Design Approaches for Executable Clinical Pathways at the Point of Care in Limited Resource Settings to Support the Clinical Decision Process: Review of the State of the Art

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Abstract. Decision support clinical pathways are used to improve the performance of the health-care management system. An effective clinical pathway (CP) helps to know the optimal treatment route that patients will follow. The extent of the CP goes from the first contact in the health-center (or hospital) to the completion of the treatment until the patient is dismissed. Up to now, far too little attention has been paid to a systematic review, the research and the development of CPs in a low resource setting (LRS). The main focus has been primarily on data-intensive environments where there is no shortage of resources. A systematic search in PubMed and Web of Science was conducted for bundling and categorizing the relevant approaches for LRS. Of 45 full reviewed articles, 25/45(55.6%) and 20/45(44.4%) of the studies were conducted using knowledge-based and data-driven approaches respectively. Among the knowledge-based studies, 9/25(36%) were reporting a stand-alone applications, 10/25(40%) attempting to deliver a paper-based CP, and the remaining focus was on web-based applications. In the data-driven approaches, 15/20(75%) tried to integrate with the electronic health record. The paper identifies the approaches for executing CPs and highlights key considerations for building LRS-compatible CPs. Data-driven CPs do not only resolve the challenges of improving the quality of existing knowledge-based CPs, but also enable evidence-based practice, improve outcomes, and reduce cost and delay.

Keywords: Limited resource setting · Clinical decision support system · Clinical workflow · Clinical pathway · Patient flow · Point of care service

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1 Introduction

Promoting healthy lives and the well-being of people is one of the main agenda points for Global Sustainable Development Goal 3 by 2030 [1]. Diverse tools have been implemented to improve the access and to assist the healthcare service in delivering patient-centered value. For instance, eHealth (telehealth) will play a leading role for universal health coverage [2] and is expected to bring *equity and extended access*, to *improve outcome* and fill the *gap in professional scarcity* at primary care level [3]. However, the success of eHealth depends on: (i) the policy environment, (ii) the flexibility of integration with the health-care delivery system, (iii) usability, (iv) public-private partnership, and (v) business models and protocols [4]. A case study on the Ethiopian Black Lion Hospital also noted that ensuring the compatibility with the medical practice and the physician's preferred work style facilitates the eHealth adoption [5].

The primary health-care management is seeking a point of care instrument to deliver appropriate, consistent, and integrated care. The Clinical pathway (CP) aims to deliver and outline an optimal logical path and plan of care from assessment to treatment at the primary and secondary health care level [6, 7, 10]. It is also known as "*care pathway, integrated care pathway, critical pathway, or care map*". CPs are utilized for various purposes, and studies demonstrated that adopting a decision support clinical pathway has a significant impact on: (I) managing the quality and standardization of health-care processes [6], (II) reducing delay [8–14], (III) improving outcomes [7, 8], (IV) increasing coherence between care units and professionals [7, 8, 10, 11, 14–22], (V) reducing the risk of errors and complications [7, 8, 15–17, 20], (VI) reducing cost [8, 10, 13–16, 18, 23], (VII) promoting evidence-based decision making [7, 8, 12, 15, 17, 18, 23–26], (VIII) improving communication and feedback e.g. within or between the health center and the hospital [12, 18–20, 25, 26], and (IX) increasing job satisfaction [6, 14]. However, previous studies on CP did not systematically consider contexts of low resource setting (LRS) but implicitly assumed a data and resource-intensive environment. For instance, Aspland et al. 2019 found, only 0.1% of the CP studies have been conducted outside America, Asia, and Europe [27]. The purpose of this review is to systematically confront existing CP publications with the low resource setting (LRS) context, explore the gaps and recommend approaches (important design considerations) for building and executing CPs. Furthermore, the motivation for this research arose from a desire to help frontline workers in low-resource settings who primarily make decisions based on hard-copy clinical guidelines (CGs), patient card-sheets, and point-of-care charts. Some of the challenges were a lack of health information infrastructure, as well as a lack of data management and decision support tools. We can also see that the patient card-sheets give insufficient information, lack referral feedback (which may result in unnecessary referrals and delays in seeking care), and many decision-support tools are out of reach for low-resource settings.

