Extending artificial intelligence research in the clinical domain: a theoretical perspective

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Abstract
Academic research to the utilization of artificial intelligence (AI) has been proliferated over the past few years. While AI and its subsets are continuously evolving in the fields of marketing, social media and finance, its application in the daily practice of clinical care is insufficiently explored. In this systematic review, we aim to landscape various application areas of clinical care in terms of the utilization of machine learning to improve patient care. Through designing a specific smart literature review approach, we give a new insight into existing literature identified with AI technologies in the clinical domain. Our review approach focuses on strategies, algorithms, applications, results, qualities, and implications using the Latent Dirichlet Allocation topic modeling. A total of 305 unique articles were reviewed, with 115 articles selected using Latent Dirichlet Allocation topic modeling, meeting our inclusion criteria. The primary result of this approach incorporates a proposition for future research direction, abilities, and influence of AI technologies and displays the areas of disease management in clinics. This research concludes with disease administrative ramifications, limitations, and directions for future research.

Keywords Machine learning · Artificial intelligence · Clinical domain · Smart literature review · Deep learning

Abbreviations
EHRS Electronic health records system
AI Artificial intelligence
LDA Latent Dirichlet Allocation

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1 Introduction

Artificial intelligence (AI) can significantly transform clinical care by supporting healthcare professionals’ translation of intricate and different data types (Beam & Kohane, 2016; Giordano et al., 2021). Assuming that AI effectively is related to automating the efforts of clinicians’ practice, it stands to improve the performance of analysis, forecast, and management decisions. The value of AI technologies in clinical care research has been well-established (Anakal & Sandhya, 2017; Evans, 2016; Goli-Malekabadi et al., 2016) for various reasons whether its resolving chemotherapy outpatients problems (Heshmat & Eltawil 2021; Ramos et al., 2020), resolving challenges in biomedicine (Kocheturov et al., 2019), the proposed approach to sustainable healthcare treatments (Malekapoor et al. 2018) and prediction and treatment recommendation for lung cancer patients (Sesen et al., 2012). Another reason behind the emergent use of AI is to require the huge analytical capacity to process electronic health records (EHR) that contains tremendous patient data, imaging and other forms of big data (Ellmann et al., 2020; Malik et al., 2018; Niu et al., 2021). AI techniques can function because of their effortless nature, productive processing, and state-of-the-art outcomes. Meanwhile, the comprehensive adoption of the electronic health records system (EHRS) holds patient information measures. AI has contributed considerably to innovative solution design for utilizing an enormous amount of information measures, ensuring accuracy and reproducibility of the data or information analysis (Yang et al., 2020).

Existing literature reviews have identified the limited scope and outcome for the utilization of AI within the clinical domain (Salazar-Reyna et al., 2020; Sone & Beheshti, 2021; Spasic & Nenadic, 2020). These reviews are mainly based on studies in a particular domain to explore issues of ML modeling. This explorative study sometimes assesses existing literature related to big data or applies data analytics to healthcare (Belle et al., 2015; Sreedevi et al., 2022). Within the solution design space in clinical care, we aim to recognize a broader
methodological scope and anticipation for possible utilization of design science research (DSR)\(^1\) for guiding machine learning-based solution model design. Preceding conducting the analysis, we choose a design strategy that includes reviewing the past literature, which encompasses DSR methodology as designing a solution model using Machine Learning (ML) technique.

Under this approach, we set up two principal goals for our literature review study reported in this paper. First, the objective is to comprehend better clinical domain research emerging topics, disease management, key design issues, and solution technologies. The second objective is to discover the replicable methodology used in the clinical or even health domain. Specifically, we expected to identify aspects of DSR in the existing research utilizing the ML and Deep Learning (DL) techniques. This evaluation will demonstrate the extent to which DSR methodologies are utilized and may be further applied in the clinical domain.

This research aims to characterize the relationship between AI techniques and clinical care disease management, in today’s more extensive landscape of technical research, through a smart review of the literature. We explore to answer the following research questions:

RQ1—What type of AI techniques are being applied to determine diseases from medical data?
RQ2—What are the areas of disease management that were identified for clinical research?
RQ3—How do these studies relate to design science research knowledge?

To answer the above questions and draw out different insights, our research smartly considers 115 research articles from four digital databases published between 2016 and 2021 (September). Eminent data-based information perception from this literature review includes:

- AI publications in the clinical domain are dramatically increasing each year through 2021.
- Most of this research utilizes existing AI techniques on well-known data extraction tasks in English clinical notes; however, there are numerous exemptions.
- There is a developing acknowledgment of AI techniques as the pattern for disease management in clinical care research and AI-based techniques in the clinical care domain.
- DSR methodologies utilization is vanishing from the innovative technological research.

In this research, we elaborate existing understanding of the computational design science paradigm (Rai, 2017) to establish a smart literature review framework using AI modeling for the clinical domain. This smart literature review has three uniqueness. First, the traditional literature review has been conducted using four databases under the guidance of the PRISMA framework. Secondly, we performed through a text mining technique called Latent Dirichlet Allocation (LDA) which is an unsupervised clustering approach commonly used for smart text analysis to investigate huge text of published articles. Third, we answer the required questions which have been established during research in the clinical domain.

2 Related work

While this research indicates different applications of AI techniques, we focus to explore on associative technologies with their applications rather than the preparation of models. Instead, we allude to the readers reading other studies (Adamidi et al., 2021; Behera et al.,

\(^1\) DSR is a problem-solving paradigm which seeks and works with aims to enhance human problem-solving or solution design knowledge through the creation of innovative artifacts—such as approach, construct, method, model, instantiation, theory, and solution prototype. Computational DSR is a rapidly growing subset of DSR, in which the design adopting computational intelligence is the vital activity of research.
AI in a clinical domain involves a multidisciplinary space of research, hence generating various other review articles as shown in Appendix 1; on record, Brnabic and Hess (2021) had a similar review focus; however, they overviewed the patient-provider decision-making process rather than the focus of the techniques utilized to determine the disease and disease management. Behera et al. (2019) addressed the context of cognitive computing in healthcare which overlaps with AI, including a significant number of technologies to control cognitive applications, such as expert systems, machine learning, neural networks, robotics, and virtual reality, and as such also provided a descriptive enumeration of cognitive computing by proposing a conceptual model. Likewise, Fan et al. (2018), analyzed the variables affecting health professionals to adopt an AI-based medical diagnosis support system, called AIMDSS utilizing the unified theory of user acceptance of technology (UTAUT).

