usually act in isolation from and often without knowledge of each other.

To confirm this assumption made based on the results of the document analysis, expert interviews were conducted to obtain information about the application areas of AI systems or plans for the use of AI systems in the future in German universities.

3.2 Expert interviews

To answer the research question and deepen the results of the document analysis, concrete AI systems in use or projects planned in the future in the German higher education sector will be named in the following. These findings are based on guideline-supported expert interviews conducted over the telephone.

Interview guide. To ensure adequate structuring, control, and comparability of the verbal data, guideline-based expert interviews were conducted (Misoch, 2014, p. 65f.). The first phase is an information phase, in which the objectives of the study are explained, further use of the statements is explained, and consent is obtained for the recording the interview. Subsequently, in a short introductory phase, a thematic introduction is given, and the definition of the term "artificial intelligence" is sought from the interviewee. In the main phase, the previously developed thematic complexes are addressed, and finally, in the last phase, additional information is requested (Misoch, 2014, p. 68ff.).

For the main phase, the research question presented was first operationalized conceptually and then instrumentally (Kaiser, 2014, p. 56). In the first step, the dimensions underlying the research question were worked out. In addition to the initial scenario, the personal field of action of the interviewee, future vision, opportunities and risks, and international vision were defined as the main categories. In the second step, these dimensions were transformed into complex questions before explicit interview questions were formulated from these complex questions (Kaiser, 2014, p. 56). Within the framework of instrumental operationalization, different types of questions were asked, such as introductory questions, as well as direct, specificative, and interpretative questions (Kaiser, 2014, p. 63ff.).

Sample. To find an adequate number of respondents who can provide competent information on the underlying question, non-university research institutions and companies dealing with the use of AI at universities were considered in addition to the universities themselves. With the help of the AI map created by *Platform for Artificial Intelligence* (acatech, 2019), which is funded by the Federal Ministry of Education and Research, listed AI research institutions and applications of AI in the educational and administrative areas of universities were identified. To this end, a filter based on the application fields "*education*" and "*administration and security"* was applied. In addition, projects at four major German research institutes (Fraunhofer-Gesellschaft, Helmholtz-Gemeinschaft, Leibniz-Gemeinschaft, and Max-Planck-Gesellschaft), if available, and relevant articles providing information on concrete applications were considered.

After respondent selection, 27 people were contacted by means of a personalized e-mail in the first wave. Of them, 12 signaled their willingness to be interviewed. In the second wave, an additional five people were contacted to be recruited according to the snowball principle. A total of N = 13 telephonic interviews were conducted. Eight of the interviewees were employees of universities, four were employees of private companies, and one was an employee of a non-university research institution. One interviewee was female, and the rest were male (see Appendix A).

Interviews. The telephonic interviews were conducted between August 6, 2019, and September 19, 2019. The average duration of the interviews was 31:20 min. In all the interviews, the principle of openness (e.g., Misoch, 2014, p. 66ff.) was considered in the sense of the quality criteria of qualitative research. The guideline was used as a point of reference so that the interviewees could be dealt with situatively, new aspects could be taken into account, and relevant remarks could be further deepened. Twelve of the 13 interviews were recorded on a tape with the explicit consent of the interviewees, so that this could be used for the subsequent recording. One of the interviewees did not consent to a tape recording, so in this case, only the notes taken during the interview were used in further stages. All other call logs were created on the basis of the tape recordings. The statements of the interviewees were paraphrased and documented on a protocol sheet—complete transcripts of the interviews not prepared because of time constraints. Subsequently, the protocol sheets were sent to the interviewees for review and approval upon request. Proposed amendments to clarify or correct the statements were incorporated.

Evaluation. For subsequent evaluation of the expert interviews, a qualitative content analysis according to Mayring (2015; Mayring & Fenzel, 2019) and the technique of content-structuring qualitative content analysis (Kuckartz, 2016, p. 97 ff.) were used. In this respect, the evaluation was performed in a strictly rule-based way (Mayring & Fenzel, 2019, p. 636). According to the systematics of the content analysis, the analysis unit is first defined. The coding unit, that is, the minimum of a category's attributable scope, is defined as a single word, the context unit as an entire section or an entire answer to a question posed. The evaluation unit is all the recorded material (Mayring & Fenzel, 2019, p. 636).

