# Chapter 9
# Potential Benefits of Artificial Intelligence in Healthcare

**Nathalie Hoppe, Ralf-Christian Härting, and Anke Rahmel**

**Abstract** Healthcare systems worldwide are confronted with numerous challenges such as an aging population, an increasing number of chronically ill patients, innovations as cost drivers and growing cost pressure. The COVID-19 pandemic causes additional burden for healthcare systems. In order to overcome these challenges, digital technologies are increasingly used. Especially the past decade witnessed a tremendous boom of artificial intelligence (AI) within the healthcare sector. AI has the potential to revolutionize healthcare and to mitigate the challenges healthcare systems are confronted with. The existing literature has frequently examined specific benefits of AI within the healthcare sector. However, there are still research gaps according to different application areas in healthcare. For this reason, an empirical study design has been conducted to investigate the potentials of AI in healthcare and to consequently identify its role. Based on a Systematic Literature Review (SLR), the following application areas for key determinants in healthcare have been identified: *management tasks*, *medical diagnostics*, *medical treatment* and *drug discovery*. By means of structural equation modeling (SEM), the study confirmed *medical diagnostics* and *drug discovery* as positive and significant influencing factors on the potential benefits of AI in healthcare. The other determinants didn't prove a significant influence. Based on the findings of the study, various recommendations have been derived to further exploit the potentials of AI in healthcare.

**Keywords** Artificial intelligence · AI · Healthcare · Potential benefits · Digitalization · Systematic literature review · Structural equation modeling

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C. P. Lim et al. (eds.), *Artificial Intelligence and Machine Learning for Healthcare*, Intelligent Systems Reference Library 229,
https://doi.org/10.1007/978-3-031-11170-9_9

## 9.1 Introduction

Artificial Intelligence (AI) is considered to be “the new electricity” [1] and thus the foundation for numerous applications. AI can be briefly defined as “intelligence demonstrated by machines” [2] and is increasingly applied in various industries such as retail, finance, manufacturing and also in healthcare [3]. It is attributed by many experts to create a new era of healthcare [4–6]. The growing availability of patient data and advances in analytics have contributed to this development [4].

Healthcare systems worldwide have to face numerous challenges such as aging populations, staff shortages and a rise of chronic diseases [7]. The COVID-19 pandemic has exacerbated these challenges by substantially increasing the demand for protective equipment, medications and medical devices [8]. To mitigate or even eliminate these challenges, new solutions have to be identified. According to the opening statement by Andrew Ng, AI can be harnessed as the “new electricity” [1] for addressing healthcare challenges. At the same time, the question arises of what concrete role AI will play in this regard.

Researchers and computer scientists have examined how various AI approaches, especially Machine Learning (ML) and Deep Learning (DL) models, can be used for specific tasks or problems [9, 10]. One research focus is the application of AI-based systems in intensive care units [11, 12]. Moreover, AI is considered to support healthcare personnel in administrative tasks [13]. Additionally, numerous scientific papers can be identified that examine the role of AI and its approaches in relation to the COVID-19 pandemic [14, 15]. Suri et al. (*in 2020*) investigate how AI and medical imaging can contribute to the severity classification of COVID-19 infections [15].

The existing literature comprises AI algorithms, models and experimental studies that predominantly address specific problems or targets within medicine and healthcare [16, 17]. A study examining the potential benefits of AI according to various application areas in healthcare has not yet been conducted. Apart from medical application areas, an additional focus is on the area of management within the healthcare sector. Due to various factors like cost and competitive pressure, a tremendous focus is on efficiency and productivity within healthcare organizations [18]. Therefore, management tasks could also be subject for improvements thanks to AI [19].

The research project is based on an empirical investigation, more precisely a quantitative study among AI experts in healthcare. Based on the findings, recommended actions for different stakeholders such as physicians, AI developers, managers and researchers will be derived.

First, the authors provide theoretical insights into AI in healthcare by addressing the beginnings of AI as well as current developments (see Sect. 9.1.2). The subsequent section represents the main part as it comprises the individual components of the research design. A systematic literature review (SLR) represents the basis for the generation of hypotheses and the creation of a conceptual model (see Sect. 9.1.3.2). The model is built as a structural equation model (SEM) which is a type of multivariate analysis, i.e. multiple variables can be analyzed simultaneously [20]. For the purpose of generating primary data and deriving statements on the hypotheses, an online survey among AI experts with focus on the healthcare sector in Germany was conducted. Within Sect. 9.1.3.3, the process of data collection is explained in detail including information on the acquisition of participants. The following section presents the results and contains the characteristics of the expert group, the examination of different quality criteria and the evaluation of the SEM. The interpretation of the results in Sect. 9.1.5 is followed by different recommended actions to fully exploit the potential benefits of AI. Finally, the authors summarize the results and give an outlook on the further development of AI in the healthcare sector (see Sect. 9.1.7).

## 9.2 Artificial Intelligence in Healthcare

The beginnings of AI in healthcare and medicine can already be traced back to the 1950s. At this time, physicians conducted first trials to support diagnostics by means of computer-aided programs [21]. One famous example is the diagnosis of abdominal pain by Gunn [22]. Nowadays, both the availability of healthcare data and various methods of big data analytics are supposed to transform healthcare sectors worldwide [4].

At the same time, the almost exploding availability of patient data from a huge variety of electronic sources represents a major challenge to healthcare professionals. Gathering this data and transforming it into a suitable decision is hardly feasible for them [6]. Over the past years, there has been an enormous rise of electronic health records (EHR). Considering the availability of medical knowledge, it is estimated that a physician would have an effort of 29 h per day assimilating new medical knowledge [6]. This is where AI plays an increasing role. Especially the past decade is characterized by a tremendous boom of AI technologies and applications. The improvements in computer processing speed, the availability of a larger amount of data and the pool of talented AI engineers have contributed to it [23].

The idea of using AI to detect and treat diseases such as cancer at an early stage is already an inspiration for many researchers and developers. Cosma et al. (*in 2017*) examine different approaches of computational intelligence for predictive modeling in prostate cancer [24]. Additionally, Carter et al. (*in 2020*) examine the effects of AI applied to breast cancer care [25].

The essential core of AI-based systems is that they require training based on data. These data are derived from numerous clinical sources like diagnosis, screening or treatment. The overall goal is to identify patterns, associations between features and relevant outcomes within the data [4]. The support of AI-based systems can cover many clinical and administrative areas such as diagnostics, therapy or documentation [23]. In order to give an insight into the present and future role of AI in healthcare, there is an introduction to current numbers and figures.

