Bayesian Networks in Healthcare: What is preventing their adoption?

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Abstract

Bayesian networks (BNs) are known to be versatile in their capability to support medical decision-making in a variety of healthcare contexts. However, despite having gained significant research attention in the literature, BN adoption in clinical practice remains an elusive problem. This is made worse by the absence, in the literature, of a comprehensive analysis of the *benefits, barriers* and *facilitating factors (BBF)* for implementing BN-based systems in healthcare. This paper seeks to address this gap. By using the ITPOSMO-BBF framework, we reviewed works describing BNs in healthcare and identified the challenges and advantages discussed by authors when proposing their BN-based systems. Several BBF factors related to data, resource, resistance, and performance were identified. Most of the discussed barriers and facilitating factors are related to information and technology, while the majority of benefits are about processes and objectives. We believe that the output of this review can enhance the dialogue among researchers by providing a deeper understanding for the neglected issue of BN adoption in practice and promoting efforts for implementing BN-based systems.

Keywords: Bayesian networks; adoption; implementation; healthcare

1. Introduction

In healthcare, clinicians make countless decisions in daily practice. These decisions include estimating the likelihood that the patient is suffering from a particular disease (diagnostic decisions), that the chosen intervention represents the optimal treatment strategy for the patient's condition (treatment decisions), or that the selected treatment will result in a certain outcome (prognostic decisions). The vast array of information now available, as well as the complex nature of human physiology, all serve to increase uncertainty and make clinical decision-making a challenging task [1], [2], [3], [4]. The often-discussed need for tools to assist decision makers has led to development of many clinical decision support (CDS) models and associated tools [5], [6], [7], [8], capable of integrating disparate sources of information and guiding clinicians in their decision-making task [9]. These tools have evolved from simple scoring systems to include complicated multivariate regression, neural networks, decision trees, and probabilistic models [10], [11], [7].

This paper focuses on a specific type of graphical probabilistic model, *the Bayesian network* (BN) [12]. BNs have become popular CDS models in medicine [13], [14]. This popularity results from their ability to: (i) model complex problems with causal dependencies where a significant degree of uncertainty is involved; (ii) combine multiple sources of information including data and experts' judgement; (iii) present as an interpretable graphical structure; and, (iv) model interventions and reason both diagnostically and prognostically.

Early attempts to use Bayesian analysis for medical problems were considered unsuccessful because BN computation was intractable [15]. Development of efficient BN inference propagation algorithms [12], [16] and continuing advances in computational power have made possible BNs capable of addressing real-world decision-support problems. This has motivated renewed research interest which has seen many thousands of publications proposing BN solutions for medical application [17]. However, despite the immense volume of published studies on medical BNs there is little evidence for their adoption in clinical practice as shown in our recent scoping review [14]. We found that the content of most literature concerning BNs developed as CDS focuses on BN development. Only a minority of published medical BN models directly contemplate the importance of and need for external validation, and fewer still pay any attention to BN usefulness and adoption in clinical practice. To the best of our knowledge, the chasm between research effort and clinical adoption has not drawn adequate attention [18], [17], [19]. Motivated by a desire to enhance dialogue among researchers and gain deeper understanding for the neglected issue of BN adoption in practice, this paper focuses on exploring the benefits, barriers and facilitating factors for implementing BN-based solutions in clinical care.

Acknowledging that a gap exists between developing an accurate model and demonstrating its clinical usefulness and impact on decision-making, several researchers have explored the stages necessary to implementing prediction models in clinical practice [20], [21], [22], [7], [23]. Additionally, several studies have investigated reasons why CDS models are not found in clinical practice [18], [24], [19]. *We extend on these and review a collection of 116 recent papers proposing medical BNs for supporting clinical decision-making, with specific attention to identifying the benefits, barriers and facilitating factors. Benefits* present as the positive outcomes that authors propose may result from implementation in clinical practice of their proposed BN-based system, such as improved patient outcomes or reduced costs and resource consumption. Benefits are usually realised by fixing one or more barriers through engagement of a facilitating factor. *Barriers* present as obstacles preventing clinical adoption of the BN, such as clinicians' reluctance or the high cost of implementation. Finally, *facilitating factors* are those elements that when applied, are able to overcome one or more existing barriers, and by doing so, promote successful implementation. Examples might include providing a user-friendly and contextual interface to minimise clinicians' reluctance to engage with new technologies.

In this paper we apply the ITPOSMO-BBF framework developed by McLachlan et al [25] to explore the chasm between recently developed medical BNs and their lack of adoption in clinical practice. We present results of a literature review of works describing BNs in healthcare and identify the benefits, barriers and facilitating factors discussed by authors when proposing their BN-based CDS solution. The results of this review can a) help identify reasons for the lack of adoption of BNs in healthcare; and b) promote efforts for clinical adoption of BN-based systems.

The remainder of this paper is organised as follows: Section 2 introduces background material regarding implementation of CDS model in clinical practice. Section 3 explains the ITPOSMO-BBF methodology used. Section 4 presents our results, while a discussion of our findings and a conclusion are provided in Sections 5.

2. Background: Implementation of Clinical Decision Support Systems

As a background to the work presented in this paper, this section presents the generally established framework for implementation of CDS systems and contextualises implementation of BN-based CDS within that framework. Based on the existing literature for implementing CDS systems [26], [21], [27], [22] the following four main stages should be followed:

Development: A CDS model is developed by: (a) identifying important predictors; (b) verifying the assumptions behind the model; (c) estimating its predictive accuracy; (d) calibration; and (e) discrimination using the data used to develop the model, called *internal validation* [28], [24]. It is a general requirement that key details that describe how a model was developed and validated be clearly reported to enable synthesis and critical appraisal of all relevant information [29], [30]. Only with full and clear reporting of the model development process and internal validation can risk of bias and potential usefulness of models be adequately assessed [29], [31], [32], [33].