For the category system, the main categories derived deductively from the question complexes were first used, in addition to some subcategories formed using the interview guide; these were then supplemented inductively based on the material from the first three interviews. All relevant text passages of the material were marked and assigned to the existing categories. If an answer could not be clearly assigned to any of the previously defined subcategories, it was first sorted into the main categories. Subsequently, all statements assigned to a category were noted in a document, and further inductive subcategories were formed based on them. Each interview was analyzed thrice until no new category could be developed. This resulted in a total of four main categories and 19 subcategories, which were listed in a coding guideline based on Ulich et al. (1985). The coding guideline contains the code and the name of the category, a stipulative definition, and an anchor example and, in the case of ambiguities in the assignment to a category, a coding rule (see Appendix B).

To ensure intra-code reliability, which can be regarded the reliability measure of the evaluation (Mayring & Fenzel, 2019, p. 636), a random sample of three interviews was coded once again without considering the previous category assignments. The results were extremely satisfactory, in that the statements were assigned to identical categories both times. In the context of inter-coder reliability, a second independent coder coded a random sample of three interviews. The coder match was calculated on this basis. Therefore, each coding was considered one coding unit. A match was coded by considering a tolerance threshold[5] in the event that both coders assigned the same category. This procedure was performed for all codings of coders 1 and 2. This means that identical text passages were nevertheless counted as two coding units (Kuckartz, 2016, p. 215). Subsequently, the percentage of agreement and the degree of agreement Kappa were calculated for the individual interviews. This calculation helped determine the percentage share of matches in the total number of codings (p0) and the probability of random matches (pE), as well as to normalize this difference against the expected frequency of random non-matches (cf. Higgins & Deeks, 2008, p. 155). The total inter-code reliability was obtained from the average correspondence for all three protocols (see Appendix C). An average agreement percentage of 78.5% and a degree of agreement of Kappa = 0.77 indicated that an "excellent agreement" was reached (Higgins & Deeks, 2008, p. 155).

In addition, following the consensual coding (Hopf & Schmidt, 1993; Kuckartz, 2016, p. 105), in the event of a lack of agreement, the corresponding text passages were discussed, and adequate coding rules were added to the category system.

In the next step, coding was carried out by making colored markings in the entire material, and the codings were assigned to the corresponding categories in tabular form, whereby the person to whom a statement is to be assigned was noted anonymously behind the statement. Based on Kuckartz (2016, p. 111ff.), the paraphrased statements were then summarized and generalized. Redundancies were highlighted in this phase so that the results of the relevant categories could be summarized, interpreted, and discussed.

4 Results

In this section, the existing applications of AI at German universities and the intentions underlying these applications are presented. The opportunities and risks associated with the use of AI systems are then sounded out before an international comparison is pre-

[5] The tolerance threshold for the correspondence of the individual codes is 90%. In concrete terms, this means that a code is considered identical even if the same text passage is coded in the core but the segment boundaries are different, for example, individual words are coded by one of the coders but not by the other (Kuckartz, 2016, p. 213f.).

sented in which the views of the experts surveyed on the state of planning and expansion in Germany relative to those in relevant comparable countries are outlined. Finally, with a focus on the future, our aim is to perform a well-founded assessment of the future development of AI applications in German universities.

4.1 Which AI-systems are already in use at German universities?

With regard to existing applications of AI at German universities, various systems and application areas can be differentiated, which can ultimately be assigned to the areas of learning analytics and predictive analytics. For example, student dropout and early-warning systems based on predictive analytics are already in use at University of Wuppertal, Technical University of Deggendorf, Karlsruhe University of Applied Sciences, and Karlsruhe Institute of Technology. These systems are used to predict potential dropouts and the success of students in their studies. According to one interviewee, the funding line "*Study Success and Drop out*" (BMBF, 2016) of the Federal Ministry of Education and Research is of particular importance. In addition to a project at the University of Wuppertal, the program supports projects at University of Duisburg-Essen, European University of Flensburg, and a joint project between Eberhard Karls University of Tübingen and University of Stuttgart. In addition, there is another project of IZA-Forschungsinstitut zur Zukunft der Arbeit GmbH, which has been completed.

According to the experts we interviewed, AI systems are also used to support teaching. Chatbots in the form of virtual tutors are in use at the Georg-August-University Göttingen and the Technical University of Deggendorf, which, similar to human tutors, can answer questions about course content. According to one of the interviewees, adaptive techniques are used in the field of blended learning to provide individual learning recommendations to students. In this way, both the teaching and learning processes are supported. The INTUITEL project under the direction of Professor Peter A. Henning of Karlsruhe University of Applied Sciences is pursuing efforts along these lines. AI methods are used in the INTUITEL project to analyze learning paths and, with the help of an intelligent tutor, develop recommendations about the learning content that a student should focus on.