Johnson et al. (2020) developed a multi-stage framework to construct an AI-based decision support tool that can assist to predict the five-year survivability of lung cancer patients. The framework is included Logistic regression, Decision trees, Random Forest, Adaptive Boosting (AdaBoost), Artificial Neural networks, and Naïve Bayes. Likewise, Oala et al. (2021) recommended a system for looking at the algorithms that give a path toward the decent and satisfactory use of ML in the clinical domain. Curiously, with their systematic review, our research offers a smart literature review that fosters a traditional literature review that adheres to the PRISMA framework guidelines and LDA topic modeling, focusing on the clinical area. Most of the current literature review focused on the medical [e.g. clinical practice improvement] domain (Forest & Martin, 2018; Pian et al., 2020; Salazar-Reyna et al., 2020; Yin et al., 2019), which are more comprehensive and of a more broad extension with a fundamental of clinical activities, where our research is basically engaged is clinical, which assist with diagnosing and privileging patients as well as consolidates clinical parts of medication.

2.1 Past reviews of ML/DL utilization in clinical care literature

Since clinical research has progressed, the region has become dynamically alluring to clinically trained professionals. This is an immediate result of its pragmatic congruity to clinical patients, specialists, clinical application designers, and professionals maintained by the ubiquity of clinical disease management techniques. Albeit the advantage is accepted by the intrigued audience, like self-organization capacities and physical or mental condition of life amid long-haul debilitated patients, clinical consideration experts, their clinical thought has not been recently studied and conceptualized as a self-evident and major sub-field of medical care research which has been presented in Table 1 below.

Previous literature reviews have typically utilized clinical categorization to distinguish research directions for specific areas of the clinical care domain, and their focus is generally specific to the journal’s interest. From the methodological perspective of ML/DL technique design, understanding the solution model space more broadly for their development and associated design issues, existing studies have been limited to developing a new theoretical understanding or framework. Although research interest is rapidly growing in clinical care (Velasquez2021), studies in the clinical domain rarely discuss issues in consideration and opportunities within solution model design research.

The typical accentuation of these reviews is instrumental: focusing on utilizing the ML/DL solution design techniques/application/algorithms for a specific disease. The review by Sone and Beheshti (2021) focused only on the ML design solution model related to brain imaging.
| Existing studies                      | Literature methodologies                      | Analysis outcomes                                                                 |
|---------------------------------------|-----------------------------------------------|-----------------------------------------------------------------------------------|
| Cabitza et al. (2018)                 | 70 articles, systematic review                 | Proposed ML/DL solution for the orthopedic issue                                   |
| Salazar-Reyna et al. (2020)           | 576 articles, systematic review                | A proposed framework to evaluate and integrate the previous literature on applying data analytics, big data, data mining, and AI to medical services designing frameworks |
| Spasic and Nenadic (2020)             | 110 articles, systematic review                | Presented the data explanation bottleneck as one of the critical obstructions to AI approaches in clinical NLP |
| Brnabic and Hess (2021)               | 34 articles, systematic review                 | Illuminating patient-provider decision-making process by proposing ML/DL techniques |
| Henn et al. (2021)                    | 47 articles, systematic review                 | Introduce procedures to assist the Clinical Decision-Making process in future abdominal surgery by joining existing clinical datasets and arising data processing |
| Robles Mendo et al. (2021)            | 20 articles, systematic review                 | Assessed business applications found in the most popular business stages           |
| Sone and Beheshti (2021)              | 84 articles, a comprehensive review           | Focused upon the existing utilization of ML models for mind imaging in epilepsy    |
| Verma et al. (2021)                   | 15 articles, systematic review                 | Presented AI-based decision-support systems for measuring clinical results         |
in epilepsy. Likewise, Cabitza et al. (2018) demonstrated ML/DL techniques to design the solution for orthopedic problems. The design process is the main object commonly used in almost every past review. Indeed, literature has also found that this is a limitation of designing the research process in this space for researchers who may investigate the solution design model.

Numerous attempts have been made to bring innovations in by utilizing traditional development system methodologies that envelop steps or iterations to recognize and analyze the requirements, design the solution model, and then validate the system within the problem domain. For instance, Hammad et al. (2019) designed a model solution for predicting cancer disease using ML techniques. The designing process encompasses simple steps of design methodologies such as problem definition, model design and evaluation. Likewise, Liew et al. (2020) utilized ML techniques to design a solution model for predicting Cervical radiculopathy disease utilizing the traditional design methodology process: problem relevance, ML model design and validation process. Most of the research contributed towards designing and developing ML/DL solution models but neglected using any design research methodologies beginning with the prerequisite identification and analysis, then model designing, and development continue through to validate the model and implementation process, which can be addressed utilizing DSR.

DSR addresses the development, implementation, evaluation, and adaptation of artifacts for problem-solving, and its focus on the design and development of solution artifacts proposes its utility for ML/DL solution model designing in the clinical care domain. This research can influence future researchers and accentuate appropriate design methodology for quality advancement design in the clinical care domain. DSR offers upgrades over conventional methodologies in designing IS artifacts, so gaining knowledge about DSR is important for clinical domain design. DSR gives methodologies that have been established in designing and the artificial sciences (Sone & Beheshti, 2021). DSR seeks to make advancements that characterize the ideas, practices, technical abilities, and items through which the examination, design, execution, utilization and management of information systems (IS) frameworks can be effectively and productively cultivated (Gregor & Hevner, 2013). DSR is especially significant for innovative solutions designs for clinical care domain applications since it better supports researchers in setting up grounded information and inserting conduct or human viewpoints into the plan of artifacts to resolve real-world issues (Schnall et al., 2014).

