AI-Based Business Models in Healthcare: An Empirical Study of Clinical Decision Support Systems

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Abstract. *Objectives:* By 2025, 90 percent of all care providers worldwide are expected to adopt cognitive AI help as evidence-driven care for their patients. Among all AI applications, clinical decision support systems (CDSS) are most likely to improve patient outcomes in the next 5–10 years. The objective of this paper is to analyze the business models of AI-based CDSS on the market to allow for generic statements on the design and state of the art of such business models. The study thereby aims at maximizing the utility of this technology by providing a basis for future business model considerations in this area.
Methods: Based on a comprehensive market analysis for AI-based solutions in the healthcare domain, we identify a sample of 36 commercially available CDSS and analyze their business models using the theoretical business model concept by Gassmann et al. [10].
Results: As a result, we identify generic attributes and alternate conditions of CDSS business models on the market in the respective key business model elements value proposition, value creation and value capture.
Conclusions: Based on the results, we develop a business model framework for AI-based CDSS that gives a first overview of the design of business models in this new technology field. Our findings contribute to closing a gap in the scientific literature and provide as a basis for future business model considerations.

Keywords: Clinical decision support systems · Artificial intelligence · Business models · Digital health

1 Introduction

The market potential of AI-supported systems in healthcare is very high and is projected to grow by on average 70% to over USD 6 billion in 2022 [1]. Clinical applications that predict diseases, personalize treatment, prevent adverse events or manage outcomes account for 50% of all revenues. By 2025, a democratization of AI is expected with more than 90% of care providers worldwide adopting cognitive AI help for their patients

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[2]. According to a study by emerj [3], there is expert consensus that among all AI applications decision support systems are most likely to improve patient outcomes in the next five to ten years with hospitals and healthcare facilities being the primary target groups. In summary, the market is highly attractive due to a large market potential for providers, a high market growth but at the same time a currently rather low market penetration rate. In light of the market's infancy, the current lack of transparency on offerings in the market as well as lack of scientific literature on business models is not surprising. The high potential of clinical decision support systems is already becoming apparent. In a study from 2019, 157 dermatologists from twelve university hospitals in Germany competed against a computer to detect skin tumors. The computer diagnosed more accurately than humans in 136 cases [4]. Most research studies, however, focus on the role of artificial intelligence for business processes in the healthcare industry or deal with the clinical and financial benefits of Clinical Decision Support Systems (CDSS) [5, 6].

The objective of the present study is to shed more light on the topic of AI-based CDSS business models. To the best of our knowledge, there is currently no database available, which provides comprehensive information on commercially available AI-based healthcare solutions. For this aim, we develop an AI-in-Healthcare market monitor to get an insight into the vibrant market. For the current study, we identify 36 AI-based decision support systems and analyze their business models using publicly available information. In the following, we describe the methods used and present the results of the business model analysis. The paper closes with a conclusion and discussion of our results.

2 Methods

The basis for our study is a comprehensive market analysis for AI solutions in the healthcare domain. Through desktop research, relevant companies, research institutes and startups, which are active in the field of AI in healthcare, were first identified based on articles, blogs, newsletters, and further sources and then saved as structured profiles in an internal company database. Currently, the database contains information on more than 1400 providers classified in startups (21%), established companies (51%) and research institutions (28%). For each provider, the database contains general information such as the provider's name, location, funding information and acquisitions as well as specific information on offered products and initiatives, indications, technologies, target groups and medical applications. To the best of our knowledge, currently no comparable database exists.

This database was the foundation for our research on business models for AI-based CDSS. Given the wide variety of systems, there is no generally accepted definition for a CDSS [6]. Systems come in different varieties and differ primarily in their level of intelligence and support. This makes them difficult to characterize formally. In the context of this paper, three criteria were applied to determine the sample of analyzed providers: First, we follow the definition, which refers to "CDSS as digital systems that provide the decision maker with the right information at the right time to support healthcare professionals in making clinical decisions" [6]. Second, only companies and startups that describe their product as an AI-based CDSS were selected from the database. Research projects were excluded from the analysis since the focus of the paper is to address existing business models in the market. In addition, only systems targeting physicians as end users were included. This leaves us with overall 33 companies and startups with 36 different CDSS systems.

2.1 Business Model Analysis Approach

Clinical decision support system providers will only be successful in the market if they commercialize the economic value of the technology used [7]. This requires the definition and development of a well-defined underlying business model for these systems. The term 'business model' is not conclusively defined in the scientific literature. Therefore, several concepts have been developed to operationalize the business model as a theoretical concept [8]. However, at the most basic economic level, a business model describes the logical approach of how an organization earns profit [9]. Gassmann, Frankenberger and Csik [10] build on this definition and define a theoretical concept – the Business Model Triangle - to describe the term business model based on the four dimensions target customer, value proposition, value creation and value capture [10] (Fig. 1).