In addition, teaching at German universities can be supported by other AI-systems. The development of so-called robo graders for automatic correction of short text answers is underway at Technical University of Deggendorf, even though the experts surveyed by us knew that these are not yet in use at German universities. In addition, for example, international students at Karlsruhe Institute of Technology are supported by automatic translation of lecture content. Humanoid robots are used in the H.E.A.R.T (Humanoid Emotional Assistant Robots in Teaching) project at Philipps University in Marburg with the aim of better supporting the lecturers classes.[6] The robots used can, for example, ask quiz questions or go into consultation hours with students.

[6] As far as the use of humanoid robots is concerned, the expert who we consulted explicitly did not speak of an artificially intelligent system because the robot can only act in the manner that it is explicitly taught or programmed to act.

In addition, the university administration uses AI systems for routine activities. According to one interviewee, the use of a chatbot is already planned at Technical University of Munich and Darmstadt University of Applied Sciences. This chatbot will advise students on their choice of subject and answer FAQs (Frequently Asked Questions) in this regard. According to an interviewee, a chatbot was used at Technical University of Berlin to answer questions about courses and modules (e.g., regarding rooms, dates, and subject areas).

Nevertheless, only a few systems are being used within university administrations. According to expert opinions, chatbots used in municipal administrations to answer FAQs can be adapted for use in the higher education sector. In addition, intelligent appointment and administration modules can be used to coordinate the work of employees in the event of illness, but according to the interviewees, such modules have not been used in German universities thus far. A similar picture emerges for staff selection and executive training. According to an expert, these processes are already supported by AI applications in the private sector but universities have not adopted them yet. University of Potsdam, however, has developed an AI system that can be used as a "universal problem solver", for example to create timetables by considering the availability of rooms, time slots, and lecturers.

While chatbots usually use machine speech recognition to understand the questioner's intentions and provide an appropriate answer, other systems, such as a dropout detector, require study history data and administrative student data. These are collected in accordance with § 3 of the Hochschulstatistikgesetz. In addition, some systems work with the contents of and recorded activities from learning management systems (e.g., Moodle or Ilias) to provide individual learning recommendations. Moreover, tests are occasionally carried out in advance to determine, for instance, a student's level of knowledge or to glean individual information about the student, such as the type of learner (auditory vs. visual). The information obtained in this way serves as input data.

Against the background of the previously conducted document analysis, one may ask who are the pioneers of the use of AI systems in German universities, if not the university management. Our interviews provide a clear answer to this question. It should be noted that at this point, according to our respondents, the initiatives have emerged bottom-up in (almost) all cases they have reported on. As a rule, individual scientists or chairs develop ideas for implementing AI applications on the basis of project proposals and calls for proposals. In one case, as one of the experts reported, a company approached universities. According to the respondents, university managers and administrations have displayed poor interest toward AI systems thus far.

4.2 What are the challenges posed by the use of AI-systems at universities?

The use of AI systems remains controversial, especially in Germany. Almost all interviewees described not only the potential that such systems can or should offer but also the various risks associated with the use of AI systems, which are often related especially to data protection. As one of the experts pointed out, this is a highly polarized debate: While AI is seen as a "do-gooder" on the one hand, Orwellian dystopias are projected on the other hand.

What is the potential for artificial intelligence in the education and higher education sector? The underlying intentions behind the use of AI systems are just as diverse as the applications themselves. According to the experts, these range from improving the quality of learning to optimizing and accelerating processes. On the one hand, an important role is ascribed to individualization. According to the experts, for example, access to education and knowledge should be simplified, and the learning process should be made more interesting. According to the various interviewees, this is made possible on the one hand by adaptive reactions of automated systems that adapt to the individual needs of the students and on the other hand by simplified access; many systems offer "easy online access" by operating a new communication channel. In addition, the applications offer real-time consulting by being available "round the clock", even, and especially, when lecturers are not available. In addition, there is a lower-threshold barrier because, according to one interviewee, communication with a chatbot is freer than communication with a lecturer.