The rise of AI technologies in healthcare is emphasized by the growth of the global market revenue. The market revenue is supposed to increase from 6.9 U.S. dollars in 2021 to 67.4 billion U.S. dollars in 2027 [26]. Additionally, the revenue for the market of *diagnostics and medical imaging* is estimated at 2.5 billion U.S. dollars and the one of *drug discovery* is estimated at 4 billion U.S. dollars by 2024 [27]. The increasing and rapid development of AI technologies in healthcare also results in a growing number of AI startups [28]. Compared to the share of AI startups worldwide, AI startups in healthcare and biotech have a share of 9% [29].

## 9.3 Research Design

The empirical study is based on a quantitative research design. In general, a distinction can be made between qualitative and quantitative research designs. Whereas qualitative research focuses on exploratory and small data sets, quantitative research comprises structured data collection with a large number of datasets [30]. In a first step of the research design, relevant questions have been identified from a systematic literature review (SLR). The derived conceptual model and hypotheses build the foundation for the data collection and further findings through an online survey.

Figure 9.1 illustrates the main elements of the research design. Based on the aim to identify the potential benefits of AI according to different application areas in healthcare, a SLR was conducted. The findings from the SLR are used to derive hypotheses and create a conceptual model that can subsequently be used for the data collection and the evaluation of the results. The data collection was carried out through an online survey and is based on a questionnaire which reflects the theoretically gained insights through the SLR. Subsequently, the data was analyzed by means of the statistical software SmartPLS [31]. The results are interpreted based on the findings from the literature and ultimately lead to answering the research question.

In the following sections, each step of the research design is explained in detail, starting with the strategy of the SLR.

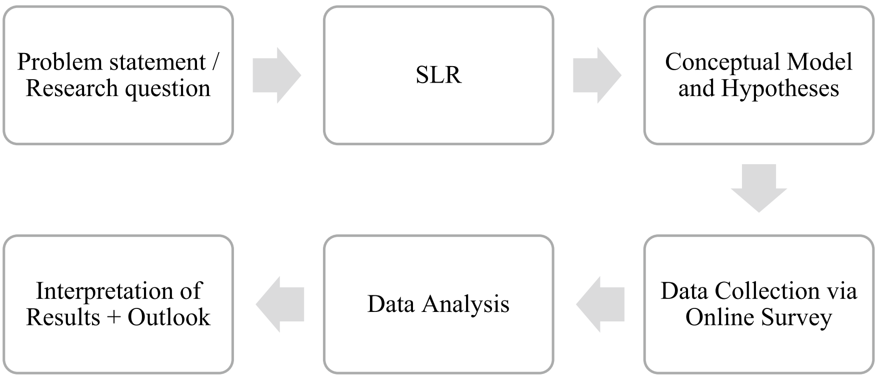


**Fig. 9.1** Research design

### 9.3.1 Systematic Literature Review (SLR)

SLRs can be, inter alia, traced back to the field of medicine. Nowadays, they are increasingly applied to other sciences like management and international development [32]. The development of a hypothesis framework is necessary for the subsequent study and consequently for answering the research question. In order to develop hypotheses, a SLR was conducted. The search strategy comprises the keywords that were used for the search, scientific databases and the quality assessment of the articles.

According to the main research question, the following keywords were used for the literature review:

> "Artificial Intelligence", "Artificial Intelligence in Healthcare", "AI in Healthcare", "Artificial Intelligence in Medicine", "Machine Learning in Healthcare", "Deep Learning in Healthcare", "Potentials of Artificial Intelligence in Healthcare", "Benefits of Precision Medicine", "Economic benefits of AI in healthcare", "Medical Artificial Intelligence", "ANN in healthcare", "Impact of Artificial Intelligence in Healthcare OR Medicine".

As the research question covers the areas of business studies, computer science and medicine/healthcare, a wide range of databases were accessed: ScienceDirect, AIS eLibrary, JSTOR, SAGE Journals, INFORMS PubsOnLine, Google Scholar, Wiley Online Library, IEEE Xplore, Springer Link, EconBiz, Taylor & Francis Online, PubMed.

In order to evaluate the scientific quality of journals and conferences, different rankings can be used. The literature review is based on two ranking portals: VHB-Jourqual3 [33] and CORE Rankings Portal [34]. The "Verband der Hochschullehrer für Betriebswirtschaft e.V. (VHB)" deals with scientific topics related to business science [35]. VHB-JOURQUAL3 is a rating of business relevant journals based on judgements of VHB members [33]. Only journals with a rating from A+ to C have been used for the literature research to ensure a good quality of the articles. The CORE (Computing Research and Education) Rankings Portal assesses especially conferences but also journals of the computing disciplines [34]. Conferences and journals ranked between A+ and B were considered to ensure a good quality of the articles.

### 9.3.2 Generation of Hypotheses and Conceptual Model

Four hypotheses were generated based on the findings of the SLR:

> *H1: Management tasks positively influence the potential benefits of AI in healthcare.*
>
> *H2: Medical diagnostics positively influences the potential benefits of AI in healthcare.*

*H3: Medical treatment positively influences the potential benefits of AI in healthcare.*
*H4: Drug discovery positively influences the potential benefits of AI in healthcare.*

These hypotheses are part of the conceptual model that was developed based on *Structural Equation Modeling (SEM).* SEM is a multivariate analysis method that enables the evaluation of multiple variables which are not directly observable. In order to describe and measure these variables, indicators have to be identified. A specific method of SEM is called *Partial Least Squares SEM* (*PLS-SEM*) which can be used for the development of theories [36].

Within SEM, hypotheses and the relation of variables are illustrated as *path models* [36]. A distinction is made between independent (exogenous) and dependent (endogenous) variables. Independent variables can be considered as causes that have effects on the dependent variable [36]. Each PLS path model consists of a s*tructural model,* also known as *inner model*, and a *measurement model,* known as *outer model*. The structural model specifies the relationship between the latent variables whereas the measurement model illustrates the relationship between the latent variables and indicators [36]. *Latent variables* are not directly observable and require suitable measurement models whereas *manifest variables* can be directly observed [37].

Figure 9.2 depicts the hypothesis model that was created based on the findings of the SLR.