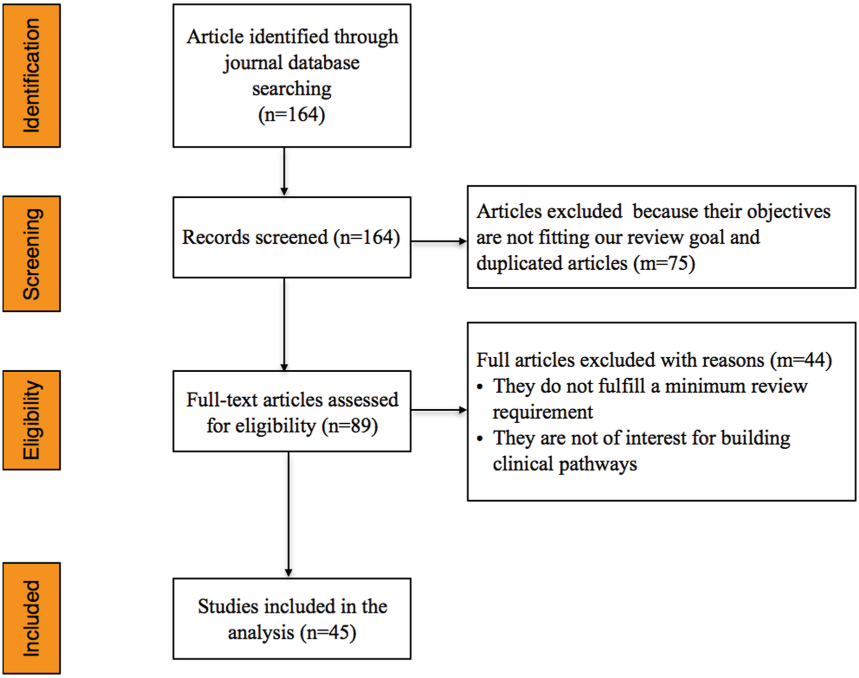

Fig. 1. Flowchart of study selection and inclusion (**n** is the number of papers at each step of inclusion and eligibility assessment, and **m** is the number of excluded papers)

2 Methods

The methodology of the review process was adopted from [28, 29] and customized to our needs. The review process was conducted based on the following steps: (I) defining the goal of the review, (II) identifying search strategies, (III) identifying databases for literature search, (IV) defining the inclusion and eligibility assessment criteria, and (V) extracting data and conducting data analysis. More information on the detailed flow of the review process is shown in Fig. 1.

2.1 Goal

The systematic review aims to explore the feasible approaches and strategies to develop an executable clinical pathway for low resource settings (LRS). To achieve this, the present review systematically confonted existing CP publications with the LRS context. Specifically, we explored: (I) which techniques and procedures are the most appropriate to design an executable clinical pathway at point of care services for better health outcomes in the context of low resource settings, and (II) what are the principles, challenges, and important considerations to build executable CPs? Furthermore, we also seek to map those techniques in the literature that have been identified with the point of care executable platforms.

2.2 Search Strategy and Literature Search

A literature search was performed using PubMed and Web of Science database. As shown in Table 1, search strategies were developed using various composite keywords. The summary of keywords and search strategies is presented in Table 1. The search criteria were intended to involve various decision support executable clinical pathway terms that have been labeled as 'clinical pathways' for promoting evidence-based management practice. We searched PubMed and Web of Science published in English without publication year restriction.

Table 1. Summary of the search strategy

Databases	Keywords and techniques
PubMed	Clinical Pathways
	((((((((clinical pathway) OR computerized clinical pathway) OR computerized clinical pathway system) OR decision support clinical pathway) OR interactive clinical pathway) OR data-driven clinical pathway) AND applicable clinical pathway) OR model-based clinical pathway) OR CDSS in low resource settings) OR patient flow analysis) OR low resource settings
	((((((((clinical pathway) OR computerized clinical pathway) OR computerized clinical pathway system) OR decision support clinical pathway) OR interactive clinical pathway) OR data-driven clinical pathway) AND applicable clinical pathway) OR model-based clinical pathway) OR CDSS in low resource settings) OR patient flow analysis) AND low resource settings
Web of Science	Ts = (clinical pathways) AND LANGUAGE: (English) Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI
	Ts = (clinical pathway OR computerized clinical pathway OR decision support clinical pathway OR interactive clinical pathway OR data-driven clinical pathway OR applicable clinical pathway OR model-based clinical pathway OR low resource settings) AND LANGUAGE: (English) Indexes = SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan = All years
	Ts = (clinical pathway OR computerized clinical pathway OR decision support clinical pathway OR interactive clinical pathway OR data-driven clinical pathway OR applicable clinical pathway OR model-based clinical pathway AND low resource settings) AND LANGUAGE: (English) Indexes = SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI Timespan = All years
	searched for: CITED WORK: (clinical pathways) Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI

(*continued*)