On the other hand, from the experts' point of view, it should be possible to explain why certain patterns in learning behaviors lead to higher or lower levels of success. According to the interviewees, the presentation of warnings in the form of emails should reduce the number of failures and non-appearances in examinations. The corresponding indications of risks in the course of the study should then be mirrored, and adjustments should be made. In addition, the interviewees emphasized that performance feedback to both students and lecturers on commitment and knowledge growth would be possible. Simultaneously, the interviewees saw the potential for teaching with the help of supporting systems and increased opportunities for direct interaction between lecturers and students, which would create more room for answering complex questions. Similarly, the acceleration of administrative processes was pointed out by the experts because routine activities, such as the answering of relatively simple, recurring questions, would be done by automated systems.

What are the possible dangers of using AI systems? Despite the many potential advantages arising from the use of AI systems according to the interviewed experts, they expressed numerous concerns regarding the use of AI systems. The risk of data misuse was the most important concern. Each AI system needs input data to generate answers, recognize patterns, or make predictions. Often, these data are not explicitly collected for use in AI systems. Thus, common questions pertaining to data protection and data misuse play a special role here. In this respect, the interviewees believed that adequate and sensitive handling of the data is particularly important. Especially data protection officers should always be involved in the development of automated systems.

Job substitution is another concern which, according to the experts, is often expressed by the population. Such a development would be fatal, especially in the case of universities that are notoriously understaffed. Many of the interviewees emphasized that the systems should be used in a supportive rather than a substitutive manner. However, according to the experts, it seems necessary to react to the developments of the times and provide further training to employees so that they can use the new qualifications to play new roles.

Moreover, according to one of the experts, there are frequent concerns expressed at conferences that the automated prediction of study (failure) success and performance feedback could negatively influence students' motivation. It is conceivable, for example, that the sending of emails with warnings of imminent failure would unsettle a student to such an extent that he or she would terminate his or her studies prematurely. This goes hand in hand with an expert's demand that the validity of predictions must be guaranteed so that reliable explanations can be provided. In this context, the importance of the explanatory nature of the systems was repeatedly addressed by the experts we interviewed. They demanded that the objective of an application and the basis for decision-making, for example, be clarified at the outset. Especially in critical scenarios, this is elementary for increasing acceptance of the systems. In addition, no infamous black box should be created that would make it impossible to understand the decision-making process and the processes behind it; instead, the system should be able to explain the decisions in a better way than before.

Ethical questions were raised repeatedly during the interviews. On the one hand, the use of large amounts of data entails not only the risk of data misuse but also the risk that the supplied data itself could be discriminatory, meaning that no fair predictions or decisions could be made. Furthermore, some experts stressed that not everything that is technically possible actually makes sense. Therefore, it had to be decided on a case-by-case basis whether the execution of certain tasks by an AI system was actually desirable. According to one of the interviewees, the ethics of AI are currently strongly influenced by China and the US, who are the pioneers in this field. However, there is a need to create a European AI with incorporated European ethical values, as requested by some experts, including fairness, transparency, and trustworthiness, which are becoming increasingly important. Similarly, concerns have been expressed that computers could make momentous decisions in the future, such as whether a prospective student will be accepted to a university.

4.3 Can artificial intelligence become an important element of the education system in future years?

With regard to the future development of AI at German universities, the experts indicated potential in various areas. In addition to learning analytics, chatbots in particular are increasingly being discussed in Germany. The majority of interviewees expect that the use of chatbots, for example, to support teaching as virtual tutors or to answer organizational questions, will become established at the administrative level in the near future. No more restrictions are seen in these areas of application. According to the experts, in addition to teaching, work is being conducted on the use of chatbots in the administrative sector; such chatbots will be capable of answering service requests or inquiries from students to the secretariat. In the opinion of the discussion partners, expansion of the applications described above is already being planned. The corresponding systems should therefore be made available to other departments and universities in the future or be usable in several languages. However, even the use of robo graders was not excluded by one of the experts, for example, to support research.

In the areas of learning analytics and eLearning, the experts indicated further potential, especially in diagnostics and performance feedback, as well as in individual learning support. This would also make it possible to improve the quality of teaching in higher education. Nevertheless, the costs and benefits, as well as the risks that can arise from the use of AI, should always be carefully weighed and considered. In this context, one of the experts predicted that only the systems that usher real progress will prevail.

According to the interviewees, other countries are already one step ahead of Germany in these areas in particular. The US and China are often cited as the pioneers of AI. Applications in the area of learning analytics for learning support or performance feedback are more common in Scandinavia than in Germany. In China, humanoid robots that take control of classrooms, with the possibility for a human to intervene, are in use already. According to the experts, procedures for predicting the final grades of students are already in use in the state of Texas. Robo graders are being used in some countries for automatic correction of free text answers, according to the experts.