According to the hypotheses, the model consists of four latent variables and 18 indicators. It considers medical application areas as well as the area of management as influences on the potential benefits of AI in healthcare. The measurement model is designed as a *reflective measurement model*. Thus, the reflective indicators can be

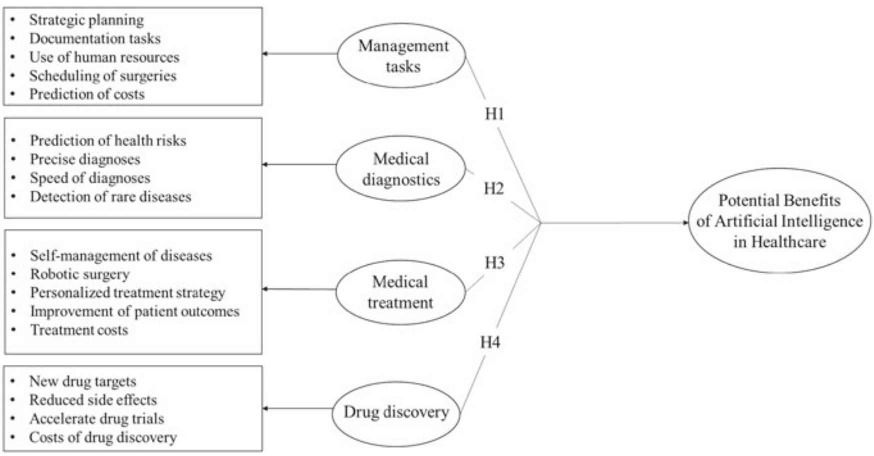


**Fig. 9.2** Conceptual model

considered as representative examples within the definition of the construct and are interchangeable [38].

The results of the SLR, and thus the evidence for the development of the hypotheses and related indicators, are outlined below. Additionally, the authors provide an overview of articles including ranking, resulting items and the assignment to different constructs (see [39]).

**Hypothesis 1—Management Tasks**

Due to various factors like cost and competitive pressure, there is a tremendous focus on efficiency and productivity within healthcare organizations [18]. Therefore, management tasks can also be subject for improvements due to AI.

*H1: Management tasks positively influence the potential benefits of AI in healthcare.*

Krämer et al. (*in 2019*) developed a ML model for the classification of hospital admissions into elective and emergency care. This approach can support case mix planning which is a key component of *strategic planning* [40]. Additionally, Akter et al. (*in 2022*) conclude that ML is able to increase hospital bedding efficiency which can lead to an improved long-term strategic planning in hospitals [9]. In doing so, they refer to Turgeman et al. (*in 2017*) who developed a ML model for predicting patients' length of stay in a hospital [41].

Kocaballi et al. [13] and Doraiswamy et al. [42] confirm with their study that AI-based systems can support *documentation tasks* like writing referrals or medical records of patients. Fairley et al. (*in 2019*) introduce an optimization and ML model to improve the efficiency of operating rooms. The authors assume that their approach can support schedulers in *calculating staffing needs* and ultimately reduce staffing requirements [17]. In addition, an *efficient use of human resources* can arise due to the ability of ML to predict how long a patient will stay in hospital [9].

Onukwugha et al. (*in 2016*) show that their survival grouping algorithm can improve the *prediction of 5-year costs* [43]. Additionally, Thesmar et al. (*in 2019*) expect AI to be able to predict upcoming health costs [44].

**Hypothesis 2—Medical Diagnostics**

The decision-making process in diagnostics can be divided into two phases, namely differential diagnosis and final or provisional diagnosis [45]. Within the first phase, the medical history of the patients, specific symptoms and laboratory tests like blood testing are considered as input data. The final/provisional diagnosis is provided by means of the medical knowledge of physicians [45]. The following results of the SLR show that AI can have the potential to improve medical diagnostics.

*H2: Medical diagnostics positively influences the potential benefits of AI in healthcare.*

Kaplan and Haenlein *(in 2020)* mention the capability of AI to "predict serious health risks such as skin cancer and strokes" [46] by even better operating than humans. Thereby, the authors allude to the third evolutionary stage, the AI super-intelligence [47]. Additionally, Garbuio and Lin (*in 2019*) refer to the medical DL company Enlitic and see AI's potential to *identify patients with risk factors* for a specific disease [28].

The ability of AI to enable more *precise diagnoses* is subject of a large number of scientific papers. Pee et al. (*in 2019*) state that medical imaging systems based on AI have the ability to review computed tomography images and can diagnose diseases with an increased accuracy [48]. Fan et al. (*in 2020*) examine the impact factors for healthcare professionals to adopt an AI-based medical diagnosis support system (AIMDSS). The authors present AIMDSS like those of Enlitic and Freenome which are able to provide more precise diagnoses than radiologists [49]. Additional evidence can be found in the paper of Yuan et al. [50]. The researchers show that their AI-based system can achieve sepsis diagnoses with an accuracy of more than 80%. It is thus outperforming the traditional SOFA score used for sepsis diagnosis [50].

Garbuio and Lin *(in 2019)* see potential in AI to enable a *faster detection* of small variations within data [28]. Especially the combination of AI with medical imaging can lead to faster diagnoses [15]. Within their case study, Pee et al. *(in 2019)* introduce a robot that is able to recommend diagnoses even faster than a human due to the large amount of data he is able to process [48].

One main benefit of AI is the ability to examine large and multidimensional datasets by determining important variables. Through the identification of (complex) patterns in patients' data the *detection of rare diseases* can be supported [44].

**Hypothesis 3—Medical Treatment**

The treatment of patients is an essential component of healthcare provision. The trend is increasingly moving towards personalized medicine to be able to take the needs of the individual patient into account [19].

*H3: Medical treatment positively influences the potential benefits of AI in healthcare.*

Bardhan et al. (*in 2020*) see the potential of AI in wearables or mobile applications to *support the management of chronic conditions* and promote healthy lifestyles. According to the authors, possible applications would be health monitoring or virtual coaching for managing diabetes [5].

Shin et al. (*in 2019*) implement two different learning algorithms in a *surgical robot* for tissue manipulation. As a result, both algorithms implemented in the surgical robot could fulfill the task and thus improve this sub-process of the surgery [51]. Moreover, AI-based systems can support surgeons by automatically guiding surgical instruments [52].