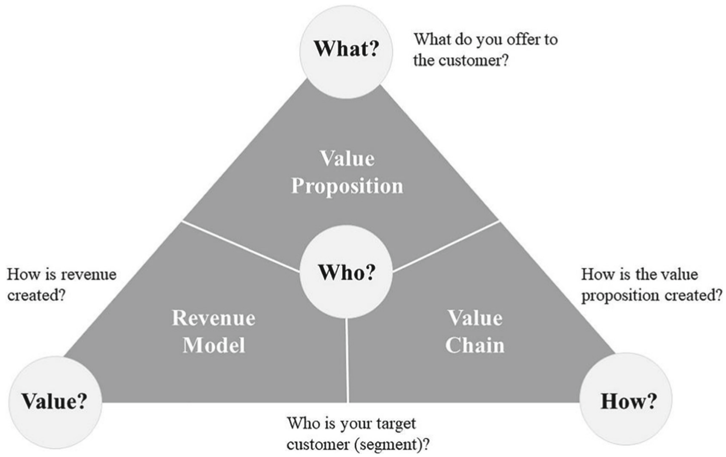

Fig. 1. The business model triangle by Gassmann, Frankenberger, and Csik [10].

Following this concept, the definition of relevant target customer segments is necessary to carefully develop the business model's value proposition. The value proposition describes all products or services a company offers to create value for its customers. The business model element value creation considers all relevant processes, activities, resources, and capabilities necessary to deliver the business' value proposition. Cost structures and revenue mechanisms are displayed in the business model element defined as value capture.

In the following, this Business Model Triangle is used to illustrate and analyze underlying business models of selected CDSS on the market. Hence, the dimensions value proposition, value creation and value capture are used to structure the business model elements for CDSS. Given the definition of CDSS used in this paper, the target group is restricted to physicians. The business model dimension target group is therefore fixed and not explicitly considered in the following business model analysis.

We conducted a morphological analysis based on information available in the company database and respective publicly accessible company websites. For the analysis, sources in English or German language were considered. Morphological analyses are commonly used to analyze multidimensional concepts such as business models [11, 12]. As a structured approach, this analysis allows to identify relevant business model attributes for products or services in a specific context [13]. Hence, the information collected on the CDSS business models is used to identify generic elements for each of the three business model dimensions. The findings are presented in a morphological box. In this representation, the identified generic business model attributes are defined as alternate conditions for CDSS business models [11].

3 Business Model Analysis

Overall, we examine 33 companies with 36 different CDSS systems. The descriptive statistics shows that most of the companies are from the United States (49%) and Europe (42%). Based on the SME definition of the European Commission [14], about half of the companies are small companies with 10 to 50 employees (49%). One third are large companies with more than 250 employees (33%), followed by microenterprises with a share of 12% and medium-sized companies with 6% (Fig. 2).

An examination of the founding year reveals that 49% of the companies are less than 10 years old and can thus be defined as startups [15]. The remaining companies are predominantly established companies that are at least 10 years old (Fig. 3).

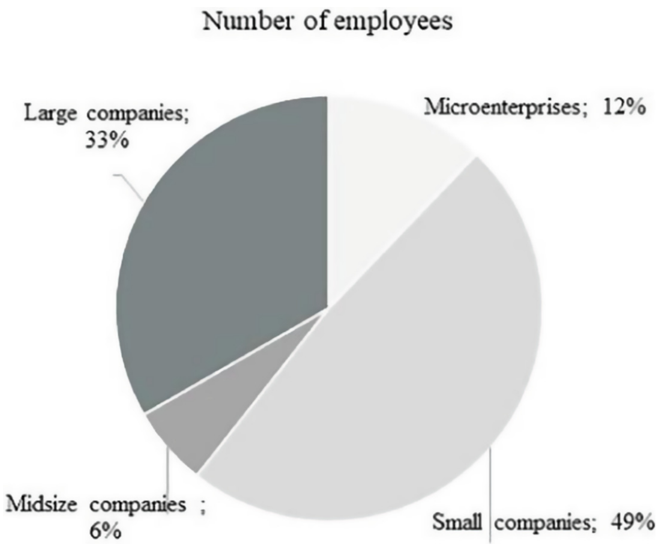

Fig. 2. Company size by number of employees.