With regard to the time horizon of the extensive use of AI applications in Germany, the opinions of the experts differed. While some assumed that within the next five years, a large part of administrative and organizational questions will be answered by automated systems and that sufficient digital data is already available for the development of mode advanced systems, others predicted that the university landscape will change very slowly and that the widespread use of AI-based technical systems could take decades. At the same time, Professor Henning of Karlsruhe University of Applied Sciences warned that there will be great disappointment because not everything that can be imagined and promised, be implemented.[7]

The majority of experts regarded Germany as lagging behind in a worldwide comparison. However, one of the interviewees[8] emphasized that Germany has a lot to show in the field of AI and can keep up with other countries. In a European comparison, however, Germany, together with Great Britain and France, is well positioned. Basically, various experts cited data protection restrictions and obstacles to the innovation process as reasons for Germany's comparatively slow progress. The latter refers to the fact that the process for project funding is considered very lengthy by the interviewees and that often only small amounts of money are available. However, weak awareness of the possibilities of AI among those in responsible positions in the education sector was also identified as a reason for the sluggish development of AI in Germany. According to an expert's assessment, people in Germany are considerably more concerned with the risks associated with innovations, and therefore, progress is slow. However, other experts saw one advantage in this: A slower pace aids the development of a more sophisticated approach and leaves room to consider which applications are actually desirable and which ones are not.

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[7] The information given here comes from the expert interview with Prof. Dr. Peter A. Henning from Karlsruhe University of Applied Sciences.

[8] see reference 7.

5 Discussion and Limitations

Based on the results of the document analysis and the statements from the expert interviews, it is clear that initiatives for the application of AI in Germany are driven from the bottom-up. In the documents analyzed, almost no evidence could be found for the use of automated systems in the higher education sector. Instead, strategic considerations continue to focus on strategies for digitizing simple (mostly administrative) processes. These findings indicate that the managements of German universities do not see any necessity for the use of AI or that the prerequisites are not given. This impression was confirmed by the statements of the experts. All existing applications were developed on the initiative of individual chairs, scientists, or private companies.

This may be an indication of why, according to the majority of experts, Germany lags in an international comparison of the application of AI. Although the Federal Government published an official AI strategy in 2018 (Federal Government, 2018), the desire to generate the corresponding innovations does not yet seem to have reached the universities. Moreover, a lack of infrastructure in the form of limited financial resources (Dede, Ho, & Mitros, 2016, p. 1f; McGuirt, Gagnon, & Meyer, 2015, p. 10) was mentioned by the experts as an obstacle to the technological renewal of universities through AI.

Thus far, the initiatives of individual scientists and companies in Germany have produced some results. An international comparison shows that German universities can demonstrate AI applications in the areas of personalized learning, automated feedback and counseling, and assistance by means of humanoid robots (Büching et al., 2019, p. 153ff.). An expansion of the use of chatbots to respond to information and service questions or in the form of virtual tutors is conceivable in the medium term on the basis of successful pilot projects. The same applies to automated feedback systems to support and individualize the learning process. The increased use of learning analytics at German universities is aimed at accelerating processes and ultimately increasing academic success. However, it should be emphasized at this point that predictive analytics especially serves to forecast the success of studies, for example, but the desired success cannot be achieved without a subsequent reaction (Dede, Ho, & Mitros, 2016, p. 10).

In addition, the expert discussions suggested that German universities are making progress in the field of learning analytics, but academic analytics has not been used yet. This refers to decision support at the administrative level in higher education institutions (Daniel, 2015, p. 911f.). Administration processes have rarely been supported with automated systems thus far. Only chatbots to answer organizational questions have been used occasionally.

Meanwhile, ethical issues are coming to the fore in the development of AI systems. Experts stressed on particular aspects pertaining to the explainability of applications and called for sufficient transparency in decision-making procedures, data basis, and purpose of the system (Daniel, 2015, p. 916). In addition, there is the risk of discrimination through data and algorithms if the data quality and the procedures used do not consider the aspect of fairness (Prinsloo & Slade, 2017, p. 118).

Owing to differences in values and mentalities, the demands for fairness, transparency, and accountability of technology play significant roles, especially in Europe.