Table 1. (*continued*)

Databases	Keywords and techniques
Google Scholar	Clinical Pathways
	"clinical pathway" OR "clinical pathway management system" OR "computerized clinical pathway" OR "decision support clinical pathway " OR "interactive clinical pathway" OR "data-driven clinical pathway" OR "applicable clinical pathway" OR "model-based clinical pathway" AND "low resource settings"
	"clinical pathway" OR "clinical pathway management system" OR "computerized clinical pathway" OR "decision support clinical pathway " OR "interactive clinical pathway" OR "data-driven clinical pathway" OR "applicable clinical pathway" OR "model-based clinical pathway" OR "low resource settings"
Manual Search	Manual searching based on citation and related articles

Additionally, Google Scholar queries and manual searches of citations and related articles of the included studies were undertaken to identify any relevant articles that might have been missed. For example, on Google scholar, we searched using the keyword "computerized clinical pathway management" queries to extract publication year, number of citations and name of the publisher. The visual illustration is presented in Fig. 2.

2.3 Eligibility Assessment

A variety of steps were performed to examine the inclusion and eligibility assessments of a specific journal or conference article. The title, abstract and objectives of individual studies were reviewed to select eligible studies. In general, studies were included if they (I) demonstrated and reported the application of CPs, (II) examined the impact of CPs such as promoting evidence-based practice, improving outcomes, reducing cost and delay, improving communication and feedback, or a combination of these items, or (III) examined factors that impact the

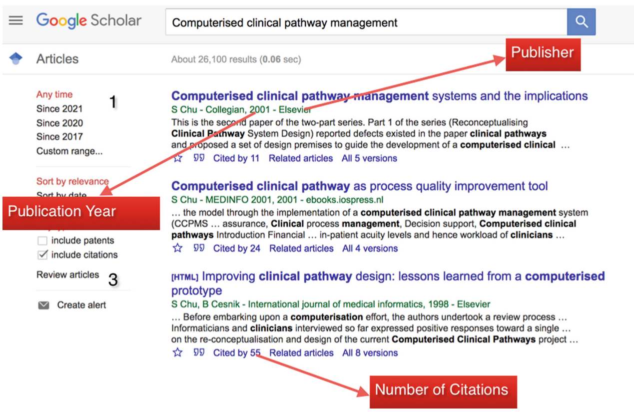

Fig. 2. Sample searching result

practice of CPs. In particular, studies that presented a situation in low resource settings were included for analysis. Then, we set the "number of citations" thresholds based on the publication year. We only considered articles with a minimum of five citations if they are published before 5 years (i.e. before 2014) and a minimum of one citation if they are published within 5 years. The search was conducted in 2019. Full articles were reviewed where it was not possible to decide about their inclusion based upon abstract-review alone. In the end, mixed-methods, cross sectional studies, survey, cohort studies, pilot studies, randomized control trails and case study reports were included and assessed based on their stated intent to bring and design effective decision support clinical pathways at the point of care service.

2.4 Data Extraction and Data Analysis

The data extraction template was adopted from [29] and customized for our needs based on the review objectives. Data from each article were extracted using a standardized excel database. the extracted information at the end of the review process are: the title, author, name of publisher, publication year, number of citations, context, mechanism and intervention strategies, characteristics (setting, platform, approaches, and techniques), the outcome of the study and the possibility to adapt (or reproduce) it in low resource settings. Data analysis and visualization were performed using our own python-based interactive tool. Then, we examined the CP design techniques, platforms, and approaches. We also summarised the included study using citations, publication year, intent, and outcomes.

3 Results

3.1 Search Results

A total of 164 articles were identified for inclusion and eligibility assessment. We excluded 75 articles after title and abstract screening and 89 articles were eligible for full article review. Of these, 45 articles were included for review and met the inclusion criteria. The included studies were published between 1992 and 2018. The review process for selecting articles with reasons is summarized in Fig. 1.

3.2 Summary Characteristics of Included Studies

Summary of the Studies Using Citations and Publication Years. Of the 45 included studies, 10/45 (22.2%), 7/45(15.6%), 5/45(11.1%), and 4/45(8.9%) were from Elsevier, BioMed Central (BMC), Springer, and IEEE respectively. The detailed summary of the studies using journal publications is presented in Fig. 3.