Hevner et al. (2004) instructions plan IS artifacts in the constructs, models, methods, and instantiations (March & Smith, 1995). Clinical domain applications and techniques are composed of alterable and versatile equipment, software, and human interfaces and present special and testing design issues, which are new and innovative methodological ideas to which DSR is significant. However, although the design steps are regularly utilized for creating ML/DL solution models and might be like the plan direction of DSR methodologies, none of the clinical studies reviewed unequivocally used DSR. Past studies have not invented the design methodologies nor evaluated their present status in the literature.

The remainder of this paper is as follows; Sect. 2 presents a brief comparison of previous literature reviews of AI used in the clinical domain. The section depicts the adopted form of DSR research methodology, including how AI techniques are developed to determine diseases from medical data. Section 4 includes the results and discussions relating to previous studies, identifying the most common areas of clinical aspects such as disease management.
3 Research method

3.1 Working definitions

AI is a wide-ranging branch of computer science that concerns building smart computing solutions capable of performing errands that commonly require human intelligence. AI leverages machines to emulate executives’ problem-solving and decision-making capabilities (Fu et al., 2020; Martinez-Ríos et al., 2021; Neuhauser et al., 2013; Sava et al., 2020). Therefore, AI has become an emerging field that combines computer, information and management sciences for developing effective data solutions to empower problem-solving. It additionally encompasses essential sub-fields, such as Machine Learning (ML) and Deep Learning (DL), which are frequently mentioned in conjunction with AI techniques. These techniques are involved in developing AI algorithms to assist in designing and evaluating data solutions that make predictions or classifications based on input datasets.

3.1.1 Adopted AI-enabled approach

For this research, AI consists of ML and DL techniques utilized in the clinical domain to build prediction models, screening models, diagnostic models or prognostic models. For example, K-means or hierarchical clustering are frequently applied for pattern detection; convolutional neural networks build models on image datasets (Yang et al., 2019). We take a wide perspective on AI techniques, to be specific, any work that computationally addresses issues, changes, or uses text and its subsidiaries. Accordingly, various data or digital content analysis tasks can be viewed as AI research activities in the clinical care domain, from delivering reliance parses, to image classification, and/or textual prediction (Fig. 1).

Finally, dissimilar to the conventional literature review (e.g. Kushwaha et al., 2021; Spasic and Nenadic 2020; Xiao et al., 2018), we have captioned this work as a smart literature review that follows the combination of traditional literature review (PRISMA guidelines) and topic modeling utilizing the LDA technique. The traditional literature review consists of a search strategy, inclusion and exclusion criteria, a selection process, and data extraction and analysis.
The research articles are classified using keywords: “Artificial Intelligence”, “Machine Learning”, “Machine Learning application”, “Machine Learning algorithms”, “Machine Learning techniques”, “Clinical”, “Clinical domain” and “Clinical sector” as this literature review is focused only on advance data analytical approach within the clinical domain, published articles between 2016 to 2021 (September). Other sources such as online media, web discussions, and messaging platforms unrelated to a clinical domain, were thus excluded. Once the literature review is completed, we received a total of 305 sample articles, and then performed the LDA topic modeling on them. That’s how we have demonstrated an LDA-based approach, which can assist healthcare, or clinical researchers analyze huge documents with little effort and a small amount of time. Our study aligned with previous systematic literature review methodology (Aghdam et al. 2020; Miah et al. 2020) that were developed on PRISMA framework.

### 3.2 DSR methodology

DSR has been a popular method for designing information system (IS) solutions (Gregor & Hevner, 2013; Hevner & Chatterjee, 2010). The design science encapsulates a result-based research paradigm that pursues the creation of novel information technology (IT) artifacts (Spasic & Nenadic, 2020). DSR endeavours to improve the functional performance of the designed artifacts through the advancement process and performance evaluation of those artifacts (Peppers et al., 2007). Such artifacts may vary from the software application, rigorous statistical models, and equations to inform narratives and depictions in a natural language (Wieringa, 2014). There is very limited literature that has used DSR as a methodology approach to design the process, even though ML/DL studies follow some steps of the DSR approach to create the artifacts unconsciously. Some studies presented in Table 2 show that DSR is applied in creating ML/DL solution models.

The principle point of the review is to recognize and examine past studies in the clinical care domain that utilized ML/DL techniques, investigate the two research questions using recent clinical studies, and explore solution design methodologies utilized in the clinical care domain for ML/DL techniques design. This broadens and updates the knowledge for future researchers. Furthermore, it details the utilization of design research methodologies

| Category       | Description                                                                 | Examples of artifact                                    |
|----------------|-----------------------------------------------------------------------------|---------------------------------------------------------|
| Computational  | Advancement of novel data portrayals, computational algorithms, business    | Support vector machine (SVM)                            |
|                | knowledge and analytics techniques, and human–computer interaction (HCI)    |                                                          |
|                | modernization                                                              |                                                          |
| Optimization   | Resolve decisional and functional issues with optimization techniques       | Ideal rule combinations for item proposals              |
| Representation | Represent peculiarities with strategies, dialects, and syntaxes              | Spatial and fleeting imperatives in reasonable data set demonstrating |
| Economics      | Planning components for the direct activities and movement of trade         | Competitive gaming model to educate the design regarding maintainable energy frameworks |

Table 2 Types of design science research. Adopted from Rai (2017)
in existing clinical domain studies, which had not been a focal point of past reviews. In the DSR literature, Hevner et al. (2004) characterized four artifacts creation called—constructs, models, methods, and instantiations to resolve major business problems. The breadth of the IS discipline has empowered four types of design science to arise: computational, optimization, representation, and economics (Rai, 2017).