External validation: After developing a CDS model it is crucial to validate its predictive accuracy on data not used during model development in a process called *external validation* [21], [34], [23], [29], [24]. External validation of model performance is crucial for verifying the model's generalisability. A clinical model is unlikely to be accepted if it has not been proven to work on disparate populations. External validation may use: (i) data collected from the same hospital but sampled from a later or earlier period, called *temporal validation*; data from different hospitals or countries, where the clinical care and definitions might be different, called *geographic validation*; or (iii) data sampled from demographically different individuals than those from which the model was developed, called *domain validation* [23], [29]. If necessary, the model can be updated using knowledge gained from the validation process.

Assessment of Clinical Usefulness: A useful model should have an impact on clinical decision making. Assessment of the clinical usefulness of a model consists of three phases. *First,* the existing clinical situation and potential benefit of the tool must be clear [18]. Questions such as: (i) *What is the targeted population?* and (ii) *Who is going to use the model, at what point during the care and for what purpose?* should be clarified [35]. Also, we must investigate how the model will integrate into the clinical workflow and any barriers we might experience, such as ethical and regulatory restrictions [36], [37], [38], [39]. *Second,* before conducting an extended impact analysis we must verify that the CDS model has potential to impact clinical decision-making [21], [18], [24], [40]. The first objective at this phase is to verify the credibility, also known as face validity, of the model [26]. A model without credibility may not include well-known predictors for disease or treatment outcome and therefore clinicians might doubt its advice [18]. Thus, clinicians should review the model's logic, comprehension and relevance. After this, the potential impact of the CDS model should be examined [41], [42] as this is the first sign for whether it is going to be used or not [27], [22]. A system that rarely updates its decision will not be used, no matter how accurate it is. Another important element of usefulness considered during this phase is the model's usability. Clinicians must be able to use and comprehend the CDS system, as a complex system is unlikely to be used [43]. Hence, a user-friendly interface and easily interpretable predictions are vital [18]. It is also crucial to have a trustworthy and explainable model whose reasoning is clear to clinicians as they are unlikely to use a model they do not understand or trust [44], [19]. *The third and final phase* before implementation is undertaking an *actual impact* analysis. The impact analysis is an evaluation that can identify whether the CDS can sustain a long-term implementation, or if there are barriers that must still be resolved. The actual impact of a CDS system will differ from its potential impact. Clinicians will not always follow the system's recommendations: they may not consult the system at all; apply it inaccurately; overrule its recommendations or be unable to implement its recommendations [21], [45], [22].

Adoption: The final stage is the acceptance and implementation of the CDS to assist decision-making and guide patient management in clinical practice. Even though this stage represents the endpoint for development and implementation, the whole process should continue as new clinical knowledge is identified, thus operating like evidence-based medical practice, as a *learning cycle* [46], [47]. New knowledge might include changes in the clinical guidelines used to define healthcare practice that should be evaluated for incorporation into the CDS.

3. Methodology

This work applies the ITPOSMO-BBF methodology [25] to a collection of literature proposing BNs for use in healthcare. We seek to provide a balanced comparison among benefits, barriers and facilitating factors as an approach to systematically assess the challenges that contribute to the lack of adoption for BNs in clinical practice. Our methodology involves three phases: Search and selection, Research framework, and Analysis.

3.1 Search and selection

We used the literature collection selected from our recent scoping review on BNs in healthcare [14]. The search term used to derive the selected literature was:

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"(((Bayes OR Bayesian) AND network) OR (probabilistic AND graphical AND
                model)) AND (medical OR clinical)"
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Terms such as *Bayesian networks* or *graphical probabilistic models* were used here because they are widely observed in the targeted literature. Different ways for explaining the medical condition do occur, in that in some papers the exact condition is mentioned while in others broader terms such as *medical* or *clinical* accompanied by *application*, *condition*, or *setting*, are used. Our scoping review settled on the broader terms *medical* or *clinical* as they were commonly found in a larger collection of papers. Searching for specific medical conditions would have been impractical as there are many thousands of distinct known conditions.

As detailed in [14], due to the high number of articles returned, further scrutiny was applied to narrow the collection to one which was reasonable to complete a defined review. This was achieved by assessing whether the described keywords were present in the title and abstract. Additional screening was conducted to exclude papers published outside the period 2012-2018, those that were not published in English, or those whose BN focus was not healthcare related. The remaining eligible papers were those possessing all the following identified characteristics in that they:

1. Describe a genuine BN model or BN adoption process
2. Are targeted clearly at a medical condition or application
3. Are intended to support clinicians or patients in decision making

3.2 Research Framework

Inspired by the research framework proposed by Yao et al. [48], the literature collection was reviewed using the logic process illustrated in Figure 1. Benefits, barriers and facilitating factors for adopting BN-based systems in healthcare were identified using content analysis (CA) and thematic analysis (TA) [49], [50]. In addition, the context in which authors described them, as well as their frequency in the collected literature was examined.