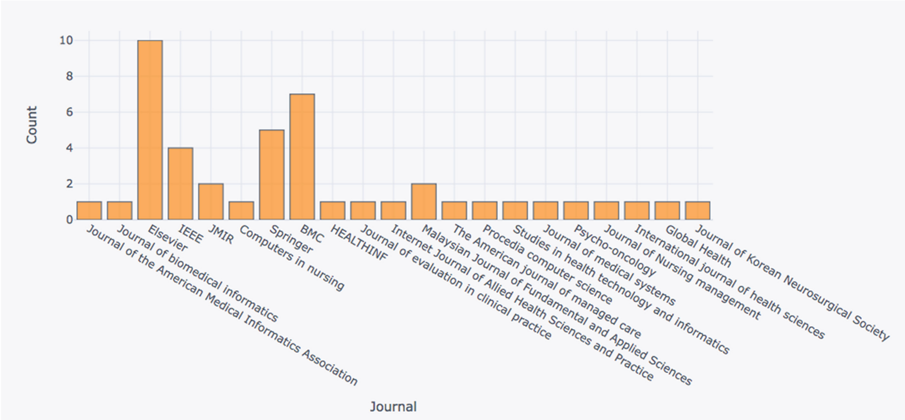

Fig. 3. Summary of journals

Of the 45 studies, 30/45(66.7%) of the articles have more than 10 citations and 33/45(73.3%) were published after 2012. Figures 4 and 5 are illustrating the detailed summary of citations and publication year respectively.

Summary of the Studies' Intent and Their Outcomes. Among the manuscripts, twenty-seven studies were demonstrating the use of CPs for the point of care decision support service and evidence based multidisciplinary care plans [9, 11–14, 20, 25, 26, 36–40, 44, 47–61]. These studies were describing that the introduction of automated and accessible CPs not only uncovered evidence and visualized specific care plans but they also compared and emphasized the contrasts between different CPs. Five studies demonstrated the advantage of computerized CPs, the functional requirements and the expected benefits [24, 31–34]. Three studies attempted to automate and generate computer interpretable CPs from CGs [23, 41, 42]. Two studies have focused on the challenge and practice of designing and implementing CPs [19, 22]. Three studies have explored

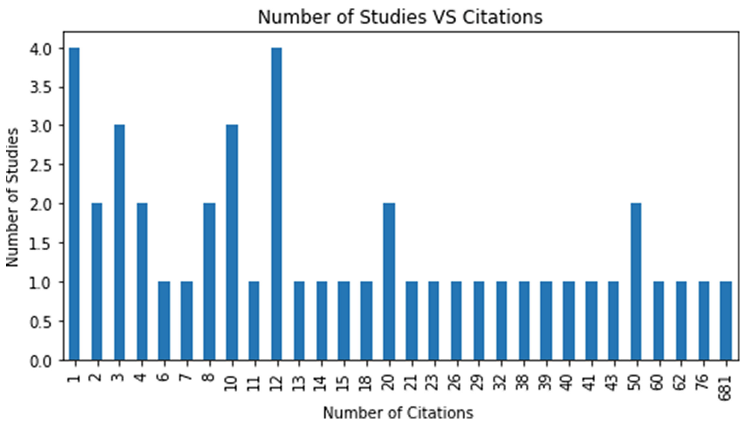

Fig. 4. Summary by citations

the patient current state, treatment intent, behavior, and outcomes [9, 52, 53]. These studies tried to characterize, cluster and visualize the visit sequence, patient condition, and progress to promote accessible and evidence-based CP. Four studies examined the use of CP for predicting and handling the variance or deviation from the specified care plan [21, 54, 62, 63]. Only one study examined the optimal mechanism for CGs and CPs representation and strategies for clinical-care improvement [45]. In this study, CGs and CPs were transformed into decision-tree for delivering quality service and coherent decision-making. However, very few studies were explicitly demonstrating CPs in low resource settings [20, 22, 26]. In low resource settings, the target of the studies was handling patient flow analysis, assisting critical care, and aiding resource management. Moreover, few studies also implement CPs for tracking performance and managing resources [49, 59, 61].