Even though countries such as the US are a few years ahead of Central Europe in the development and application of predictive analytics, experts see this “weakness” as an opportunity: On the one hand, time is available to think carefully about which systems can actually provide an advantage in the German higher education system and are therefore desirable at all. On the other hand, room is available for consideration as to how the development and use of AI applications should be specifically designed so that “European values” can be incorporated, and the demands for fairness, transparency, and accountability of technology can be implemented. Remarkably, the assessments of the experts interviewed by us revealed an attitude toward the promises of AI that can also be found in the social science literature critical of technology: “Just because it is accessible does not make it ethical” (boyd & Crawford, 2012, p. 671).

If the German federal government wants to implement its goal of “making Germany and Europe a leading AI location” (Federal Government, 2018, p. 8, translated by the authors), strategic planning is required in all areas of life. If the use of AI applications at German universities is desired, the provision of appropriate resources is necessary.

Owing to the initiatives of the researchers, the focus of emerging AI applications is mostly on their own areas work within the universities. Dropout systems or virtual tutors, for example, are often only used by individual departments, and as a result, not all students at a university can access these systems. It seems unrealistic that in the foreseeable future, German higher education institutions will adopt a uniform approach (be it application or ostracism) toward AI systems because there are no recognizable approaches to coordination and coordination among higher education managers or at the political level. In the medium term, this suggests that the use of technical systems with AI could become a relevant field of university competition in which the aim would be to seek comparative advantages or avoid disadvantages (e.g., through loss of reputation) (Marcinkowski et al., 2019).

Limitations. In case of the present study, indifferent information was used to some extent in relation to document analysis. While some universities do not have any official documents with current validity that provide information on the progress of digitization, others have formulated official digitization or eLearning strategies that did not yield any meaningful conclusions on specific AI applications.

With regard to the expert interviews, interviewees could not be recruited from every potential application area of AI in higher education institutions. Further analysis of administrative applications would therefore be useful. Moreover, the sampling and the guidelines developed for the investigation were not exhaustive. The guideline-based expert interviews were conducted to obtain an initial overview of the field of AI in German universities. It is important to observe future developments. Furthermore, it became clear during the interviews that many universities and institutes have little insight into what is already being planned or implemented in projects at other locations. Cross-location development of AI systems for the higher education sector has not occurred thus far.

6 Bottom line

In summary, it can be said that the use of AI at German universities is largely in its infancy. The planning required for nationwide deployment of AI does not seem to be in sight yet. Nevertheless, individual scientists and chairs are already making decisive progress. Various systems that are usually specialized for discrete areas are already in use, and they can be divided into various areas of application: On the one hand, learning-analytics-based support systems for students are used to increase learning success. Blended learning methods are used to individualize learning contents and provide personal learning support. In addition, virtual tutors or systems for the automatic translation of lecture contents are in use. On the other hand, predictive analytics in the form of dropout and early-warning systems are used to predict the course and success of studies. On these bases, warnings can be sent to students in the form of emails.

In addition, support systems for teaching and instructors are used to relieve instructors of everyday routine tasks. Such systems can provide advice and support to students by using speech recognition software. Moreover, humanoid robots are being used to support teaching. In addition, robo graders are already being researched, although they have not been officially used yet.

In university administration, support systems are occasionally used, which should help relieve the staff of routine tasks. For instance, chatbots are used to provide information on courses and modules or the choice of subject. It is expected that for the foreseeable future, new systems based on learning analytics and chatbots will be developed.

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Appendix

Appendix A – Interview List

No.	Date	Duration (min)	Gender	Institution
1	08/06/19	24:18	Male	University
2	08/06/19	38:17	Male	University
3	08/07/19	27:22	Male	Technical University
4	08/07/19	22:46	Male	Private Company
5	08/12/19	41:15	Male	Private Company
6	08/12/19	41:18	Male	University of Applied Sciences
7	08/12/19	31:41	Male	Technical University
8	08/12/19	28:03	Male	University
9	08/14/19	47:24	Male	University
10	08/14/19	22:47	Male	Private Company
11	08/15/19	27:54	Male	University
12	08/19/19	38:58	Male	Private Company
13	09/19/19	28:20	Female	Non-university Research Institution