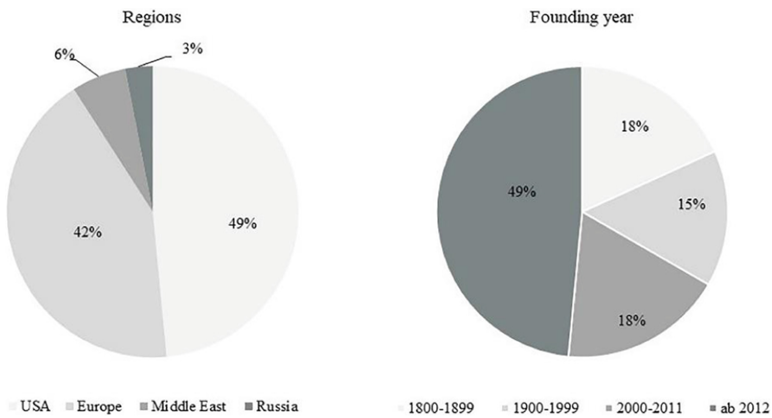

Fig. 3. Companies by geographical region and founding year.

4 Results

The results of the CDSS business model analysis and the characteristics of the respective business model elements value proposition, value creation and value capture are shown in the CDSS business model framework (Fig. 4).

Figure 4 shows a systematic presentation of the 36 different products. This is done by dividing the offerings into three business model elements and which target group was addressed. With their common categories of the main characteristics. These are assigned to categories which mentioned most frequently, with a list of the main properties. This

Business Model Elements	Attributes	Alternate Conditions					
Value Proposition	level of care	prevention	diagnosis	therapy recommendation	therapy support		
	indication	oncology	cardiology	radiology	pneumology	pharmacology	other indications
	impact	efficiency improvement / cost savings	patient engagement				
Value Creation	database	clinical trials	knowledge database	clinical guidelines	expert knowledge	monitoring of vital data	
	methods	machine learning	data analytics	statistical methods	clinical pathway	imaging	
	interfaces	electronic health records	clinical information system	mobile applications for physicians or patients			
Value Capture	pricing model	full licence	partial license	single purchase options			
	additional services	laboratory service					
Target Group	physicians						

Fig. 4. CDSS business model framework.

toll gives a brief overview of what is actually offered by the 36 products before continuing with the further analysis.

4.1 Value Proposition

The business model analysis shows that the *value proposition* of clinical decision support systems is mainly composed of three different attributes. These attributes can be divided into level of care and indication addressed as well as impact. We defined the levels of care based on the five pillars of health care, which consist of prevention, diagnosis, therapy, rehabilitation, and care [16]. Overall, four different levels of care were identified that are in focus of the analyzed CDSS, with many (N = 23) of them operating on at least two levels simultaneously. The four levels of care represent prevention, diagnosis, therapy recommendation and therapy support. Diagnosis and therapy recommendation are the most frequent care levels, with a share of 58% each, followed by therapy support with a share of 44%. Only six of the CDSS (17%) are used for prevention purposes. A statistically significant correlation was identified between the care levels of diagnosis and therapy support (p = 0,023).

83% of all CDSS' value propositions include statements concerning efficiency improvements or cost savings on their website. Furthermore, almost 60% of the systems described an improvement in the treatment pathway through the clinic with more compliance (patient engagement).

With respect to indications, 18 different indications were identified, with several CDSS covering multiple indications (17 out of 36 CDSS). The predominant indication is oncology with 14 CDSS, followed by cardiology and radiology with shares of 22% and 19% of the products, and pneumology and pharmacology with a share of 17% and 14% of all products.

A statistically significant correlation was only found between oncology and radiology ($p = 0{,}049$). In summary, the value proposition analysis for the CDSS shows that most systems focus on supporting the medical practitioner with diagnosis and therapy recommendation for indications in the field of oncology, cardiology and radiology thus leaving many green field opportunities for researchers and companies. The primary communicated impact of these systems is efficiency improvement for medical practitioners and patient engagement in the therapy process.

4.2 Value Creation

Our business model analysis shows that the CDSS' *value creation* can be stratified along the lines of databases, methods and interfaces that can be used to enhance the decision support process. With regards to the underlying data, the largest share of CDSS considers clinical trials for the decision support process, whereas 14 systems are linked to a knowledge database such as cancer registries or drug databases. In addition, some CDSS take expert knowledge (e.g., curatorship of experts and their knowledge) into account. Furthermore, monitoring of vital data or the consideration of clinical guidelines are relevant databases for clinical decision support processes.