Among the four, computational design science gives IS researchers three substantial guidelines to design novel algorithms, computational models, and frameworks for advanced data analytics applications (e.g., LDA topic modeling). To start with, the IT artifact’s design can be enlivened by key domain attributes. A recent study in the healthcare domain, conducted by Lin et al. (2017), where key context-oriented signals from EHRs directed a novel Bayesian Multi-Task Learning approach for anticipating adverse occasions. Second, analysts ought to demonstrate the uniqueness of their design and its technical predominance over chosen baseline approaches through quantitative measurements (e.g., accuracy). At last, the artifact’s design ought to contribute to arranged executions (e.g., programming), or well-developed design theory to IS knowledge base (Gregor & Hevner, 2013; Rai, 2017). Executing every rule requires figuring out the application (in this review, smart literature review) for which the artifact is being created.

### 3.2.1 Justification of DSR selection

Our proposed smart literature review adapts the design science research methodology to conduct the design and analysis studies of the clinical domain. DSR is a scientific methodology of critical thinking developed explicitly for an Information system (IS) and Information technology (IT). DSR incorporates creating new knowledge through the design of new or innovative artifacts, analysis of utilization and execution of these artifacts to improve the clinical decision support system (CDSS) (Hevner, 2007; Hevner & Chatterjee, 2010; Vaishnavi, 2007). Hevner et al. (2004) designed seven guidelines for DSR methodology are characterized as adhering to (1) design as an artifact, (2) problem identification, (3) design evaluation, (4) research contributions, (5) research rigor, (6) design a search process, and (7) communication of research. The research design of the scientific methodology applied to the current research is referenced to the seven guidelines given by Hevner et al. (2004) to adequately conduct DSR and ensure that the research processes and conclusions are coherent. The below table summarises our task schema for a DSR study that is adopted and also outlines the relevance of the proposed DSR research (Table 3).

As per Kuechler and Vaishnavi (2008), DSR consolidates the introduction of the latest information through the design of the latest or innovative artifacts, investigation of use and execution of these artifacts to improve information systems. As this proposed literature review tries to gauge the techniques being applied to determine the diseases and areas of disease management in the clinical domain, the DSR methodology is the most fitting choice. The researchers additionally described DSR as a pertinent methodology since it acknowledges artifact creation and research iteration.
### Table 3 DSR Guidelines. Adopted from Hevner et al., (2004)

| Guidelines of DSR                      | Relevance of proposed research                                                                 |
|----------------------------------------|------------------------------------------------------------------------------------------------|
| Guideline 1: design as an artefact      | An LDA topic model using a ML approach is developed to conduct the smart literature review in the clinical domain |
| Guideline 2: problem relevance          | The outlined smart literature review solution addresses a literature review problem in the clinical domain |
| Guideline 3: design evaluation          | An evaluation is conducted using indication of traditional literature and significance of the proposed approach |
| Guideline 4: research contributions     | The developed approach utilized an original DSR to show its contribution to the clinical domain imaginatively |
| Guideline 5: research rigor             | The guideline is accomplished through the specification of the approach and its usefulness which is rigorously defined |
| Guideline 6: design as a search process | The design tasks accomplished through a consolidated development methodology which empowers the clinical domain to develop solutions according to the problem space and available technologies |
| Guideline 7: communication of research  | The design effort is accomplished through smart literature review demonstration to focus on the clinical domain and is introduced utilizing particular and regular guides to exhibit the functionality of the methodology |

### 4 Sample analysis process: PRISMA framework and topic modeling

#### 4.1 Sample selection process

In recent years, AI applications in the clinical domain have been rapidly growing under a wide spectrum of healthcare requirements such as: predicting the disease forecast, early detection of diseases, administering disease management, monitoring patient’s performance, and developing or maintaining the disease plan (Elragal and Haddara, 2019; Fohner et al., 2019). In this research, we only focus on AI applications in the context of the clinical domain. This study employs the smart literature review method to provide a comprehensive review and utilization of the techniques of ML/DL in the clinical domain. This literature review is conducted following the PRISMA framework proposed by Page et al., (2021). The following figure visualizes the main steps adapted from the PRISMA framework to achieve the objective of this research.

#### 4.1.1 Search strategy

Numerous databases were used to accomplish the review objectives and search for the studies distributed between January 2016 and September 2021. Research work before just 2015 was viewed as a component of the analysis, as this was generally the time since when AI began getting traction in solving genuine issues. The research articles published in outlets like journals and conference proceedings focusing on the broader research community were considered for the current analysis. We investigated the databases and selected the following to conduct quality research in the clinical domain. The electronic databases are IEEE, Google Scholar, Scopus, and PubMed. Next, the search keywords were matched with Boolean operators AND and OR to join the keywords or add the equivalents to create Boolean articulations.
The keywords (‘Artificial Intelligence’, ‘Machine Learning’, ‘Machine Learning application’, ‘Machine Learning algorithms’, ‘Machine Learning techniques’, ‘Clinical’, ‘Clinical domain’, ‘Clinical sector’) are chosen to find any studies focused on the research objectives.

4.1.2 Inclusion and exclusion criteria

The search process was completed from 2016 to 2021 (September), and the language is limited to English only. The full-text studies and journal and conference articles were considered. The duplicate studies were excluded as well as reports, book notes, posters and book sections. A systematic review was accomplished by the PRISMA guidelines utilizing IEEE, Google Scholar, Scopus, and PubMed Databases, focusing on clinical care that used ML to resolve a clinical issue. Included studies were published from January 1, 2016, to September 1, 2021, and provided measurements on the performance of the used ML algorithms.

4.1.3 Selection process

The PRISMA framework has opted for six steps process. The initial identification of articles was 534,327 and excluded non-English studies, removed duplicates, excluded review studies other than conference and journal articles, and removed grey literature. After the selection process, 305 articles were selected.