Paranjape et al. (*in 2020*) show the potential of ML algorithms by means of two medical application areas: Lung cancer and sepsis. ML can provide personalized radiation therapy and a *treatment strategy tailored to the patient* [6]. Further evidence that AI can support personalized treatment can be found in the study of Bertsimas et al. [16]. The authors developed different data-driven models for personalized coronary artery disease management as well as supervised ML algorithms for regression models. Overall, the authors see ML's potential of identifying an optimal treatment strategy for patients [16].

Schinkel et al. (*in 2019*) demonstrate that the early diagnosis of diseases and early initiation of treatment by means of AI-based systems can ultimately lead to an *improvement of patient outcomes* [53]. Additionally, Garbuio and Lin (*in 2019*) indicate that AI-based systems have been improving health outcomes [28].

Within the scope of their analysis, Vemulapalli et al. (*in 2016*) examine the use of AI-based methods like Bayesian networks for chronic disease management. As a result, the researchers are able to demonstrate the ability of Bayesian networks to reveal non-obvious correlations in the data. The use of these algorithms can lead to the *reduction of treatment costs* [54]. Additionally, the AI algorithm of Yuan et al. (*in 2020*) not only leads to more precise sepsis diagnoses but can also lead to cost reduction due to early treatment [50].

**Hypothesis 4—Drug Discovery**

Drug discovery is a decisive factor for healthcare provision and can be divided into different phases. It mainly includes target selection and validation, compound screening and lead optimization, preclinical studies and clinical trials. After the selection of targets appropriate for a specific disease, various molecular components are identified. Various preclinical and clinical studies follow [55]. AI is supposed to support drug discovery in various task which are presented below.

*H4: Drug discovery positively influences the potential benefits of AI in healthcare.*

Davenport and Ronanki (*in 2018*) refer to Pfizer using IBM Watson to support drug discovery in immuno-oncology. The system is based on the combination of an extended literature review and Pfizer's data. Finding hidden patterns can accelerate the *identification of new drug targets* [56]. Akter et al. (*in 2022*) introduce the cooperation of Novartis and Intel on the development of deep neural networks to accelerate drug discovery [9]. Additionally, Dezső and Ceccarelli (*in 2020*) show that their ML approach can predict and identify new drug targets in oncology. With this method, they offer a *cost-effective* and efficient solution for drug discovery [57].

Akay and Hess (*in 2019*) examine the potentials as well as needs of ML and DL applications in medicine and technology. Accordingly, DL combined with predictive analysis and patient database meta-searches can support drug design and prevent serious side-effects during the drug regimen [10]. The study of Doraiswamy et al. (*in 2020*) among psychiatrists additionally discovered that AI/ML is able to provide personalized drug targets with *reduced side effects* [42].

Garbuio and Lin (*in 2019*) introduce Enlitic, a medical deep learning company based in San Francisco that offers clinical decision support products. By analyzing health data, the system can *accelerate drug trials* [28].

### *9.3.3 Data Collection*

Subsequent to the presentation of the conceptual model and the hypotheses, the procedure of data collection is explained in detail. Figure 9.3 depicts the different steps of the data collection.


**Fig. 9.3** Main steps of the data collection

The questionnaire was created based on the conceptual model (see Sect. 9.1.3.2) and includes 19 questions. The questions on the conceptual model correspond to section B.

Additionally, three further sections were included:

(A) Experience with AI in Healthcare
(B) Assessment of the Potential Benefits of AI in Healthcare
(C) Enterprise-specific Questions
(D) Socio-demographic Questions.

The results are presented in detail within Sect. 9.1.4.

LimeSurvey was selected as tool for data collection. It is an online survey tool that allows the integration of different question types into the survey [58]. A pre-test was carried out to review the comprehensibility of the questions, eliminate content overlaps and test the usability of the survey. The pre-test proved to be an essential part of the preliminary work and considerations.

The target group of the online survey includes experts on AI in healthcare. In detail, it comprises employees in the areas of management, consulting, computer science, engineering, medicine, health sciences and pharmacy. The main focus has been on the German healthcare sector. To gain comprehensive insights, users, developers and manufacturers as well as researchers have been included. Section 9.1.4.1 presents the main characteristics of the expert group.

## 9.4 Results

This section presents the results of the expert survey. First of all, the process of data analysis is introduced, followed by the sample characteristics including the experience with AI in healthcare as well as socio-demographic and enterprise-specific questions. Section 9.1.4.2 examines the quality criteria of the model, followed by the results of the SEM in Sect. 9.1.4.3.

### *9.4.1 Data Analysis and Sample Characteristics*

A total of 127 complete responses were indicated via the survey tool LimeSurvey [58]. This number also included participants who selected “No” when asked about their experience with AI in healthcare. Due to the implemented “exit scenario”, people without experience with AI in healthcare were excluded. This results in 105 complete responses used for the subsequent evaluation.

There are various software tools to evaluate models based on SEM. As the conceptual model presented in Sect. 9.1.3.2 is based on PLS-SEM, the most suitable software is SmartPLS [31]. It has a high level of usability and extended reporting features [59] and is thus used for the evaluation of the results.

The participants who indicated having no experience with AI in healthcare were asked if they plan to address the topic in the future. 77% indicate that they will address AI within healthcare in the future. 18% may want to engage with it while 5% of the participants do not want to deal with AI in healthcare.

91 participants indicated that their enterprise is located in Germany. Additionally, 6 participants stated that their organization is operating globally. Two experts are from the United States, respectively one expert is from Brazil and Israel. 4 experts did not provide an answer in which country their enterprise is located.

Examining the gender of the participants, 85.7% are male. 11.4% are female and 2.9% of the experts did not indicate an answer.

In order to more precisely assess the experience of the participants, they were asked on how many years of experience they have with AI in healthcare. Most of the experts have 1–2 years of experience with AI in healthcare, followed by 30 respondents who have 3–4 years of experience. 27 participants have even more than 6 years of experience with AI in healthcare. The experience of 9 participants amounts to 5–6 years while 7 respondents have less than one year of experience with AI in healthcare. The results show that the experience of the experts varies considerably in terms of years.