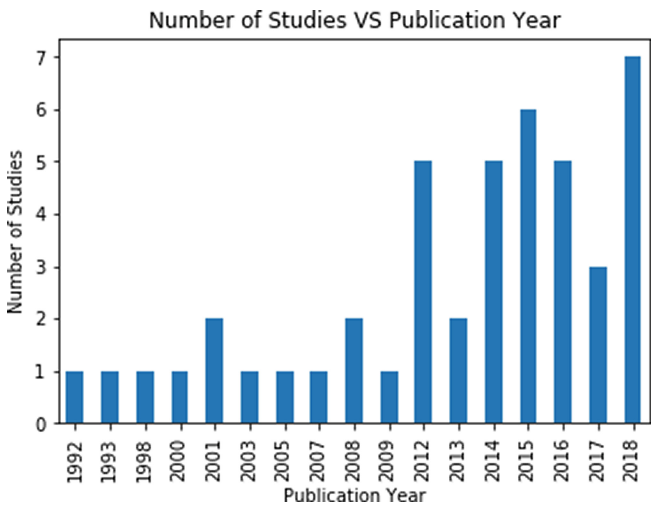

Fig. 5. Summary by publication year

In summary, among the reported outcomes, the included studies: (I) outlined the functional requirements for designing CPs, (II) disclosed the way to assist the process of intervention, and to reduce the treatment waiting times (visit sequence, condition, progress), outcome prediction, and quality of evidence, (III) brought easiness of data extraction for collaboration and monitoring, (IV) reported a significant impact on reducing errors, reducing cost and length of patient stay, and (V) described the variance (or deviation) from the specified care plan.

3.3 Clinical Pathway Design Approaches, Platforms, and Techniques

Of the 45 full reviewed articles, 25/45 (55.6%) and 20/45 (44.4%) of the studies were conducted using knowledge-based and data-driven approaches respectively. From the 25 knowledge-based studies, paper-based follow-up (10/25, 40%), stand-alone applications (9/25, 36%), and web-based applications (6/25, 24%) were the most commonly reported CP execution platforms. The paper-based follow-up mainly used face-to-face communication at the point of care services. Additionally, it also includes a telephone follow-up and conversation. In the data-driven approaches, 15/20(75%) of the studies tried to integrate with the electronic health record while the remaining focused on delivering web-based and standalone CP applications. Overall, paper-based follow-up (10/45, 22.2%), stand-alone applications (11/45, 24.4%), web-based applications (9/45, 20%), and integration with heath records (15/45, 33.3%) were the most commonly reported CP execution platforms. The results obtained from the analysis of platforms and approaches are summarized in Table 2.

Table 2. Summary of CP execution approaches and platforms at point of care

Approaches	Number of studies	Platforms			
		Paper-based (Including phone follow-up)	Standalone application	Web-based application	Integrated with health records (HR)
Knowledge-based approaches	25/45 (55.6%)	10/25 (40%)	9/25 (36%)	6/25 (24%)	–
Data-driven approaches	20/45 (44.4%)	–	2/20 (10%)	3/20 (15%)	15/20 (75%)
Total	45	10/45 (22.2%)	11/45 (24.4%)	9/45 (20%)	15/45 (33.3%)

As shown in Table 3, automation was demonstrated using stand-alone and web-based platforms. Additionally, rule-based logic and probabilistic techniques were used for the implementation of stand-alone and web-based CPs. Whereas learning algorithms, visualization, and recommendation techniques were employed on health records for delivering data-driven CPs. Results obtained from the mapping of CP platforms on implementation techniques are presented in Table 3. The mapping of CP platforms and implementation techniques includes CP execution platforms that have been integrated into health records (HR), stand-alone, and web-based applications. However, CP follow-ups, assessments, requirement analysis, and reviews were also conducted using paper-based platforms.

Table 3. Mapping of CP execution platforms with techniques

Platform	Techniques	Number of studies
Integrated into HR	Learning algorithm and clustering, Markov chain modeling	1
	Frequent sequence mining algorithm & visualization using Sankey diagram	1
	Hierarchical task networks or Hierarchical clustering and Markov chains	1
	Hybrid learning algorithm	1
	K-means with Levenshtein distance	1
	Neural network	2
	Probabilistic	1
	Rule Based or Fuzzy rule, extended fuzzy Petri net	3
	Statistical machine-learning algorithms	1
	Visualization techniques and/or, score system and graphical representation	2
	Rating based recommendation	1
Standalone APP	Automation	7
	Decision trees	1
	Hierarchical task networks or Hierarchical clustering and Markov chains	1
	Probabilistic	1
	Rule Based or Fuzzy rule, extended fuzzy Petri net	1
WEB APP	Automation	6
	Probabilistic	2
	Rule Based or Fuzzy rule, extended fuzzy Petri net	1

We also observed that the overall trend is moving towards integrating CPs with electronic health records for enabling the use of learning algorithms, improving data visualization and recommendation techniques. As can be seen from the Fig. 6, the trend of executing clinical pathways is shifting from knowledge-driven to data-driven approaches. In general, as illustrated on the y-axis in Fig. 7, a total of 14 techniques were extracted to design an executable CP. Information on the summary of CP studies based on their approaches, platforms, and implementation techniques between 1992 and 2018 are presented in Figs. 6 and 7.