Concerning methods, the analyzed CDSS mostly state to use machine learning (52%), data analytics (50%) or statistical methods (50%) for decision support. In addition, 18 systems refer to clinical pathways for the decision support process. Imaging is used as a method by 11 systems. Interfaces used by CDSS are electronic health records (58%), clinical information systems (27%) or mobile applications for physicians or patients (25%). The AI Pathway Companion from Siemens Healthineers [17], for example, is a tool to support medical decision-making. It uses artificial intelligence to incorporate all relevant disease-specific and patient-related data into the decision-making process. This also includes the interface to the patient file. The goal is to establish a patient-specific therapy pathway. The value creation analysis for the CDSS shows that the decision support is mainly based on machine learning or statistical methods. These methods frequently consider clinical guidelines and pathways or additional patient data to obtain a valid result.

4.3 Value Capture

The business model analysis in the element *value capture* shows that two pricing models predominate. The systems use a software licensing model in most of the cases (64%), 6 systems offer single purchase options for e.g., additional hardware such as connectors on their website. Moreover, the systems do not use a uniform licensing model. The models differ in their designs between e.g., subscription licenses - from a monthly to an annual subscription – to a feature license, which limits the features an end user can use. When offering such a licensing model, 39% of the systems offer a modular system. Selected CDSS also offer additional services such as a laboratory services e.g., for blood sample analysis (11%). These systems, for example, apply AI-methods to genomics on results from separately analyzed patient samples or offer a service for the physician to analyze patient samples within 4 weeks. These services additionally support the decision process.

5 Conclusion

Based on the analysis, we develop a business model framework for AI-based CDSS. The framework contains generic attributes and their alternate conditions for CDSS business models and gives a first overview on the design of business models in this new technology field. The analysis shows that these systems currently focus mainly on the leading causes of death i.e., heart diseases and cancer [18]. The support of these systems focuses on varying levels of care such as prevention, diagnosis, therapy recommendation using machine learning and statistical methods. The majority of analyzed CDSS use licensing as a pricing model, which is of little surprise since these are classical software products.

Only a few CDSS additionally offer laboratory services within the scope of decision support. These include the processing of e.g., tissue or blood samples to create genetic maps or compare them with existing databases. Most of the manufacturers promise an improved treatment pathway and patient process and advertise potential efficiency gains.

AI technologies are taking off in healthcare today for different reasons: First, there is mounting pressure to reduce health care costs and improve outcomes in developed countries. Second, there has been an explosion in the availability of health care data. Third, advances in hard- and software make it possible to harness that data in new, powerful ways. As AI-based innovations take off, they will allow providers to diagnose disease earlier with greater accuracy—and ultimately manage it more effectively. Such advances will be critical drivers that help deliver value-based healthcare i.e. the best patient outcomes at the lowest possible cost [19]. Critical for the implementation of value-based healthcare are economically sustainable business models for AI-based solutions. Due to the infancy of the market, little is known about AI-based business models so far. The objective of this paper is thus to analyze the business models for AI-based clinical decision support systems, which are expected to enter the markets with greatest likelihood first.

6 Discussion

Our analysis is based on an AI in Healthcare market monitor which currently contains profiles of more than 1400 companies and their products for AI healthcare applications. The focus of the study was on CDSS products which are already available on the market. For the empirical study, a sample of 36 commercially available CDSS were identified and analyzed using the theoretical business model concept of Gassmann, Frankenberger, and Csik [10].

The business model analysis reveals that AI-based clinical decision support systems have both similarities and differences with respect to the design of their business models. We thus derive a business model framework that provides an overview of possible business model characteristics in the field of AI-based CDSS.

The importance of AI-based CDSS in patient care is undisputed. Still these systems are rarely used in everyday clinical practice. Not least because several ethical and legal issues remain to be resolved [20]. For this reason, a uniform and rapid legal basis and security for providers and users of such systems would be urgently required at an international level to improve patient care and further advance the development of new innovative business models. This would ensure a high level of acceptance among physicians and patients alike, which is an important prerequisite for such innovations in practice [21]. Our study has several limitations, which are related to the availability of information regarding the examined CDSS business models. The analysis is mainly based on information available on publicly accessible company websites. Furthermore, only systems marketed on websites in German or English language are included. Hence, this restriction is likely to exclude additional relevant systems on the market or business model aspects, which are not transparently communicated on the respective company websites. The desktop research approach further limits the validity of statements related to the business models. Moreover, the identification and definition of attributes in the respective business model elements was necessary to allow for a comparison of the individual systems. These designations may not be able to describe all systems in detail and should be considered as a selection of relevant characteristics. While this paper certainly contributes to the literature on AI-based business models in healthcare, future analyses will be required to extend the sample of analysis and the definition of respective business model elements.

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