In addition, the experts were asked which application areas in healthcare their experience refers to (see Fig. 9.4). The participants had the option to indicate multiple responses. 35.3% of the participants have experience with AI related to diagnostics. 16.4% refer their experience to treatment, followed by health prevention (11.8%). 10.1% of the participants relate their experience to the manufacturing of medical devices. Further application areas are drug discovery / drug manufacturing and administration with respectively 8%. The participants had the opportunity to add further application areas. This results in the following additional application areas: Patient monitoring, translation of AI to the clinical setting, guidance to care, clinical evaluation, speech recognition, structuring of medical data, performance analysis of medical devices, research, supply chain monitoring, standardization and benchmarking of AI in healthcare, sales effectiveness and AI-based suggestion in healthcare.

The question on AI approaches (see Fig. 9.5) shows that most of the experience refers to ML, followed by DL with 23.1%. The participants had again the opportunity to provide multiple responses. 21.9% of the experts indicate that their experience refers to Artificial Neural Networks (ANN) which can also be assigned to ML/DL [60]. While 14% are experienced in predictive analytics, 6.1% of the participants are experienced in Natural Language Processing (NLP). 3.2% of the experts have experience with robotics. In addition, the experts indicated the following AI approaches: medical image analysis and image processing, surgical data science, probabilistic

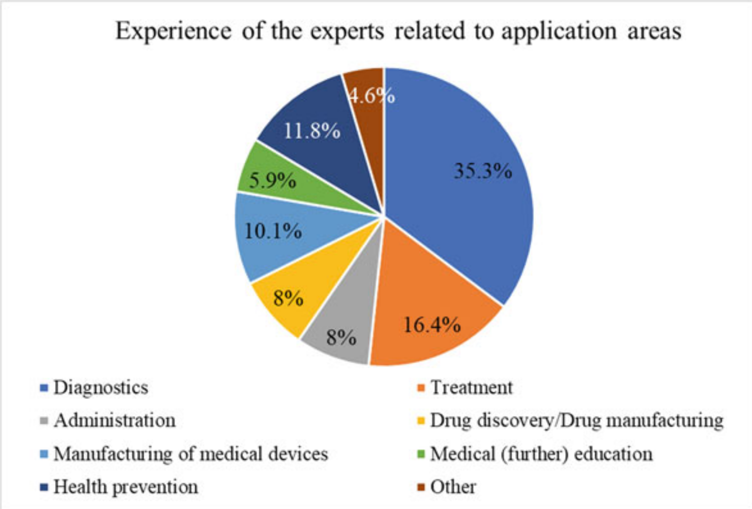


**Fig. 9.4** Experience of the experts related to application areas

reasoning, cognitive modeling as well as fuzzy logic. Cognitive modeling contains theories describing the reasoning in people [61]. Fuzzy logic is based on the fuzzy set theory which comprises linguistic variables, fuzzy if–then rules and more [61].

According to their function in the enterprise, 42.9% of the experts can be attributed to the field of *management and administrative staff.* 28.6% of the participants are computer/data scientists while 14.3% are (AI) engineers. Additionally, 8 research

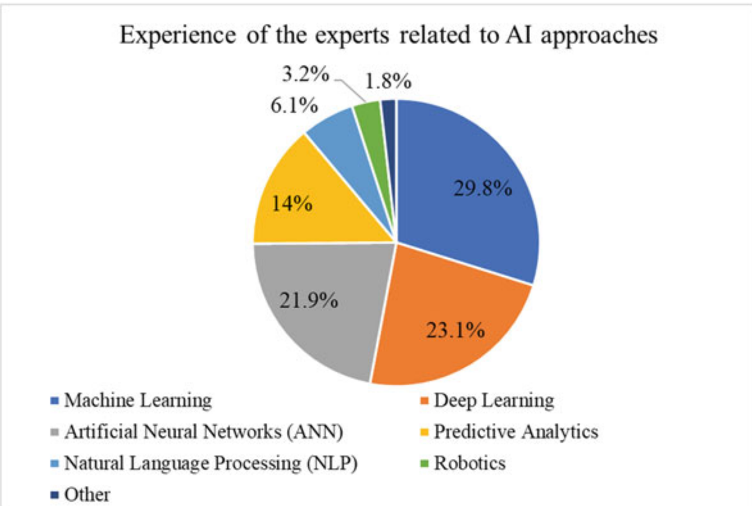


**Fig. 9.5** Experience of the experts related to AI approaches

scientists took part in the survey. 5 experts are physicians and 2 participants did not indicate an answer. In order to assess the size of the enterprise, the number of employees and the amount of turnover were queried. 52 enterprises have more than 250 employees whereas 35 have less than 50 employees. 10.5% of the companies employ 50–250 people and 7 participants did not indicate an answer on the number of employees in their enterprise.

Considering the amount of turnover in 2019, 34 enterprises record a turnover of more than 50 million euros. In contrast, 21.9% of the enterprises have a turnover of less than 10 million euros. Three enterprises record a turnover of 10–50 million euros. It has to be noted that the majority did not indicate the amount of turnover. According to the recommendation of the European Commission, enterprises with less than 250 employees and an annual turnover below 50 million euros can be attributed to the category of micro, small and medium-sized enterprises (SMEs) [62]. Accordingly, about one third of the enterprises can be considered to be SMEs.

The experts were also asked to which category their enterprise can be assigned. 30 enterprises can be attributed to the area of software and IT. 22 enterprises can be assigned to medical technology. 14 participants work in a hospital while 12.4% of the experts assign themselves to research institutes or universities. Additionally, nine pharmaceutical enterprises are represented. Respectively one expert works in a nursing home, non-profit organization or has no current enterprise.

The COVID-19 pandemic is affecting all sectors and especially the healthcare sector, which is facing an increasing number of patients [8]. In order to investigate whether the pandemic also has an impact on the use, development or general engagement with AI in healthcare, the following statement was included into the questionnaire (see Fig. 9.6).

20 experts completely agree with the statement whereas 30 participants rather agree. 31 experts responded neutrally. 14.3% rather disagree and 9 participants completely disagree that the COVID-19 pandemic has led to an increased focus on

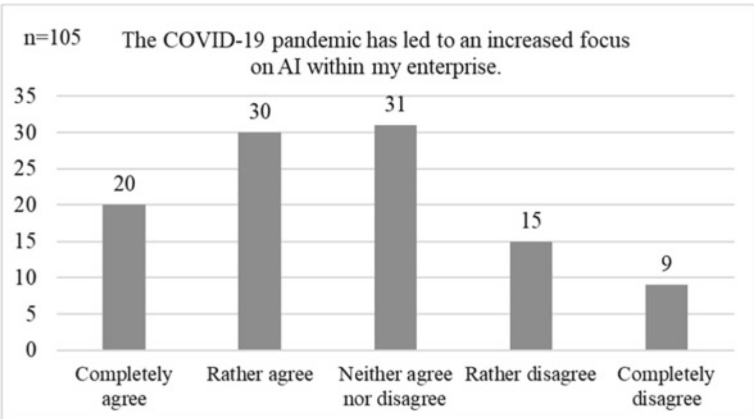


**Fig. 9.6** Impact of the COVID-19 pandemic on the focus of AI

AI within the enterprise. The responses show that nearly half of the experts perceive an increased focus on AI within their enterprise.