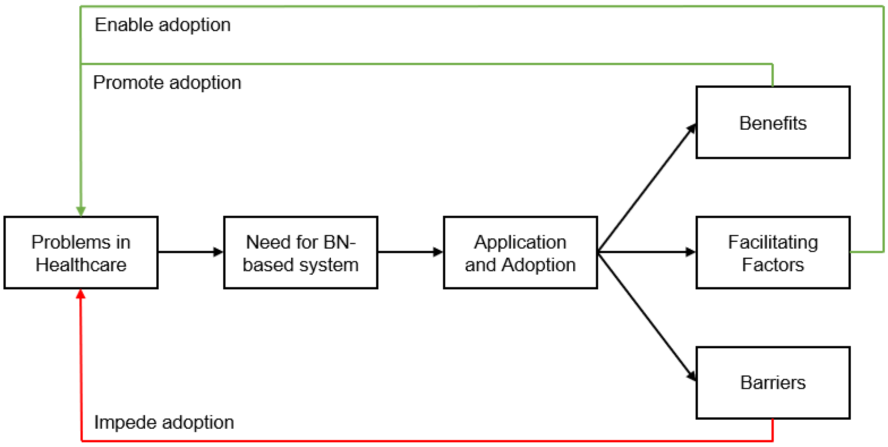

Figure 1. Research framework

3.3 Analysis

Authors often represented the same general idea in a variety of ways. CA and TA are separate but interrelated qualitative approaches for descriptive data analysis [50]. CA is an accepted systematic coding and categorisation method for investigating texts and resolving a quantitative description of the features [51], [50]. CA establishes categories and then records the instances in which that category is evident or can be inferred from within the collected texts being analysed [51]. TA is a more qualitative method used to identify, analyse and report patterns, or themes, that emerge as being important within the material being analysed [49], [51], [50]. TA provides the systematic element characteristic of CA, while additionally affording the ability to combine analysis of frequency with analysis of *in context* meaning, therefore providing a more truly qualitative analysis [51]. CA and TA are established methods regularly used in clinical, nursing and other healthcare contexts [49], [51], [50]. While CA resolved many common concepts, it is only once TA was applied that these concepts could be described by their underlying contextual themes. The concepts and themes identified through these processes provided the necessary knowledge and data to support our ITPOSMO-BBF analysis.

One widely used approach for evaluating information technology implementation is ITPOSMO [52]. ITPOSMO stands for: (1) Information; (2) Technology; (3) Processes, (4) Objectives; (5) Staffing and skills; (6) Management systems and structures; and (7) Other resources, which includes such things as time and money. Heeks et al [52] describe these *seven dimensions,* grouped into four *aspects*, (1) Information and Technology, (2) Process and Objectives and values, (3) Staffing and skills and Management, and (4) Other resources, as being capable of exploring the gap between a system’s design and the reality of its implementation. The ITPOSMO framework was initially proposed for evaluation of e-government projects [52], [53], [54] but has also been used to investigate how technology can improve healthcare practices [48] or identify problems in cloud health information system projects [55]. Recently, an extension, ITPOSMO-BBF, was presented for comparative analysis of barriers, benefits, and facilitators in health information technology: and was specifically applied to evaluation of *electronic health records* (EHR) and *learning health systems* (LHS) implementations [25].

Advantages for using the ITPOSMO-BBF framework in this study are that; (1) apart from simply identifying barriers and facilitating factors for adopting BN-based systems in healthcare, we can also quantify their relationships; (2) we can identify benefits when adopting BN-based systems in healthcare; and (3) while ITPOSMO was developed as a retrospective analysis of completed projects, ITPOSMO-BBF can be used to understand, plan for, and mitigate potential barriers prior to adoption. The last advantage is especially important in this study as most published BN models are developed with the potential to be used in clinical practice, but adoption in clinical settings remains elusive.

For each of the four ITPOSMO-BBF aspects, the frequency of (1) benefits; (2) facilitating factors; and (3) barriers in the studied literature are presented following the layout illustrated in Figure 2. The (4) relationship between a barrier and a facilitator is also provided using a weighted line, with the thickness of the line indicating the number of authors who identified that particular relationship.

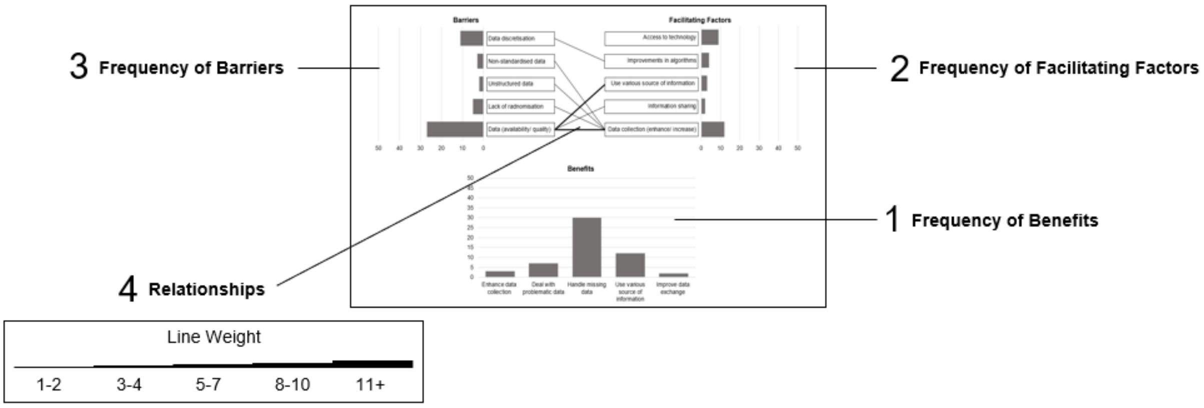

Figure 2. Visualisation of the ITPOSMO analysis

4. Results

4.1 Results of literature search

The literature collection was drawn from our recent scoping review on BNs in healthcare [14]. The search initially identified 3810 papers. In addition to the exclusions described in Section 3.1, we excluded papers that were focused on Bayesian statistics or meta-analyses rather than BNs. Graphical models, such as naive BNs, which are the simplest BNs and structurally assume all variables are independent, and other similar approaches including neural networks, were also excluded. This resulted in 123 papers for inclusion [14]. However, for the purpose of this study 7 additional papers were excluded that did not provide sufficient information for assessing benefits, barriers or facilitating factors for adoption of their BN model in clinical practice. Thus, the final literature collection for this work contains 116 papers describing 111 unique BN-based CDS systems, and it can be found in https://pambayesian.org/wp-content/uploads/2020/06/BBF_Results.xlsx.