Appendix B – Coding Scheme

Code	Kategorienbezeichnung	Definition	Ankerbeispiel	Codierregeln
A	**Anwendungen**	Informationen über aktuelle Anwendungen/Projekte, sowie definitorische Begriffsgrundlagen, Ziel des Projektes & Drahtzieher/Ideengeber		
A1	Begriff	Verwendeter Arbeitsbegriff in Bezug auf das Projekt – z. B. Künstliche Intelligenz, Machine Learning, Neuronale Netze	- „Also ich mag es immer ganz gerne über Machine Learning zu sprechen (…)“ (I1)	
A2	Begriffsdefinitionen	Inhaltliches Verständnis des verwendeten Begriffs, definitorische Erklärung	- „Sondern es geht letztendlich darum, dass wir ähnlich wie bei einer Regressionsanalyse (..) mit gelabelten Daten Merkmale finden, die etwas erklären.“ (I1)	
A3	Aktuelle Projekte/Anwendungen	Name der Anwendung, Einordnung in Anwendungsbereiche – z. B. Chatbot, Robotik	- „Wir prognostizieren Studienabbrüche anhand von administrativen Daten, mittels Machine Learning.“ (I1)	
A4	Funktionsweise der Anwendung	Informationen über die Funktions- und Nutzungsweise der Anwendung	- „Die Methoden der künstlichen Intelligenz, dass heißt die Spracherkennung, die wir dafür nutzen, die basiert auf einem Trainingsdatensatz (…). Mit denen wir trainiert haben, dass das Ole-System die Texteingaben der Studierenden erkennt und entsprechend (…) den Nutzungsintentionen zuordnet. Und aufbauend auf diesen Nutzungsintentionen kann dann eine Antwort generiert werden.“ (I11)	Gemeint ist lediglich die inhaltliche Funktionsweise, technische Erläuterungen folgen in Kategorie A5

A5	Technische Verfahren	Technische Funktionsweise der Anwendungen, sowie angewendete (technische) Verfahren	-	„Und dann wenden wir unsere Verfahren darauf an, ein neuronales Netz und einen Entscheidungsbaum und auch eine Regression und bündeln das ganze nachher nochmal über ein Boosting (…)“ (I1)	
A6	Daten	Verwendete Datengrundlage auf Basis dessen das System arbeitet/analysiert/berechnet etc.	-	„Wir nehmen (..) die Daten, die nach §3 Hochschulstatistikgesetz sowieso erhoben werden müssen – also sprich die administrativen.“ (I1)	
A7	Intention	Benefit, den die Anwendung für Nutzer generieren soll, Ziel der Anwendung	-	„Das heißt er (..) soll Fragen beantworten, die Studierende haben, die Lernbezogen sind. (…). Es ist ein ergänzendes System und zwar genau dann, wenn die Dozierenden oder Tutorinnen und Tutoren eben nicht zur Verfügung stehen.“ (I11)	
A8	Initiator	Drahtzieher und Ideengeber des Projekts bzw. der Anwendung	-	„Ja, das [die Initiative] kam von uns aus beziehungsweise von mir aus.“ (I8)	
A9	Zukünftige Projekte	Zukünftige Anwendungen oder Projekte, die bereits in Planung sind sowie Weiterentwicklung bestehender Anwendungen/ Projekte	-	„Ich arbeite noch an weiteren auch tutorenbasierten Systemen, die im Prinzip das Ganze auf andere Fachbereiche übertragen und dort dann auf die Spezifika eingehen.“ (I11)	
B	**Chancen & Risiken**	Subjektiv gesehene Potenziale und Hindernisse durch den Einsatz von künstlich intelligenten Systemen an Hochschulen			
B1	Chancen & Potenziale	Vorteile, die der Einsatz von künstlicher Intelligenz an Hochschulen bewirken kann	-	„Also für Studierende denke ich, dass man beispielsweise eine bessere Unterstützung (..) in den eigentlichen Lernprozessen bekommen kann. Das heißt ein individualisierteres Lernen kann ermöglicht werden.“ (I11)	Chancen & Potenziale können sich für Studierende & Mitarbeiter (d. h. Lehrende oder Verwaltungsmitarbeiter) als auch für die Gesellschaft ergeben