4.1.4 Data extraction

Once we had selected 305 articles, we then performed the data extraction to achieve the objective. The Endnote application extracts the metadata, and all the articles were downloaded in pdf format and kept in one folder.

4.1.5 Quality evaluation

To ensure the current study’s discoveries are based on the work well tested and established theoretical literature, we limited the research articles based on the ranking; A*, A, and B ranked journals as per the Australian Medical Research Council journal list or ranks of 4*, 3 or 2 in Scientific Journal Ranking list. These research articles were also individually validated for considerable quality criteria: their scientific rigor, research methodology deployed AI solutions, theoretical framework used from clinical studies, and finally, relevance. Senior authors further validated the relevance by looking through the articles individually. Eventually, the articles were manually dropped, which did not fit into the current study’s scope after the authors’ discussion (Fig. 2).

4.2 Topic modeling using LDA

The 305 articles were finalized after the traditional literature review process; then, we performed topic modeling using Latent Dirichlet Allocation (LDA), where all the pdf research articles were combined into one single text file using an ML algorithm, and then LDA was utilized, which is unsupervised, probabilistic machine learning algorithm (Kar et al., 2015; Li et al., 2018, 2019; Momtazi, 2018) which discovered 9 topics by calculating patterns of word co-occurrence across 305 research articles. Among those 9 topics, topic numbers 0 and
6 have presented the highest percentage and were used in 115 research articles used in this current research.

5 Findings

Our findings incorporate observational and analysis-based components. In the observational aspect, we anticipate that DSR can guide ML/DL-based oriented research in the clinical domain, based on our gained evidence. The below table is the example outcome that indicates ways of adopting DSR (Table 4).
The research conducted by Butgereit et al. (2018) used the DSR methodology inspired by Kuechler and Vaishnavi (2008). DSR models consist of five steps: awareness, suggestion, development, evaluation and conclusion to prepare ML models.

Velasquez (2021) utilized DSR, which directs the design and investigation of artifacts regarding stakeholders. The research focused on the understandability of the Business Process Model (BPM). The artifacts are created based on ML model designing, consisting of three phases—problem investigation, treatment design, and treatment validation to explore relationships to predict indicator values. Hirt et al. (2017) applied DSR methodology to develop a supervised machine learning model artifact that comprises model initiation, error estimation and deployment using five steps process, inspired by Kuechler and Vaishnavi (2008), where the authors started by reviewing relevant literature and conduct exploratory interviews with two specialists from the industry to confirm the awareness of the issue, then the authors explained the suggestion and development of novel process model and tested the drafted artifacts for sustainability in an illustrative scenario using Peffers’s et al. (2007) DSR approach and finally obtained knowledge from the completed design cycle.

From the analysis aspect, our discoveries were uncovered in two separate analyses. First, we briefly portray the ML/DL techniques utilized in past studies and demonstrate which technique has been used most over the last 5 years and calculated in the graph of several sample studies. We then focused more detail on the techniques and technologies used to assist in disease management.

**RQ1** What type of AI techniques are being applied to determine diseases from medical data?

Figure 3 illustrates the ascent and fall of broad categories of AI architectures. This research focuses on Neural Networks (NN), Boosting techniques (BST), Decision tree (DT), Random Forest (RF), Support Vector Machine(SVM), Logistic regression, and Ensemble model, where research articles utilized Ensemble only papers used ML technique, for example, SVM and DT. In the figure, we present that Boosting and Neural Network utilize more than other techniques. It also illustrates the development of broad architectures in AI utilize more than other techniques. It also illustrates the development of broad architectures in AI utilize more than other techniques. The number of ML and DL techniques is relative to the number of those techniques utilized in the studies; some studies used many ML/DL techniques to find the best fitting or validity purposes. Overall, Neural network variants which are DL techniques, were the most common (31), Boosting was second (22), Decision tree and Random Forest were third (19), Logistic regression was fourth (18), and Ensemble only fifth (12).

The volume of AI publications is expanding rapidly every year (10 times increased between 2016 and 2021), as presented in the figure below, and the equivalent is valid for each type.
of architecture. Over the years, Deep Learning architecture utilization has increased, and RNN, ANN, long short-term memory (LSTM), and bidirectional long-short-term memory (Bi-LSTM) have been utilized more than traditional ML techniques (Fig. 4).

Appendix 1 has demonstrated a range of facts regarding the past literature, such as the model, variables, aim for conducting the research, and result models they have acquired.

**RQ2** Scope—What are the areas of disease management that were identified for clinical research?
Figure 5 illustrates that breast cancer and diabetes disease were highly addressed in 115 research articles. We categorized the literature into four categories: Cancer, Diabetes, virus, and others based on visual analytics. Note that the research which does not fall into any first three categories will fall into another category. The example of some diseases which are coming into other—Sepsis, Non-alcoholic fatty liver, Creutzfeldt-Jakob, Genomic diagnostic, assertion detection, Chronic Obstructive Pulmonary Disease, Hyperuricemia diagnosis, multiple sclerosis, Juvenile idiopathic arthritis, Deep vein thrombosis, co-morbidity recognition, antidepressant treatment, neonatal care, autism spectrum disorders (ASD), clinical relation extraction, Laryngopharyngeal Reflux Disease, HIV Disease, chronic disease patient, acute exacerbation of chronic obstructive pulmonary disease (AECOPD), Predict Anaplastic Lymphoma Kinase (ALK).

The figure below represents which model in the past studies have opted for as a result. It illustrates that DL model utilization has increased over the 5 years and shows 34% of the total research articles, while ML is second with 33% and ensemble model is third at 13% and other models on fourth with 12% (Fig. 6).