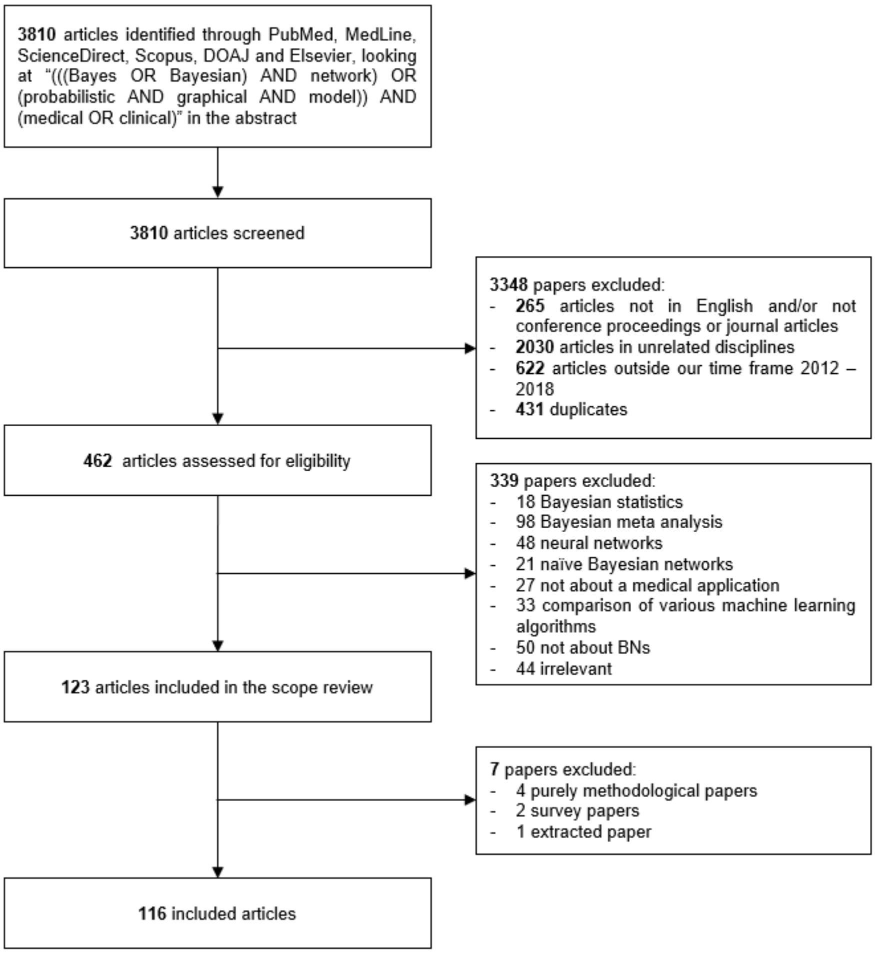

Figure 3. Literature selection

4.2 Content and thematic analysis

CA and TA were used to identify benefits, barriers and facilitating factors that impact or support adoption of BN-based systems in healthcare. Using TA four main themes were identified within the collected literature; (1) data, (2) resource, (3) resistance, and (4) performance. Each theme clusters a set of related contents. The contents corresponding to each theme are described in Table 1 and the Appendix. As observed in Table 1 contents are divided regarding whether they have been encountered as benefits, barriers or facilitating factors. For instance, on one hand, Velikova et al. [56] mention that using a BN-based CDS as a home-monitoring system has the benefit of enhancing data collection as it gives access to a large collection of clinical and laboratory data. On the other hand, Vemulapalli et al. [57] mention the same content of enhanced data collection as a facilitating factor for overcoming the barrier of not having sufficient or well-structured patient-centric healthcare data.

Table 1. Themes and contexts identified in the selected literature

Themes	**Contexts**		
	Benefits	**Barriers**	**Facilitating Factors**
Data	enhance data collection, deal with problematic data, use various source of information, improve data exchange	Availability/ quality, lack of randomisation, unstructured, not standardised, discretisation	enhance data collection, information sharing among clinicians, use various sources of information
Resource	cost saving		improvements in algorithms and software,

			access to technology, user-friendly interface
Resistance	easy to understand, applicable in medical situations with uncertainty, predictions in the presence of missing data, incremental data entry, confidence in the prediction, flexibility, query any given node	clinicians' resistance, lack of credibility, lack of clinical impact	Explanation of reasoning, clinical involvement, follow current practice, impact analysis
Performance	improved accuracy, improve quality of care, care process standardisation, risk understanding, multiple reasoning approaches, accelerate clinical decisions, assist clinical decisions, improve patient outcome, fit constantly evolving information, explore numerous causal relationships	poor predictive accuracy, lack of generalisability	internal validation, validate in different populations

4.3 ITPOSMO-BBF framework

This section presents results of our analysis of the literature, including the frequency with which authors discussed themes in context, as described in Table 1. The themes and contexts are mapped to the four ITPOSMO aspects (1) Information and Technology (IT), (2) Process and Objectives and values (PO), (3) Staffing and skills and Management (SM), and (4) Other resources (O).

Information and Technology

A number of IT barriers were described and are shown in Figure 4. Several authors reported that quality and availability of medical data was lacking [58], [59], [60], [61], affecting BN-based system performance and usability [62], [63], [64]. Incomplete data can result from numerous causes not limited to cost limitations with regards to equipment or inadequate assessment of patient-related factors [65], [66], [61]. However, even if data is available it may exist unstructured [67], [68], [69]. Different countries, or even hospitals within countries, store data using different classification standards which complicates integration and aggregation of patient datasets [58], [70], [60]. Another barrier of BN-based systems was their limited capability to address continuous data. Data discretisation is often required, which does not generally follow clinical reasoning and can result in information loss [71], [72], [73], [74]. Finally, BN-based systems usually rely on non-randomised observational data. True causal relationships such as those observed between drugs and adverse events are not easily detected from observational data [75], [76], [77], [78].

Several authors identified that government incentives to transition from paper-based patient information to electronic medical records improves availability of healthcare data while also providing an opportunity to implement BN-based systems [62], [57], [79]. Additionally, standardised note templates with predefined fields and responses can enable relevant structured data to be populated directly into clinical databases [67], [69], [60]. Richer datasets can support higher predictive capability, delivering superior and more useful CDS systems [80], [58], [81], [82]. Data availability can also be improved by developing technologies for healthcare providers to share information between facilities [60], [79]. In addition, integrating different sources of information with experts judgement can sometimes overcome limitations in the data alone [71], [68], [80]. Advances in software tools to better deal with continuous data and enable access to faster and more flexible technology can overcome barriers of data discretisation and make BN-based systems more accessible [83], [74], [84], [79], [56], [85].