### *9.4.2 Examination of Quality Criteria*

Section 9.1.4.3 focuses on the evaluation of the hypothesis model using SEM. In order to assess the quality of the model, various quality criteria are initially considered within this section.

The main quality criteria to assess the quality of a measurement are *objectivity*, *reliability* and *validity*. *Objectivity* can be assumed when different investigators obtain the same results. In addition, participants should not be influenced and the same results should lead to the same conclusions. *Reliability* reflects the stability of the measuring instrument. The third criterion *validity* indicates the accuracy of the measuring instrument and its fit to the measurement target [37].

To examine the *reliability,* two criteria can be used. The quality criterium *Composite Reliability (CR)* determines the reliability of internal consistency by taking into account different indicator loadings. In order to confirm the reliability of the indicators, values of at least 0.6 are acceptable [37]. *Cronbach's Alpha (CA)* additionally makes statements on the reliability of internal consistency. In contrast to CR, it assumes equal indicator loadings [37]. To confirm an *acceptable* reliability, CA values should be at least 0.7 in constructs with four or more indicators [38].

*Convergence validity* is the extent to which a measurement correlates positively with an alternative measurement of the same construct. The items belonging to a construct should share a large amount of variance. The convergence validity can either be examined by considering the loadings of the indicators or by means of *average variance extracted (AVE)* [37]. The focus of the following section is on AVE. Outer loadings are especially considered in reflective measurement models and determine the contribution of an indicator toward the construct it is assigned to [37]. The target value of the AVE to be able to confirm a variance has to exceed the threshold of 0.5 [63]. The *coefficient of determination* $R^2$ describes the proportion of the variance explained by a linear regression [64]. Values of 0.67 can be considered "substantial" whereas results of 0.33 are "moderate" and values up to 0.19 are considered "weak" [63].

The higher the $R^2$ value, the better is the explanation of the dependent variable by the latent variables in the structural model [37].

Table 9.1 provides an overview of the quality criteria.

First, the CR values are being considered. All values clearly exceed the threshold of 0.6. *Drug discovery* has the highest value of 0.893, followed by *medical diagnostics* with a value of 0.855 and *medical treatment* with 0.826. The construct *management tasks* shows a CR value of 0.808. Additionally, all CA values exceed the threshold of 0.7 and thus represent an acceptable internal consistency.

The examination of *AVE* shows that the values of *drug discovery* and *medical diagnostics* are above the threshold of 0.5. Consequently, the constructs explain

**Table 9.1** Quality criteria

| | Composite reliability (CR) | Cronbach's Alpha (CA) | Average variance extracted (AVE) |
|---|---|---|---|
| Management tasks | 0.808 | 0.711 | 0.459 |
| Medical diagnostics | 0.855 | 0.770 | 0.599 |
| Medical treatment | 0.826 | 0.738 | 0.489 |
| Drug discovery | 0.893 | 0.846 | 0.676 |

more than half of the variance of their indicators [37]. In contrast, the values of *medical treatment* and *management tasks* are below the target value. However, they are only slightly below the threshold.

To examine how adequately the dependent variable "Potential benefits of AI in healthcare" is explained by the four independent variables, $R^2$ was examined. The $R^2$ value of 0.261 represents a result considered as "weak" to "moderate" [63].

### *9.4.3 Evaluation of the SEM*

After examining the quality criteria, the model based on SEM is being evaluated. Figure 9.7 shows the structural model with the t-statistics and significance levels of the respective paths.

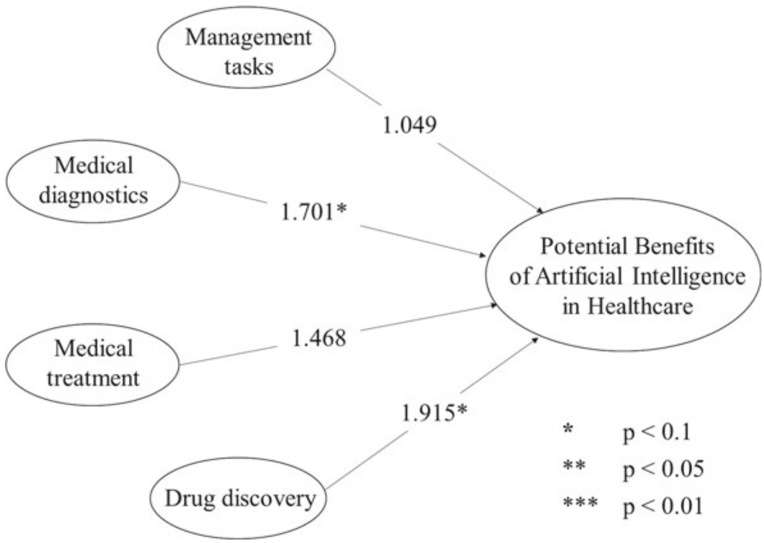


**Fig. 9.7** T-statistics of the path model

**Table 9.2** Results of the SEM

| | Original sample (O) | Sample mean (M) | Standard deviation | T-statistics | *P*-value |
|---|---|---|---|---|---|
| Management tasks | 0.095 | 0.115 | 0.090 | 1.049 | 0.295 |
| Medical diagnostics | 0.205 | 0.198 | 0.120 | 1.701 | 0.089 |
| Medical treatment | 0.175 | 0.178 | 0.119 | 1.468 | 0.142 |
| Drug discovery | 0.162 | 0.167 | 0.084 | 1.915 | 0.056 |

In the following section, the results are discussed in more detail in order to be able to derive statements relating to the hypotheses. Table 9.2 illustrates the individual values.