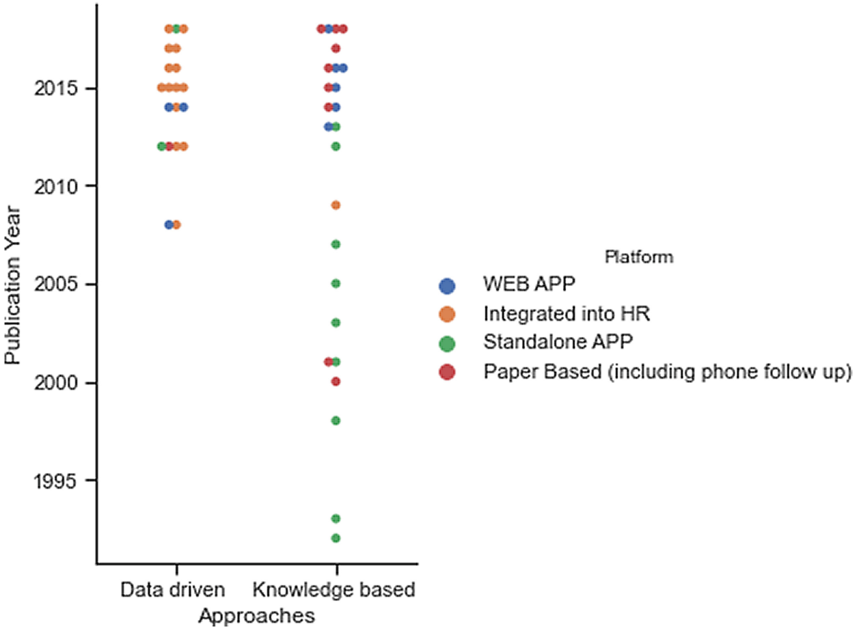

Fig. 6. Summary of CP studies publication year, approaches, and platforms

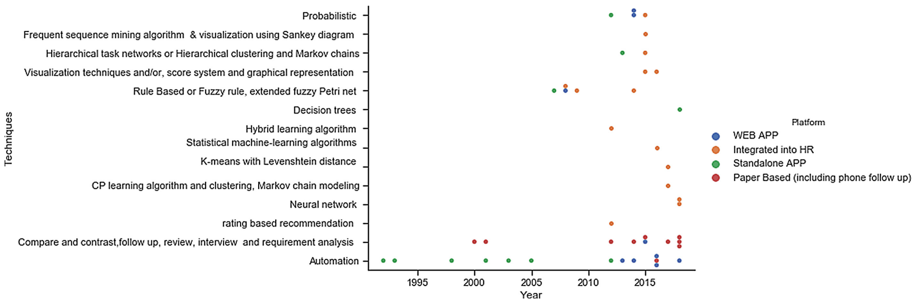

Fig. 7. Summary of CP studies based on platform and techniques over the years

4 Discussion

The clinical decision support system has improved over the years and is moving towards "*delivering ubiquitous accessibility and availability of data, any form of knowledge representation, shared decision making, continuous feedback and improvement*" [30]. Our systematic review was designed to explore the diversity and the relevance of the approaches used, and to identify the mechanisms and implementation strategies for designing CPs in LRS.

This review has shown that knowledge-based and data-driven approaches were found to be the major approaches for designing executable clinical pathways at the point of care to support the clinical decision process. Further analysis showed that the *knowledge-based* approaches can be categorized into paper-based, Information Technology (IT)-based, and model-based implementations for executing CPs at the point of care while the *data-driven* approaches can be subdivided into ontology, probabilistic, and artificial neural network (machine learning) techniques. The data-driven approach relies on the integration with the electronic health record, events, and logs. For instance, in the current review, among the data-driven approaches 75% of the studies demonstrated integration with the existing electronic health record. In all, based on our observations, we classify the CP approaches into two distinct categories (and three distinct sub-categories) depending on the design principles, strategies, and methodologies. A detailed summary of our observations is presented in Fig. 8.