Application of these facilitating factors to resolve the barriers identified earlier may give rise to numerous benefits described by many authors. Adoption of a BN-based systems in practice may enhance data collection. For example, BN-based systems can be used to systematically collect important clinical data [71], [67], [56]. BN-based systems can also be used to make health information more widely accessible [86], [67]. BN-based systems are able to deal with noisy, incomplete and heterogeneous data [87], [88], [69], [61], [89] and perform reasoning using data from multiple sources, including historical data, sensors, and experts [90], [56], [59], [85]. This capability to handle heterogeneous information is essential to delivering precision medicine [80].

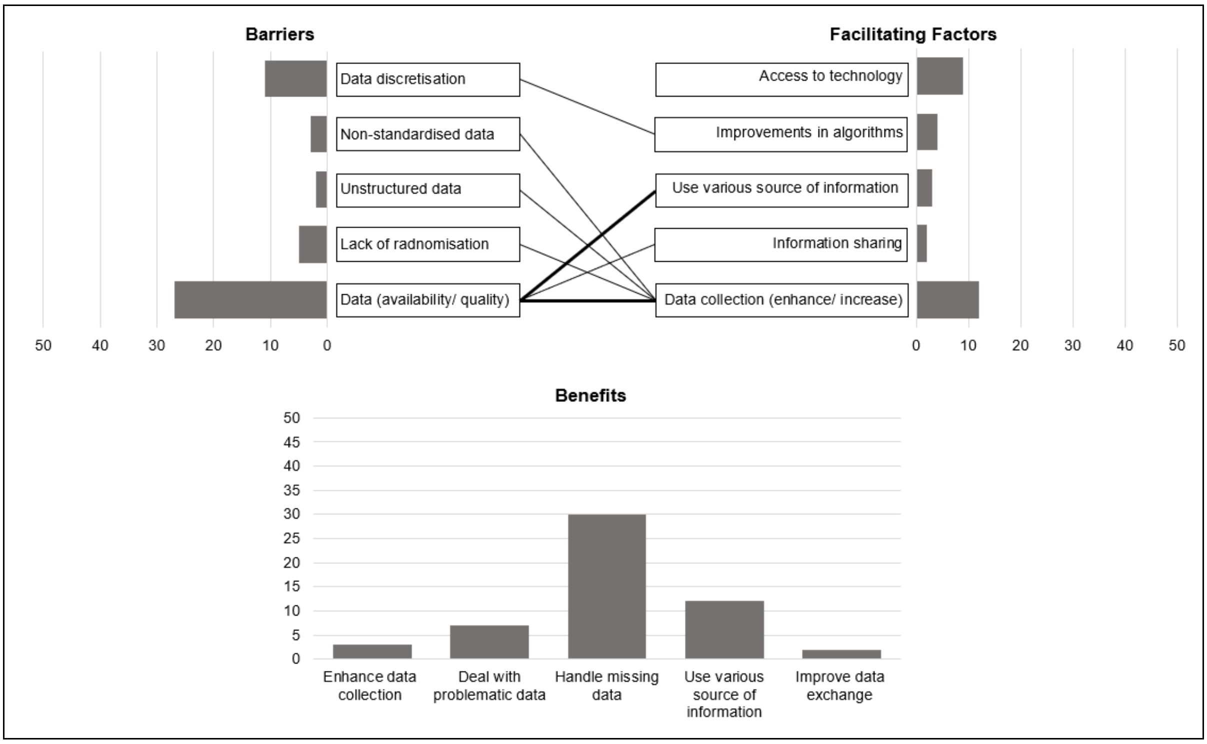

Figure 4. Barriers, facilitating factors and benefits regarding Information and Technology (**IT**POSMO)

Process and Objectives

Lack of clinical impact, shown in Figure 5, was the main PO barrier for acceptance of BN-based systems in healthcare [91]. Evaluating the system's impact on clinical decision making, its usefulness in practice, and the degree of practitioner acceptance were considered important and necessary steps to aid adoption in practice [92], [81], [74], [93]. Further, BN-based systems should adhere with and be integrated into current clinical practice in order to be accepted by clinicians [84], [94], [59].

Even if PO barriers and facilitating factors are largely ignored, many benefits were discussed in the literature. BN-based systems are suitable tools in helping medical-related problems such as diagnosis, prognosis and treatment selection due to the uncertain nature of these problems and the BN's ability to efficiently deal with this uncertainty [95], [91], [96], [97], [98], [61], [93]. The BNs ability to perform more than just reasoning from evidence makes it a valuable tool in clinical decision making [83], [59], [62]. Another important benefit is that they can update their prediction as new patient information becomes available [84], [62], [99], [97]. As clinical knowledge and data increase and new standards for evidence-based clinical practice are implemented, BN-based systems can be updated to maintain relevance [62], [100], [96], [101]. This continual apprenticeship makes it possible to refine the predictive quality of the model and adapt medical practices [86]. Moreover, BN-based systems can enhance clinical objectives, such as aiding and accelerating clinical decision making [83], [94], [82], [93], [102], [81], [103], improving understanding of significant associated risk [104], [105], improving patient outcomes [83], [60], [77] and improving overall quality of care [102], [85]. In this way BN-based systems can standardise medical care by providing a consistent standard of advice [86].