B2	Risiken, Hindernisse & Konflikte	Nachteile oder Konflikte, die durch den Einsatz von künstlicher Intelligenz an Hochschulen entstehen können	-	„Weiterhin muss man sich natürlich auch ethische Fragen stellen; ob das Ganze (..) entsprechend auch den eigenen Vorstellungen entspricht. Das heißt ein wesentlicher Punkt ist: Möchte man, dass manche Aufgaben in der universitären Hochschullehre durch Systeme voll automatisch abgedeckt werden (…).“ (I11)	Gesehene Gefahren und Risiken oder drohende Konflikte können sich sowohl auf die Funktionsweise des Systems, als auch auf das Output oder die Reaktion auf selbiges beziehen, sowie generelle Bedenken gegenüber dem Einsatz von KI, z. B. ethischer Art
B3	Gegenmaßnahmen	Mögliche Wege/Maßnahmen den befürchteten Konflikten entgegenzuwirken	-	„Das heißt Verlässlichkeit ist ein essentieller Punkt, in dem wir bei unserem (..) Projekt auch verstärkt drauf geachtet haben; Dass da eben viele qualitätssichernde Maßnahmen im Hintergrund ablaufen mit denen wir wirklich versuchen diese Verlässlichkeit sicherzustellen.“ (I11)	Gegenmaßnahmen, die möglichen Konflikten im Zusammenhang mit dem Einsatz von KI entgegenwirken können, können sowohl tatsächlich im System berücksichtigt werden, als auch lediglich vom Befragten als wünschenswert geäußert werden
B4	Reaktionen von Nutzern/Betroffenen	Ausmaß der Akzeptanz von Nutzern der Anwendung	-	„Also prinzipiell ist die Akzeptanz von solchen Systemen, das haben wir jetzt in mehreren Studien (…) schon analysiert, meines Erachtens nach eher eigentlich relativ hoch.“ (I11)	
B5	Abwägung KI an Hochschulen	Abwägung von Nutzen und Kosten durch den Einsatz von KI an Hochschulen	-	„Man muss sich im Einzelfall damit auseinandersetzen, ob es [der Einsatz von KI] in Einzelfällen Sinn ergibt oder nicht.“ (I11)	Gemeint ist, ob der Interviewpartner zu einem Entschluss kommt, ob der Einsatz von KI nach Abwägung der Chancen und Risiken wünschenswert ist oder nicht
C	**Zukunftsvision**	Subjektive Vorstellungen über zukünftige Entwicklungen von			

		künstlich intelligenten Systemen an deutschen Hochschulen			
C1	Wunsch zukünftiger Entwicklungen	Wunschvorstellung technologischer Innovationen an Hochschulen	-	„Das Ziel oder für mich die optimale Entwicklung wäre, wenn ich in 2, 3, 5 Jahren alle meine Verwaltungsprozesse irgendwie digital von zuhause aus durchführen kann, dann wenn ich Zeit habe.“ (I12)	
C2	Realistische Einschätzung zukünftiger Anwendungen	Realistische Einschätzung konkreter Anwendungen, die in der Zukunft an Hochschulen zum Einsatz kommen können	-	„Ich denke, dass im Bereich E-Learning noch viel passieren wird. Also gerade jetzt auch im Bereich Diagnostik oder Beurteilung der Leistungsfähigkeit.“ (I1)	Subjektive Einschätzung des Experten, welche Systeme er in (naher) Zukunft in Deutschland für einsatzfähig hält.
C3	Einschätzung des Fortschritts	Realistische Einschätzung des zukünftigen Fortschritts bzw. der Entwicklungen an deutschen Hochschulen	-	„Ich stell mir in fünf Jahren eine Hochschule vor, dass (…) 50-60% der Anfragen [in einem Prüfungsamt] der Chatbot wegpuffert. Und nur wenn er keine Antwort weiß, auf die Person zugeschaltet wird. Also ich spreche jetzt von der Hochschulverwaltung.“ (I3)	
D	**Internationaler Weitblick**	Internationaler Vergleich von KI an deutschen Hochschulen			
D1	Wissen über Anwendungen im Ausland	Informationen über konkrete Projekte/Anwendungen an Hochschulen im Ausland	-	„Es gibt so Sachen wie automatische Auswertung von Freitextantworten (…) automatische Korrekturen von Klausuren (…).“ (I11)	
D2	Deutschland im internationalen Vergleich	Einschätzung der Positionierung Deutschlands im internationalen Vergleich in Bezug auf den Einsatz von KI	-	„Sehr zurückhaltend. Also fast (…) gar nicht. Da sind wir noch nicht bei.“ (I1)	

Appendix C – Interraterreliability

	agreement (p0)	Degree of agreement (kappa)
Interview I	78.4%	0.77
Interview II	75.4%	0.74
Interview III	81.6%	0.81
average agreement	78.5%	0.77