The first group facilitates evidence-based decision-making using knowledge-based CPs. In this category, a group of experts and interdisciplinary teams will start designing knowledge-based CPs from the existing CGs, accepted standards, best practices or an extensive literature review. The knowledge-based CP can be executed in three ways:

– First, using a paper-based system. The main challenges of the paper-based approach are time-consumption, resource-intensiveness, lack of adaptiveness and flexibility to accommodate dynamic change [31, 32].
– The IT-based system is often based on the automation of the paper-based approach to facilitate the delivery and quality of healthcare service. The IT-based system [21, 24, 33–41] demonstrated the development of computerized management CPs through algorithms for recommendation or a management portal. However, there is still a need to differentiate clearly between the clinical pathway and automated clinical guidelines, and a need to put usable intelligent recommendation (or wizards) into the clinical routine [34, 36, 41]. IT is used for modeling tasks and activities, but it is challenging to model the whole life cycle management of clinical pathways. Moreover, communication between IT and the domain experts is often still an issue.
– Finally, using the model (CGs) based approach. The model-based approach attempted to bring the overall treatment of a specific disease in one concrete setting based on a clinical guideline [23, 42–44]. The paper- and IT-based systems focused on the development of CPs for one specific condition and setting. Commonly, guideline-based representation languages as rule-based languages and the ready-to-use (or executable) pathway models are generated to deliver assistance for the domain expert. However, as stated in [23, 42–44], it is important to consider the inter-sectoral pathway (multi-disease/case pathways) and cycle pathway during CGs based implementation.

Overall, the knowledge-based CP is concentrated on delivering static, stand-alone, disease-specific, and nonadaptive pathways. It is also practiced in a low resource setting, e.g. paper-based flow charts and integrated symptom-based guidelines used as a point of care instrument for assisting the frontline workers [46].

In the second group, the data-driven CPs, it was demonstrated that complex and heterogeneous scenarios can be captured. The goal is to learn CPs from actual practice data to enable shared decision-making, promote exploration for better understanding and management, and maximize clinical efficiency through evidence-based practice and optimal clinical outcomes. Many studies have explored the practice of data-driven approaches for different settings and disease conditions [9, 47–63]. However, the data driven CPs need to be integrated with ontology, probabilistic, or artificial neural network (machine learning) approaches for enabling an efficient and adaptive service. Ontology (semantics) based techniques [54–58] focused on the subjects and their relationships, not so much on the presentation of the data. However, a variety of factors have been described that limit the practicality of ontology-based CPs. For instance, the care plan [57]: (I) is too general and requires more detail, (II) lacks the required universally accepted standards, and (III) requires to consider the plan of care experience, hospital (health-center) characteristics, pathway summarization of different hospitals (health-centers) that need to be aggregated to deliver adaptively and universally accepted CPs. Probabilistic-based techniques [9, 59–61] employed probabilistic CPs to visualize, explore and discover a series of healthcare system challenges. However, when the number of attributes increases, the probabilistic techniques grow in size which results in an exponential increase of the number of lookups to perform the CP recommendations [59].Therefore, a trade-off is required to understand and manage CP complexity by probabilities of occurence. Though most of the existing clinical decision support systems appear to be aimed at assisting the clinical workflows, management of information, and decision-making, there is a need to

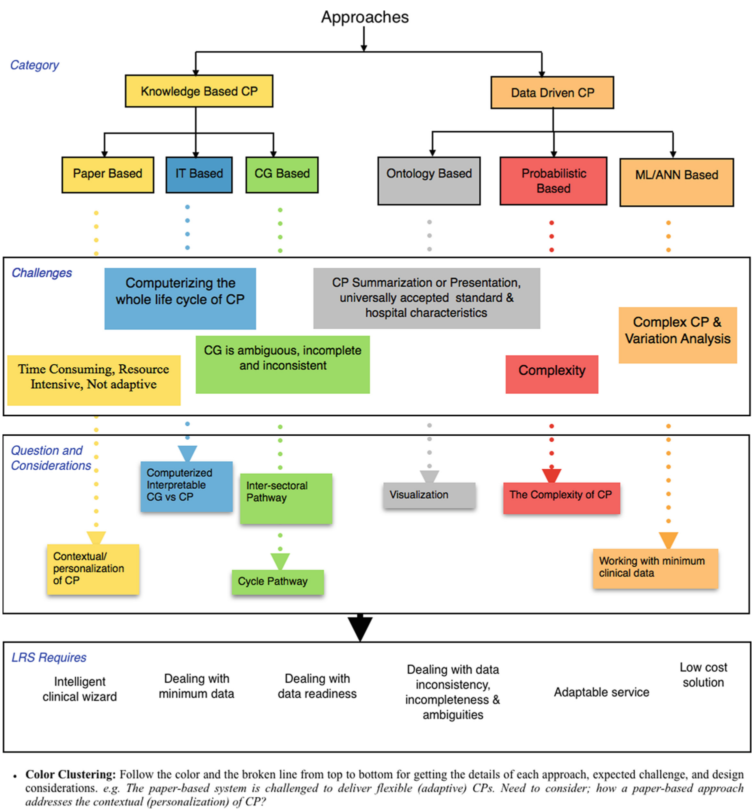

Fig. 8. Summary of approaches, challenges and considerations

deliver personalized care, evidence-based practice by keeping the latest practice guideline and react to the patient's condition. Artificial neural network (machine learning) techniques have been demonstrated to be successful for delivering personalized care, promoting evidence-based practice, slashing cost, and predicting variance [8, 62, 63].