The aforementioned findings represent that our method has successfully been applied to bring a lot of useful details from past publications. Complementing the view of computational design science research, our convergent view has been demonstrated through the presented review analysis. That gives proof of a new concept to relate to how AI capabilities enhance the current view of research practices, which can be informed through the computational DSR paradigm. We argue that this is the innovative component of knowledge that researchers could take away and extend the view with relevant topics for further evaluation on more generic AI studies.
6 Discussion

This paper introduced a new insight into AI in terms of the applications of ML/DL in the clinical research domain. We have discovered a new prospect of using the DSR in ML/DL-based solution development research. There are very few studies in the clinical domain that explicitly use DSR as their methodological approach. Most of the existing studies utilize traditional framework development, but the evaluation stage is frequently missing, and informed participation all through improvement is rare. This builds up prior discoveries that testing was absent and that frequently developers came up short on the clinical information to apply to their ideal interest group. Most papers depicted the design process, with very few more theoretically focused artifacts being created. Although various clinical applications have been developed, without a DSR framework being utilized, the theoretical contribution or specification of the design is not always clear, restricting their utilization as design artifacts for later transformation or generalizable information.

It is evident that DL in the clinical domain has been broadly acknowledged. This acknowledgment is exhibited in that DL approaches are progressively considered about the gauge procedure, with no correlation with traditional ML. Furthermore, despite their beginning in the computer science and AI communities, DL-based approaches have completely saturated the medical informatics community and entered trustworthy clinical journals. The ramifications are that informaticians and clinicians will progressively embrace DL advancements in clinical settings as they become more recognizable. This is both a chance and a peril, so health experts need to properly acknowledge and perceive the related dangers.

Various usually held studies were validated in our information investigation. DL-NN has ruled as the most used model in past studies. A comparable impact was noted for Boosting and Decision tree techniques. Additionally, most research will be published in 2021 on ML/DL utilization in the clinical domain, which has been presented in Appendix 1, demonstrated a range of facts in regards to the past literature, such as the model, variables, target for conducting the research, and result models they have procured. This study has recommended some possible future trends in DL in the clinical domain. As a result of the expense of
explaining clinical corpora and the protection worries with sharing the training information, space transformation and transfer learning techniques are significant. There has been minimal methodical investigation on this issue from a deep learning perspective because of the absence of persuading results.

Regardless of this, we also accept that underutilized clinical information resources. However, the mantra of deep learning has been to "allow the loads to figure out what is significant" as opposed to handcrafting highlights; DL algorithms and inputs need human contribution, as proven by a recent push to think about inductive predisposition. Information resources might give measurable and objective means to direct information-driven DL algorithms, and the clinical domain is exceptionally outfitted with such resources. Further, it is obvious from other subfields, including ML for the clinical domain, that deep learning is not generally successful (Christodoulou et al., 2019; Xu et al., 2019). In this case, we imply that it frequently neglects to outperform essential models, such as logistic regression. We would contend that now it is dangerous only to differentiate DL-based models, especially deploying the applications in the clinical domain. However, this paper also exhibits that it is logically ignorant not to measure up to some DL gauge. Also, arising DL practice proposes some instability encompassing initialization and hyperparameter choice.

6.1 Implications

6.1.1 Contribution to the theory

Firstly, we conduct a literature review study on the clinical domain to explore which AI techniques have been used to determine the diseases which focus on published articles between the year 2016 and 2021. We find deeper insights into those articles to detect the diseases using advanced technology. While broader studies have already indicated healthcare and medical diagnosis adoption of different applications, none of them has focused on how to improve the literature review using a combination of traditional literature review and artificial intelligence (Kushwaha et al., 2021; Wagner et al., 2022; Xiao et al., 2018). This study endeavours to disclose to new and future researchers on how to conduct a smart literature investigation to obtain accurate insightful results. Hence, our research broadens the existing body of knowledge by introducing a smart literature review idea to save future researchers time and effort.

Secondly, this study incorporates ML/DL with DSR methodology to explain the designing a new approach. Specifically, our review makes a clear distinction for various guidelines of DSR, which is largely disregarded by previous researchers on novel innovation acknowledgment. In the context of smart literature review acknowledgment, we emphasize the initial stage of DSR in ML/DL deployment studies, where researchers and clinical professionals have no prior interaction with DSR guidelines in reality. Besides, we firstly introduce DSR as a guide to conduct the research utilizing seven guidelines (1) design as an artifact, (2) problem identification, (3) design evaluation, (4) research contributions, (5) research rigor, (6) design a search process, and (7) communication of research. While DSR has been generally utilized for guiding research in different areas, those concentrates mainly centered on explaining some steps which do not explore enough of utilizing practically (Butgereit et al., 2018; Hirt et al., 2017). However, there is deficient research considering how DSR guidelines can be utilized in ML/DL research. This research is attempting to expand DSR methodology with ML/DL technology to analyze the past literature. At first, we present a smart literature review to review the past literature promptly. The review is developed using the LDA
topic modelling technique in the clinical domain in which we integrate DSR methodology guidelines to conduct innovative research using advanced technology.

6.1.2 Implications for practice

From a practical perspective, there are significant implications for this smart literature review. Firstly, there is the conceivable selection bias inherent to the search strategies utilized. This incorporates bias in the sorting of searches we proceeded with the basic limitations of search engines. For instance, we have used only four digital databases and analyzed only articles published in English. We also think about that as an incredible assortment of relevant articles does not expressly contain the keywords of our research in their titles; accordingly, extra articles were manually added based on the author’s research experience. Based on the current research inclusion criteria the particular DL model referenced in the title was rarely found which can be a surprising factor. Another limitation is that it is infeasible to address the whole clinical domain. We would have expected to limit our concentration, such as one disease management, which would have been a very different scope than the current review.

7 Concluding remarks and future research

The smart literature review using topic modeling has been addressed over the past. However, the smart literature review has not been addressed adequately to date within the clinical domain. Disease management and types of disease that were identified using AI are the advantages explained in this research.