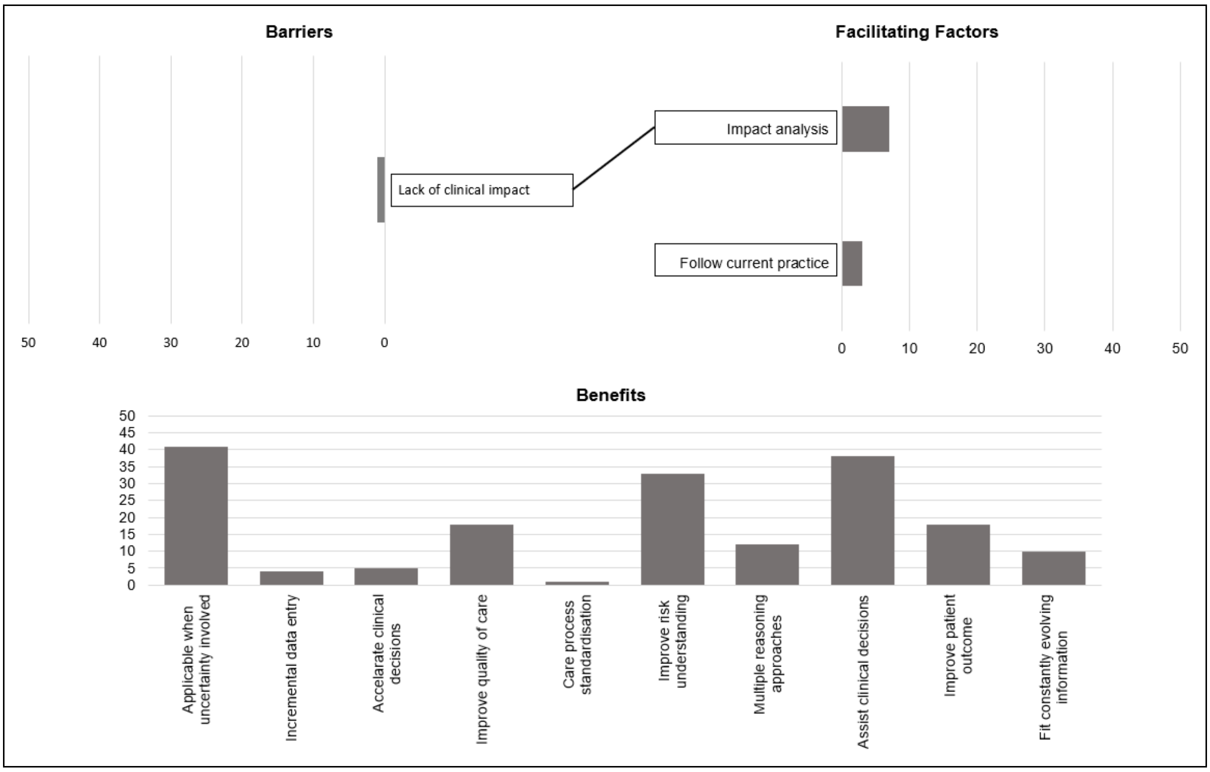

Figure 5. Barriers, facilitating factors and benefits regarding Process and Objectives (IT**PO**SMO)

Skills and Management

Clinicians' resistance to health IT systems was the most impactful of the two SM barriers discussed in the literature and shown in Figure 6. Attaining cooperation and acceptance of clinicians is crucial for wider adoption of any health IT, but especially BN-based systems. Although progress has been made, BN-based tools remain rarely used in clinical practice, possibly because the medical field tends to be cautious about adopting new technology unless its advantages are entirely clear [100], [56]. BNs are not the first modelling technique considered by health policymakers who are generally more familiar with regression models [77]. Another barrier to widespread adoption of BN-based systems is the requirement for extensive development effort and subjectivity involved when relying on clinicians' judgement [81]. Clinicians can also resist processes that may interfere with their daily workflow or challenge their autonomy [59]. And finally, another barrier related to clinician's resistance arises when a model lacks credibility, also known as face validity [92], [91], [56], [65], [66].

Most effort aimed at facilitating adoption of BN-based systems has gone towards resolving clinicians' resistance. Clinical involvement was considered an important facilitating factor for resolving both clinicians' resistance and the lack of credibility. Cooperating with multiple clinicians has been considered beneficial to developing a credible BN-based system that captures medical knowledge, property desired by clinicians [95], [56], [106], [66], [81]. BN-based systems should be reviewed by clinicians in order to obtain their input and agreement if we are to achieve adoption in practice [92], [77], [107]. In addition, development of a user-friendly interface was described as important element for assisting adoption [71], [83], [108], [99], [109]. A BN-based system's interpretability was also mentioned as a facilitator for overcoming clinicians' resistance. Their graphical structure can make them more comprehensible, which is important in medical applications [79], [66], [70]. An explanation of the system's prediction could also be beneficial [56], [104]. The fact that BN-based systems can be easily understood is also one of their main benefits [110], [77], [109], [111].