A two-sided test with a significance level of 10% was conducted. Considering the original sample, values of at least 0.2 are considered "meaningful" [65]. Additionally, the t-value is used as a decisive criterion. T-statistics are used to determine the significance of a parameter estimator. For a two-sided test with a significance level of 10%, the critical t-value is 1.65. If the measured t-value exceeds the critical t-value, the null hypothesis can be rejected [59]. In order to confirm the significance, the *p*-value has to be below 0.1 [37].

***H1:*** *Management tasks positively influence the potential benefits of AI in healthcare.*

Considering the *t-statistics,* the value is below the critical t-value of 1.65. Additionally, the *p*-value of 0.295 exceeds the threshold value of 0.1. Consequently, the hypothesis has to be rejected. A slightly positive but no significant influence on the potential benefits of AI in healthcare can be assumed.

***H2:*** *Medical diagnostics positively influences the potential benefits of AI in healthcare.*

The t-value of 1.701 exceeds the critical t-value while the *p*-value is below the threshold of 0.1. Additionally, the value of the original sample exceeds the desired threshold of 0.2. A positive and significant influence can be assumed. Consequently, *hypothesis 2 can be accepted*. Medical diagnostics positively influences the potential benefits of AI in healthcare.

***H3:*** *Medical treatment positively influences the potential benefits of AI in healthcare.*

The t-value of 1.468 is below the critical t-value and the *p*-value exceeds the mark of 0.1. With an o-value of 0.175, the construct shows a positive but no statistically significant influence. Therefore, *the hypothesis has to be rejected*.

***H4:*** *Drug discovery positively influences the potential benefits of AI in healthcare.*

The t-value of 1.915 exceeds the threshold. Additionally, the *p*-value is below 0.1 whereby a significant influence can be assumed. As the o-value is below 0.2, a weak positive influence is implied. Nevertheless, based on the confirmed *p*-values and t-values, hypothesis 4 can be accepted. With a *p*-value of 0.056, the construct shows the most significant influence on the potential benefits of AI in healthcare.

In summary, the experts consider AI to offer significant potential benefits within the application areas *medical diagnostics* and *drug discovery.*

## 9.5 Interpretation

The COVID-19 pandemic represents a massive and global challenge. It has caused more than 6 million deaths worldwide [66], overwhelmed healthcare systems as well as the economy [14]. As the empirical investigation shows, nearly half of the experts perceive an increased focus on AI within their enterprise due to the COVID-19 pandemic. It can be assumed that the pandemic has increased the need for assistive technologies like AI. The literature additionally shows that new AI approaches emerged since the COVID-19 pandemic. Researchers investigate how AI can support drug discovery and vaccine development [14] or how image-based AI can contribute to tissue characterization and classification of COVID-19 patients [15].

Considering the results of the SEM, the determinants *medical diagnostics* and *drug discovery* respectively show a positive and significant influence on the potential benefits of AI in the healthcare sector. Whereas *medical diagnostics* shows the most positive influence, *drug discovery* has the most significant influence. In the following, the construct *medical diagnostics* is examined more closely.

According to the findings from the literature, *medical diagnostics* has been confirmed by the experts to be a beneficial application area of AI. For example, AI-based systems can support the prediction of health risks like strokes [28, 46]. The prediction of health risks is essential for the prevention and early treatment of diseases [50]. AI can therefore be a decisive contribution. AI-based systems can further increase the precision of diagnoses [48] and could ultimately reduce false diagnoses. Furthermore, the speed of diagnoses can be enhanced by means of AI [28, 48]. This can lead to *increased efficiency* and more time for physicians to care for patients. It could ultimately improve the interaction between patients and physicians [48].

Additionally, the literature shows that AI is already widely used for diagnostics [15, 49, 50] which is also reflected by the results of the study. More than 35% of the experts indicated that their experience with AI refers to diagnostics. Considering the construct *drug discovery,* a positive significant influence can be assumed. However, the construct *drug discovery* presumably has only a weak influence, as the original sample value is below the desired threshold of 0.2 [65]. AI is able to support the development of drugs with reduced side effects. It has the potential to enhance optical drug design and reduce side effects during the drug regimen [10]. Through the use of AI and the increased efficiency, the costs of drug discovery can be reduced [57]. The results show that AI is also able to accelerate drug trials, as stated by Garbuio and Lin (*in 2019*) [28]. Additionally, AI-based systems can accelerate the identification of new drug targets [9, 57] which can also have a positive influence on the development of vaccine and medication against COVID-19 [14].

The construct *medical treatment* could not be confirmed as significant influencing factor on the potential benefits of AI in healthcare. However, the assumption that AI can lead to the *improvement of patient outcomes* shows the best indicator loading. AI technologies such as ML algorithms can contribute to the improvement of patient outcomes [16, 53]. The non-significant results might be due to the fact that medical treatment usually requires direct contact to physicians and caregivers. Kocaballi et al. [13] identified within their study that empathy still represents a main task of physicians. AI-based systems can hardly replace this contact.

Whereas in the area of diagnostics procedures could be more standardized, the individual treatment of patients is very important [19].

The application area *management tasks* is also not considered by the experts to have a significant influence on the potential benefits of AI in healthcare. The results could be caused by the fact that management tasks usually require a high level of sense-making and judgmental competence in order to derive comprehensible decisions [67]. According to the results, AI-based systems may be rather considered as assistants to managers allowing them to focus on complex and meaningful tasks [67]. Consequently, AI can lead to *an efficient use of human resources* within healthcare [17], thereby facilitating staffing [9]. The results could also stem from the circumstance that AI has not yet been widely applied to management tasks.

According to the literature, there is also a challenge in creating *transparency*. This is especially emphasized by the "black box problem" referring to the difficulty for healthcare professionals and patients to understand the decisions made by AI systems [68, 69]. Another challenge is how to determine who is responsible or even legally liable for medical errors. The more stakeholders are involved in the development or use of AI, the more difficult it is to define those responsibilities [70].

Through the survey and the literature review, various challenges of AI in healthcare emerged. To mitigate the challenges, recommended activities are provided in the following section.

## 9.6 Recommended Activities: Cooperation and Exchange Between Different Stakeholders

The stakeholders considered here correspond to the professions indicated by the experts. The professions of the experts cover management/administrative staff, engineers, data/computer scientists, research scientists and physicians. As patients are a key group of stakeholders within the healthcare sector and should also benefit from AI, they are also integrated in the recommendation.