In this study, we performed a smart literature review and analyzed 115 selected articles that demonstrated the utilization of artificial intelligence in the clinical domain. The proposed literature review confirmed that the publication related to AI in the clinical domain is increasing rapidly. The utilization of AI algorithms over the years also displayed whether it disease prevention or detection, presented Neural Network is the most common technique (31), Boosting was second (22), Decision tree and Random Forest were third (19), Logistic regression was fourth (18), and Ensemble only fifth (12). The review also displayed the areas of disease management that were identified for clinical research using 115 articles. The proposed research also displayed how AI-based studies are related to design science research knowledge using some examples. Based on the smart literature review we provide some research avenues. A future research study developed utilizing more databases as search engines to get more accurate results. Another future research is to develop other literature review using other topic modeling techniques such as network language processing and contrasts the outcomes obtained with the results of this research. Also, further research should evaluate the model by comparing it with another model to find comparison between accuracies of the results. Future research can be conducted by modifying inclusion and exclusion criteria such as year, ranking etc. and utilizing some other framework instead of PRISMA to address more articles.

Appendix 1: Brief overview of selected articles highlighting ML/DL in the clinical domain
| Author            | Year | Algorithm                          | variables | Disease management                      | Sample size | Study objectives                                                                 | Results               |
|-------------------|------|------------------------------------|-----------|-----------------------------------------|-------------|-----------------------------------------------------------------------------------|-----------------------|
| Anakal and Sandhya (2017) | 2017 | Ensemble, SVM, neural network, DT   | 11 variables | Chronic obstructive pulmonary disease | 50 patients | Developed a portable spirometer to generate the treatment plan for COPD          | Ensemble model       |
| Balkan and Subbian (2018)  | 2018 | RF                                 | 10 variables | ICU database                   | 135,680 records | Demonstration of ML techniques to collaborate teleICU database to evaluate an existing empirical scoring system currently used critically | RF and APACHE        |
| Iqbal et al. (2018)       | 2018 | ASP, ANN, classification, RBR       | 2 variables | Chronic disease patient            | 15 patients | Systems built especially for independent living and provide analysis             | ANN produced better accuracy |
| Ma et al. (2018)          | 2018 | LRM Bayesian network               | 11 variables | Non-alcoholic fatty liver disease    | 2522 records | 5 important features BMI, triglycerides, gamma-glutamyl transpeptidase (γGT), the serum alanine aminotransferase (ALT), and uric acid, were the top | Bayesian network model |
| Author            | Year | Algorithm            | variables | Disease management                  | Sample size | Study objectives                                                                 | Results          |
|-------------------|------|----------------------|-----------|-------------------------------------|-------------|----------------------------------------------------------------------------------|------------------|
| Orlenko et al.    | 2018 | AutoML               | 4 variables | Homocysteine plasma concentration | 546 patients | Enhance clinical metabolic profiling and advance translational research endeavors | AutoML           |
| Chen (2019)       | 2019 | RNN, Embedding, AM   | 8 variables | Assertion detection in CNLP         | 186 records | Attention-based Bidirectional Long Short-Term Memory networks)                   | Deep learning    |
| Dias et al.       | 2019 | CNN, RN              | 7 variables | Genomic diagnostic detection       | 74 records  | Focus on emerging methods for specific tasks in clinical genomics, including variant calling, genome | Deep learning    |
| Fu et al. (2019)  | 2019 | XGBoost, RF          | 40 variables | Early detection of Sepsis          | 40,446 ICU patients | Developed an Ensemble model for early six-hour detection of sepsis               | Ensemble model   |
| Hammad et al.     | 2019 | LR, SVM, NB          | 5 variables | Breast cancer                      | 116 records | A comprehensive view of the patient’s risk level; and risk factor analysis       | SVM              |
| Jarrin et al.     | 2019 | LR, SVM              | 1 variable  | ZIKA virus                         | 20 patients | Be used in primary care for early diagnosis and prognosis                         | SVM              |
| Author               | Year  | Algorithm                  | variables | Disease management       | Sample size | Study objectives                                                                                                                                                                                                 | Results |
|----------------------|-------|----------------------------|-----------|--------------------------|-------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------|
| Li et al. (2019)     | 2019  | CNN, CRNN, NLP, Bi-LSTM, SDP| 8 variables | clinical relation extraction | 426 patients | Propose a new neural network design by modeling SDP along with sentence sequence to extract multi-relations from clinical text                                                                                     | SDP     |
| Bello-Chavolla et al. (2020) | 2020  | SNNN, K-Means              | 4 variables | Diabetes management      | 1132 data sample | SNNN models trained using population-based data can better reproduce diabetes subgroup classification                                                                                                           | SNNN    |
| Ellmann et al. (2020) | 2020  | SVM                        | 6 variables | Breast MRI               | 173 patients | Investigated whether the integration of machine learning (ML) into MRI interpretation can provide exact decision rules for the management of suspicious breast masses                                               | SVM     |
| Guo et al. (2020)    | 2020  | SVM                        | 72 variables | Laryngopharyngeal Reflux Disease | 134 patients | Improve the clinical diagnosis of LPRD                                                                                                                                                                           | SVM     |
| Author          | Year | Algorithm       | Disease management | Variables | Sample size | Study objectives                                                                 | Results                          |
|-----------------|------|-----------------|--------------------|-----------|-------------|-----------------------------------------------------------------------------------|----------------------------------|
| Haq et al.      | 2020 | ACC, MCC, K-Fold, LOSO, DT | Diabetes detection management | 8 variables | 2000 records | Develop a classification system to identify diabetes and can be deployed in an e-healthcare environment | Ensemble Ada Boost and RF         |
| Kumar et al.    | 2020 | NB, RF, SVM, KNN, RT | Co-morbidity recognition | 16 variables | n2c2 dataset | Develop a classification system to identify whether a certain health condition occurs for a patient by studying his/her past clinical records | Ensemble model                   |
| Küpper et al.   | 2020 | SVM             | Autism spectrum disorders (ASD) | 11 variables | 673 records | Predictive features of autism spectrum disorders                                  | SVM                              |