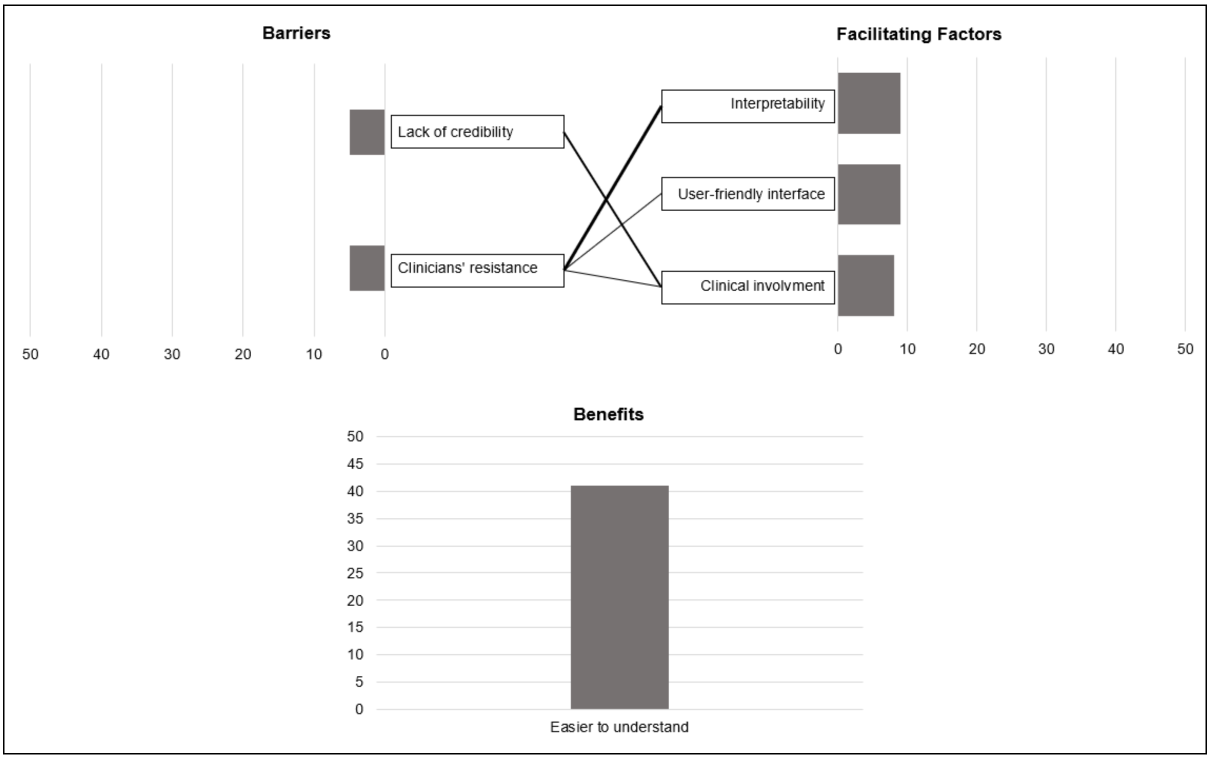

Figure 6. Barriers, facilitating factors and benefits regarding Skills and Management (ITPO**SM**O)

Other Resources

The other resources and constraints (O) barriers and facilitating factors, shown in Figure 7, contain those attributes that did not naturally fall within the other ITPOSMO aspects, and which are mainly about the system's overall performance. A model with poor predictive accuracy cannot be applied in clinical practice [91], [76], [108]. Validating the system's performance was considered as a necessary facilitating factor for assisting its adoption [83], [58], [112], [98]. In addition, even if the BN-based system has a good predictive performance, it will fail to be accepted in practice, if it has no generalisability [91], [113], [77]. Thus, external validation must be undertaken in different cohorts and geographical areas before the BN-based system can be used routinely in clinical practice [114], [60], [85], [115], [93].

Several benefits were mentioned in the literature. Using BN-based systems to optimise processes at all stages of care, as explained in PO benefits, can significantly benefit with respect to healthcare cost [75], [57], [61], [116]. BN-based systems, as opposed to deterministic approaches, also provide confidence in the prediction [90], [91], [117], [67], resulting in a greater flexibility [113]. It is also possible to query any given node in the BN, making BN-based systems substantially more useful in clinical practice when compared to models constructed with reliance on specific outcome variables [59], [94], [118]. Further, unlike logistic regressions and other modelling techniques, BN-based systems are not limited to linear relationships. In contrast, they are able to model complex relationships between variables when conditions of causality and conditional independence are involved, which is of significant benefit in clinical decision making [113], [60], [119], [118]. Finally, BN-based systems have a reputation for achieving accurate results [91], [70], [114], [120], [112].

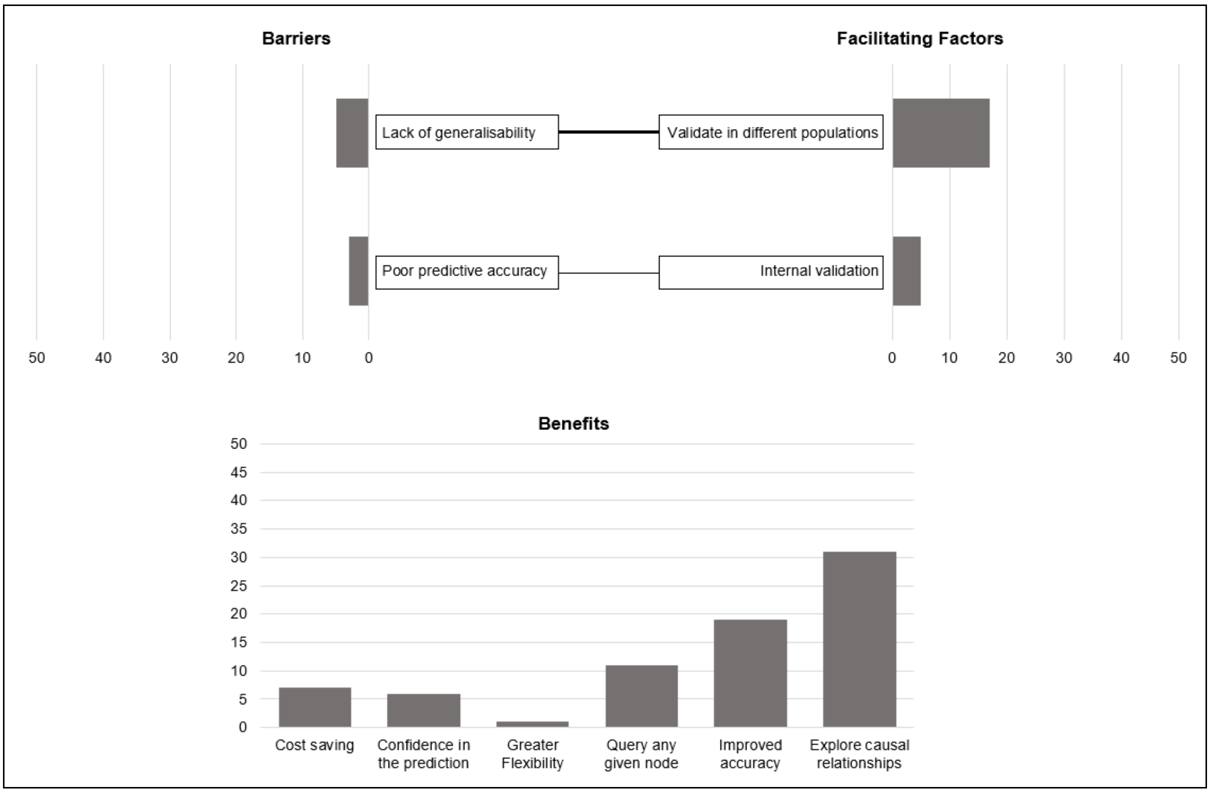

Figure 7. Barriers, facilitating factors and benefits regarding Other resources (ITPOSM**O**)