Overall, we found that the trend of executing clinical pathways is shifting from knowledge-driven to data-driven approaches by integration with electronic medical records for assisting healthcare professionals and frontline workers. However, there is no "*one technology for all*" approach for designing applicable clinical pathways (or plans of care) to support and promote an evidence-based decision process. Both the knowledge-based and data-driven approaches have their own pros and cons. More information on the challenges, considerations, and LRS requirements is presented in Fig. 8. Even though data-driven clinical pathways are more advantageous than knowledge-driven approaches, enabling and putting evidence into practice is challenging in health systems with limited resources. Besides that, a complex healthcare decision must allow for many pathways, be updated in real time as new information is provided and encourage patient preference and participation.

Furthermore, a search of the literature revealed only few studies which attempt to examine the application of CPs in LRS. Hence, we considered it useful in this review to make a summary of previous observations [27] from a broader perspective than only the LRS one. In LRS, most of the primary and first-level care follows a paper-based system as a dominant practice. Designing a CP that is working with minimum clinical data is required while maintaining the CP's reliability and maneuverability. A need exists to design an executable clinical pathway solution that is accessible to low-resource health facilities that can tightly interface with the existing workflow. The LRS requires to deal with minimum clinical data, data readiness, data inconsistency, and incompleteness. Designing a low-cost solution, intelligent clinical wizards, and adaptable services is also crucial. It is also important to consider other available health information to explore the existing best practice and clinical guidelines. The lack of the expected resources and limited digitization will challenge the practice of data-driven CPs. Therefore, the implementation and selection of the CP approach depend on the strategies, resources (e.g. practical guidelines), principles, standards of care, best practices, and intended goals [10, 11, 15]. Besides these, as noted in [4, 7, 8], the effectiveness of CPs highly depends on (A) the recognized clinical guidelines and policy, (B) the key stakeholders and their drivers, (C) the quality of the evidence-based approach, (D) the integration of the existing workflow, (E) the complexity of the used techniques, logic, and ability to adopt contextual decision making - for example rule-based and decision tree logic are challenged to deliver meaningful contextual and non-linear workflow clinical pathways, (F) the accessibility and treatment options, and (G) patient preference and participation.

This review has limitations. In addition to PubMed and the Web of Science database, we have employed Google Scholar queries and manual searches. We were discarded articles from inclusion based on the citation threshold. However, potential studies from other sources not indexed to one of these databases might be missed. Moreover, studies published in languages other than English are often missed.

5 Conclusion

The purpose of this review was to explore feasible approaches and strategies to develop an executable clinical pathway for low resource settings. We have provided a review of the decision support clinical pathway by: (I) reviewing the applications and publications between 1992 and 2018, (II) summarizing the approaches, and (III) presenting the important considerations for designing executable CPs and it's expected benefits.

The included studies highlight the importance of CPs for promoting evidence-based healthcare, assisting the care process, and improving the quality of care. The CP can be designed based on the guidelines, the standard of care, and best practices. Findings from studies included in this review indicate that knowledge-based and data-driven approaches are the main approaches for designing CPs. Knowledge-driven CPs can be executed using a paper-based, IT-, or model-based system. Integrating with the existing electronic health record, web-based and standalone CP applications are the modalities of data-driven CP execution. Taken together, this review observed that the trend of executing clinical pathways is shifting from knowledge-driven to data-driven approaches. However, most of the primary and first-level care in low resource settings follows a paper-based system as a dominant practice in-comparison with the IT and model-based approaches. Therefore, it is required to design a mechanism for evidence-based practice to improve outcomes and feedback. Exploring a trade-off mechanism for promoting data-driven decision-making approaches may help to explore, visualize, and discover a series of health-care system challenges such as: (I) assisting low clinical competence, limited medical staff, and shortage of equipment, and (II) improving clinical outcomes, workflows and temporal relationships for clinical pathway workflow management. However, infrastructure, data readiness, data inconsistency, incompleteness, and ambiguities as well as adaptability (understanding the context) still are major challenges of clinical data.

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