| Langer et al.   | 2020 | ANN, MLP, RF, NB | Coronavirus disease 199 patients | 6 variables | 199 patients | Predict Reverse transcription-polymerase Chain Reaction (RT-PCR) for Severe Acute Respiratory Syndrome coronavirus | ANN                              |
| Author        | Year | Algorithm                              | variables | Disease management                  | Sample size | Study objectives                                                                 | Results            |
|---------------|------|----------------------------------------|-----------|-------------------------------------|-------------|----------------------------------------------------------------------------------|--------------------|
| Liew et al.   | 2020 | LASSO, Stepwise regression, Boosting, MuARS | 6 variables | Cervical Radiculopathy              | 201 patients | Developed a model with Cervical radiculopathy patients                           | MUARS              |
| Mo et al.     | 2020 | XGBoost, RF, GBDT, Extreme RT, LR       | 47 variables | Juvenile idiopathic arthritis       | 87 patients | Predict the efficacy of etanercept in the treatments of JIA                      | XGBoost            |
| Paul et al.   | 2020 | Gradient-boosted multivariate regressions, LR | 10 variables | HIV disease                         | 105 patients | Reveals Novel Neuroimaging and Clinical Signatures of Frailty in HIV             | GBMR               |
| Peng et al.   | 2020 | DT                                     | 28 variables | Acute exacerbation of chronic obstructive pulmonary disease (AECOPD) | 410 patient records | Assess the severity of the patient at an early stage                           | DT                 |
| Rajpurkar et al. | 2020 | LR, GBDT, ElecTreeScore                | 21 variables | Antidepressant treatment            | 518 patients | Predict improvement in individual symptoms                                      | ElecTreeScore      |
| Author          | Year | Algorithm                  | Variables | Disease management       | Sample size | Study objectives                                                                 | Results |
|-----------------|------|----------------------------|-----------|--------------------------|-------------|----------------------------------------------------------------------------------|---------|
| Seccia et al.   | 2020 | RF, SVM, KNN, AdaBoost     | 56 variables | Multiple sclerosis       | 1624 patients | To predict whether a patient will shift from the initial Relapsing–Remitting (RR) to the Secondary Progressive (SP) form of the disease—multiple sclerosis |         |
| Silitonga et al. | 2020 | BA                         | 8 variables | Dengue disease management | 2680 patients | Correlation Between Laboratory Characteristics and Clinical Degree of Dengue     | BA      |
| Bai et al.      | 2021 | LR, KNN, CatBoost, RF, XGBoost | 18 variables | Hyperuricemia diagnosis  | 656 patients  | Monitor the prognosis of patients with ST-segment elevation myocardial infarction (STEMI) complicated by hyperuricemia | boost   |
| Chang et al.    | 2021 | LASSO, RF                  | 2 variables | Predict Anaplastic Lymphoma Kinase (ALK) | 526 patient records | Diagnose ALK mutation status for lung adenocarcinoma patients                   | LASSO   |
| Author              | Year  | Algorithm                    | variables | Disease management          | Sample size       | Study objectives                                                                                                                                                                                                 | Results                                      |
|---------------------|-------|------------------------------|-----------|------------------------------|-------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------|
| Greenbury et al. (2021) | 2021  | K-Means, Gaussian distribution | 6 variables | Neonatal care               | 45,679 records    | Developed a framework for the potential of agnostic machine learning approaches to deliver clinical practice insights and generate hypotheses using routine data                                                            | Dirichlet Process Gaussian Mixture Model (DPGMM) |
| Hussain et al. (2021)   | 2021  | RF, SVM, KNN, GBM, XGB        | 24 variables | Chronic obstructive pulmonary disease | 466 patients       | Focuses clearly on predictive models utilized in the diagnosis of COPD                                                                                                                                            | Soft voting ensemble (SVE)                   |
| Luo et al. (2021)      | 2021  | GLM, SVM, XGBoost, RF         | 6 variables | Deep vein thrombosis        | 518 patients      | Optimized the current intervention and diagnostic process for deep vein thrombosis                                                                                                                              | SVM                                          |
| Author          | Year | Algorithm       | Disease management | Variables | Study objectives                                                                 | Results                                                                                                                                 |
|-----------------|------|-----------------|--------------------|-----------|-----------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Ma et al. (2021) | 2021 | 2021 Tabnet, XGBoost, Deep FM, AutoML | 5 variables        | Predict CT anomaly detection                                                       | Ensembl model                                                                                                                          | Shown that age, lymphocytes, ferritin, neutrophils, and C-reactive protein are the most related clinical indicators for predicting CT outcomes for pediatric patients with positive RT-PCR testing |
| MacKay et al. (2021) | 2021 | 2021 SVM, RF, MLP, EGBT, LR | 4 variables        | Administrative claims to predict clinical outcomes                                | Developed a robust model, claim-based that applies to both medical and surgical patient population                                        | 770,777 beneficiaries                                                                                                                                 |
| Rajagopal and Arock (2021) | 2021 | 2021 LR, KNN, DTC, RFC, XGBoost | 4 variables        | Creutzfeldt-Jakob disease                                                         | Provide visualization of clinical parameters for drug discovery pattern                                                                | 200 patient records                                                                                                                                 |

**Results**

- Ensemble model
- XGBoost model
| Author          | Year | Algorithm                | variables | Disease management | Sample size | Study objectives                                                                                                                                                                                                 | Results |
|-----------------|------|--------------------------|-----------|--------------------|-------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------|
| Romeo et al.    | 2021 | RF, SMOTE                | 10 variables | Breast cancer       | 135 patients | Combined with ML showed promising results to differentiate benign from malignant breast lesions on ultrasound images                                                                                                   | RF      |
| Yin et al.      | 2021 | MDL, NB, K-Means, NMF, DT| 3 variables | Lung cancer         | 2502 patient records | Various models predicted different performances, and detection could be done at an early stage of lung cancer                                                                                                   | Integrated application based on supervised and unsupervised ML |
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