Factors such as perceived performance anxiety and communication barriers decrease the intention to use AI [3]. Some studies indicate that health professionals could be afraid of being replaced by AI-based systems [13, 46]. As the study shows, AI does not (yet) demonstrate significant potential benefits in all areas that were examined. Empathy and human connection can only hardly be provided by AI [13].

Developers and manufacturers, like data scientists and AI engineers, can play a central role in increasing the willingness to use AI-based systems among healthcare professionals. Specific workshops and continuous support by developers and manufacturers could help healthcare professionals to deal with AI-based systems well and safely. This requires time investments in the first step. The fact that AI-based systems can lead to time savings (e.g. by accelerating diagnostics) would make this investment worthwhile. A basic understanding of AI could help healthcare professionals to create transparency regarding the functionality of AI. The developers and manufacturers should therefore support the implementation process at different levels within the healthcare facility.

Through a continuous exchange between users and manufacturers, support can be provided in case of problems and users can give feedback to developers. Through the practical experience of the users, the developers can obtain suggestions for improvement or align the systems according to the needs in the healthcare sector. As health professionals are directly involved into clinical processes, the insights can be more specified than the ones of developers and manufacturers. This process could support the continuous development of AI-based systems.

In order to provide a functioning and reliable human-AI collaboration, not only healthcare professionals but also patients should be integrated into the use of AI [3]. One of the most important goals in healthcare is to maintain and regain patients' health through the provision of optimal healthcare [8]. Patients should be made aware of the benefits and limitations of AI-based systems. As suggested by Esmaeilzadeh (*in 2020*), patients' concerns about AI-based systems should be addressed before the implementation of such systems [3]. However, generating transparency is hindered by the "black box problem" [68]. Consequently, decisions made by AI-based systems are not always transparent. Physicians should therefore explain to their patients both the role that human caregivers play and the role of AI-based systems in a diagnostic or treatment process. Additionally, physicians should communicate the potential benefits of AI compared to other methods, thereby also referring to potential risks. Thus, possible misperceptions of AI by patients can be reduced or even eliminated [70]. In return, patients could share their experiences of AI-based systems with physicians so they can in turn provide feedback to AI developers.

Digital transformation in healthcare organizations is confronted with regulation and statutory requirements [71]. When AI is going to be implemented, it should be holistically integrated into the (digital) infrastructure and organizational culture [72]. Managers should take the role of a "guiding light" in order to exploit the potentials of AI. Another important task is to increase the employees' awareness of what AI can achieve and what not [70]. The systems should be designed to meet the needs of both patients and employees. In order to ensure this requirement, the management should maintain a continuous exchange with the developers. Tasks of the upper management would be to understand the capabilities of AI-based systems and to decide whether existing capabilities should be improved or whether there is a need for new capabilities [72]. As there is the risk of organizational resistance [73], AI acceptance should already be realized during the implementation process [72]. According to Lee et al. (*in 2019*), possible measures that could increase acceptance are pilot projects and AI training [73]. Another main task for managers would be to develop an AI strategy [73] in order to holistically integrate AI into organizational processes.

While researchers and consultants provide theoretically founded insights, health professionals and developers can in turn provide researchers with practical insights. Accordingly, there should be a continuous exchange between researchers, developers/manufacturers and healthcare professionals.

## 9.7 Conclusion and Outlook

The empirical investigation confirmed *medical diagnostics* and *drug discovery* as positive and significant influencing factors on the potential benefits of AI in healthcare. In contrast, *management tasks* and *medical treatment* could not be confirmed as significant influencing factors. AI can increase the precision [48, 49], the speed of diagnoses [15] and predict health risks [46]. In drug discovery, there is potential for the development of drugs with reduced side effects [42]. Drug trials can be accelerated [28] and costs for drug discovery can be reduced [57].

The feedback from the experts revealed that the intention to use AI-based systems plays a decisive role. Accordingly, physicians could feel that their decision-making authority is impaired by the use of AI. Some even express the fear of being replaced by AI. As the study shows, AI-based systems cannot completely replace physicians and nurses at the current state of development. Especially in medical treatment, human intervention and providing empathy towards patients are important aspects AI can only hardly fulfill. However, AI could contribute to increased efficiency, thereby reducing the workload of healthcare personnel [74]. This could ultimately allow more time for physicians to provide empathetic care and to focus on complex cases. AI can play a critical role in improving healthcare processes as an assistant to healthcare professionals.

The mixed results of the investigation might be partly caused by the fact that AI is still rarely used within the German healthcare sector. This also illustrates that the study is subject to some limitations. First of all, the study could be extended by including more experts from other countries. This would provide a more generalized view on the potential benefits of AI in healthcare. Additionally, the sample size of 105 is rather small. Increasing the sample size could help to derive more general statements. Another approach could be to conduct the empirical investigation solely among users or exclusively among developers. This would allow to attribute the results to a more specific target group. Future research could focus on how to eliminate or mitigate the challenges associated with AI in healthcare.

The potential benefits of AI in healthcare are promising. However, there are hurdles such as data privacy, ethical concerns and missing transparency that impede the full exploitation of the potential benefits. The future challenge will be to generate the balance between necessary regulation, especially with regard to data protection, and the necessary "design freedom" for AI developers [75].

To pursue the developments of AI in the healthcare sector, the research areas "Management for Small and Medium-sized Enterprises" and "Healthcare Management" at Aalen University are continuing their research in this field. Currently, the barriers of AI in the healthcare sector are empirically investigated in order to be able to derive suggestions for improvement for the application and development of AI-based systems.

Returning to the opening quote "AI is the new electricity" by Andrew Ng [1], parallels can certainly be drawn between the beginnings of electricity and AI. Just a few hundred years ago, the subject on electricity was associated with numerous myths. The invention of electric light and widespread power supplies finally led to a tremendous boom at the turn of the nineteenth century [76]. Despite the current boom of AI, it still does not seem to be truly tangible for some people and is associated with some myths. Taking electricity as an example, continuous developments and appropriate responses and actions to failures can contribute decisively to a long-term and beneficial establishment of AI. This can ultimately lead to an increased acceptance of AI among people. Reliable and ethically oriented AI-based systems are especially important in the healthcare sector, where uncertainty, medical errors and additional risks can have serious consequences. The idea of AI revolutionizing healthcare by reducing the workload of health professionals, improving patient outcomes and add benefit to many other areas within healthcare sectors is definitely worth holding on to AI.

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