5. Discussion and Conclusions

Despite the large volume of published studies on medical BNs, there is little evidence for their adoption in clinical practice. There has been little attention paid to the gap between developing an accurate BN and demonstrating its clinical usefulness for decision making. In this paper we have provided a deeper insight into the gap. Using the ITPOSMOS-BBF framework we have identified the *benefits, barriers* and *facilitating factors* discussed in the literature for adopting BN-based systems in clinical practice. This is an important study because most published BN models are developed with potential for positive effect if applied in clinical practice, yet their adoption remains elusive.

The barriers discussed in the literature that seem to obstruct BN-based system adoption in clinical practice can be grouped into: (1) data inadequacies; (2) clinicians' resistance to new technologies; (3) BN-based systems that lack of clinical credibility; (4) failure to demonstrate clinical impact; (5) absence of an acceptable predictive performance; and (6) absence of evidence for a model's generalisability. Similarly, the facilitating factors mentioned in the studied literature for overcoming existing barriers and enabling adoption can be categorised into: (1) data collection improvements; (2) software and technological improvements; (3) having interpretable and easy to use BN-based systems; (4) clinical involvement in the development or review of the model; (5) investigation of model's clinical impact; (6) internal validation of the model's performance; and (7) external validation of the model.

As presented in Section 4, the frequency with which authors discussed the identified barriers and facilitating factors was quite low. Even rarer were authors who actually connected some form of facilitating factor with the barriers they had identified. For instance, having a user-friendly interface was described as a necessary step for adopting a BN-based system in practice, yet this was rarely reported as a facilitating factor for reducing the barrier of clinicians' resistance. This lack of more profound thinking that might link the barriers faced when implementing BN-based systems in practice with solutions to overcome those barriers is very likely the reason we see such a chasm between research effort and adoption in practice.

While very few authors demonstrate understanding of the barriers that can prevent BNs from being adopted in clinical practice, many benefits that could arise from implementing them were presented and thoroughly discussed in the literature. Most discussed benefits fell within the PO aspect and concerned the positive contribution BNs could make to meeting clinical objectives, such as assisting clinical decisions, improving understanding of associated risks, or improving the overall quality of care. The PO aspect is a prime example of the most significant issue in BN literature: that while many benefits can be identified by authors, the barriers limiting our ability to realise those benefits, and any facilitating factors to aid mitigation of barriers, are subjects that both remain notably neglected. Thus, BN developers should move from "why does it fail" towards "how to succeed" and address the barriers earlier to avoid the adoption challenges continuing [121].

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Appendix

An extension of Table 1 in which each theme and context are connected to specific literature identified using the row number in https://pambayesian.org/wp-content/uploads/2020/06/BBF_Results.xlsx.

Themes	Contexts					
	Benefits		Barriers		Facilitating Factors	
Data	Enhance data collection, deal with problematic data, use various source of information, improve data exchange	Rows: 4, 10, 16, 20, 26, 31, 37, 48, 52, 55, 57, 61, 74, 76, 82, 87, 91, 97, 100, 114, 117	Availability/ quality, lack of randomisation, unstructured, not standardised, discretisation	Rows: 4-5, 7, 9-12, 15-17, 24-25, 30, 34, 38, 4, 49, 53, 56-57, 59-60, 63-64, 68, 74-75, 82, 87, 90-91, 93, 95, 97, 104-105, 108-110, 114, 119	enhance data collection, information sharing among clinicians, use various source of information	Rows: 4, 5, 10, 16, 17, 44, 60, 65, 85, 91, 93, 101, 110, 114
Resource	cost saving	Rows: 9, 11, 23, 24, 68, 100, 101			improvements in algorithms and software, access to technology, user-friendly interface	Rows: 4, 6, 8, 10, 14, 17, 30, 64, 70, 74, 78, 85, 97, 98, 100, 102, 107, 113
Resistance	Easy to understand, applicable in medical situations with uncertainty, provide predictions in the presence of missing data, incremental data entry, confidence in the prediction, flexibility, query any given node	Rows: 4-6, 9-16, 18, 20-21, 23 25-27, 29, 32, 36-37, 39, 41, 43-46, 48-57, 59-60, 62-64, 66, 70-72, 74-78, 80, 82-87, 89, 91, 93-100, 102-103, 107, 110-114	clinicians' resistance, lack of credibility, lack of clinical impact	Rows: 9, 11, 15, 16, 30, 41, 60, 80, 87, 100, 108	Explanation of reasoning, clinical involvement, follow current practice, impact analysis	Rows: 8, 9, 13, 15, 16, 27, 30, 45, 59, 64, 70, 78, 81, 84, 85, 87, 98, 99, 100, 102, 107
Performance	improved accuracy, improve quality of care, care process standardisation, risk understanding, multiple reasoning approaches, accelerate clinical decisions, assist clinical decisions, improve patient outcome, fit constantly evolving information, explore causal relationships	Rows: 4-16, 20, 23-27, 29-46, 48-51, 53-60, 62-64, 66-87, 91-105, 107, 110, 112-115	poor predictive accuracy, lack of generalisability	Rows: 14, 15, 41, 49, 103, 115	internal validation, validate in different populations	Rows: 5, 6, 7, 10, 16, 20, 25, 26, 27, 33, 40, 44, 46, 63, 71, 75, 78, 84, 95, 97, 104, 114