

Review

Applied Bayesian Networks Rely on Expert Knowledge and Scarce Data Sharing

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Abstract

In this descriptive scoping review, we assessed how Bayesian network structures are built and learned in applied work by screening 5993 recent papers (2020–2025) whose abstracts mention “Bayesian (belief) network” and deeming 3661 relevant. Among these relevant papers, expert knowledge was used in 2059 papers (56.2%): 1785 (48.8%) relied on expert knowledge alone, whereas 274 (7.5%) combined expert input with algorithmic structure learning. Automatic structure learning thus remains underused. Data sharing was scarce: only 129 studies (3.5%) provided functional dataset links, which we curated into an open benchmark index. Among 1106 papers (30.2%) using algorithms without expert knowledge, score-based methods were most common (797, 72.1%; mainly Hill climbing, K2, and tabu), followed by constraint-based methods (194, 17.5%; mainly PC and Grow–Shrink), fixed- or restricted-topology BN classifiers (143, 12.9%; mainly TAN and naive Bayes), and hybrid methods (131, 11.8%; mainly MMHC); bootstrapping appeared in 223 papers (6.1%). Reported practice thus remains concentrated around familiar algorithms.

Keywords: Bayesian networks; structure learning; causal discovery; reproducibility; open datasets

MSC: 62C10; 62-02; 62-08; 68T05; 68T37



Academic Editor: Manuel Alberto M. Ferreira

Received: 15 June 2026

Revised: 11 July 2026

Accepted: 18 July 2026

Published: 23 July 2026

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1. Introduction

To model uncertainty and interdependence among variables in a complex system, Bayesian networks (BNs) are increasingly used across environmental sciences, ecology, and water resources [1–8]; fisheries and aquatic systems [9,10]; medicine, public health, oncology, and medical informatics [11–15]; engineering, construction, materials, energy, and infrastructure [4,16–22]; computer science, telecommunications, and cybersecurity [23–25]; transportation, maritime systems, and operations research [17,26,27]; computational biology and systems biology [15,28,29]; automation, chemistry, and instrumentation [30]; psychology [31]; and business and economics [27]. Their ability to represent joint probability distributions through a graph-based structure makes them both intuitive and powerful. Formally, a BN is a directed acyclic graph (DAG) in which nodes correspond to random variables and links represent conditional dependencies. The joint probability distribution

over the variables then factorizes into the product of the probability distributions of each variable conditioned on its parent set. This factorization allows BNs to capture complex interdependencies in a compact and computationally efficient way, making them well suited for both inference and prediction.

The network structure can be learned fully automatically from data, an approach called “structure learning,” which is usually grouped into three families. Constraint-based algorithms, such as PC/PC-stable and Grow–Shrink, infer adjacencies through conditional independence tests and then orient edges using logical rules [32–34]. Score-based procedures optimize a goodness-of-fit criterion, commonly the Akaike information criterion (AIC) or Bayesian information criterion (BIC), over DAG space using search heuristics such as greedy Hill climbing, tabu search, or the K2 family [35–43]. Hybrid methods combine these ideas, typically restricting candidate neighborhoods through conditional independence tests before applying a score-based search, as in Max-Min Hill climbing (MMHC) [44]. Beyond this taxonomy, recent papers describe exact, Bayesian, extendable/iterative, continuous optimization, distributed, federated, and privacy-preserving approaches that broaden the BN structure learning landscape [45–52]. Automated model search and workflow automation are also expanding more broadly in machine learning and scientific modelling [53,54].

Despite these advantages, practical implementations of BNs often fall short of their full potential. Two recurring issues are (i) relying on expert-elicited structures in lieu of automatic structure learning [55,56] and (ii) not providing the underlying datasets, which impedes replication and benchmarking. It remains an open question how widespread these practices are, which fields rely most on expert-driven models, and—among studies that perform structure learning—which algorithms and search/score configurations are most used.

Prior surveys are valuable for organizing algorithms and theory, but they do not answer the above questions. For example, Scanagatta et al. review structure learning families, missing data strategies, and software [45]; Kitson et al. catalogue 74 algorithms and evaluation practices [46]; and Vowels et al. emphasize modern DAG discovery, including continuous optimization approaches [47]. Benchmark-style comparisons study accuracy and speed across algorithm families [40]. Domain-focused reviews, such as agriculture-focused work [57] or application overviews [55], synthesize uses within specific sectors. None of these map, at scale, how often expert elicitation replaces automatic learning across fields, how frequently datasets are shared with working links, or which structure learning algorithms dominate in practice across domains.

We address this gap with a descriptive scoping review of 5993 studies (2020–2025), aiming to quantify reported practices rather than to rank structure learning algorithms or synthesize comparative performance. We code discipline, data availability, use of expert knowledge, overlap between expert knowledge and algorithmic learning, structure learning family, fixed- or restricted-topology BN classifiers, named algorithms, and bootstrapping. We also release a curated dataset index with working links to support replication and benchmarking. The contribution is a field-wide quantification of reported applied BN practices to support more standardized empirical comparisons, without adjudicating the performance of structure learning methods.

2. Methods

To investigate the prevalence and diversity of structure learning approaches in Bayesian network research, a comprehensive review of the literature was conducted in Web of Science Core Collection on 31 December 2025, using the abstract query AB = (“Bayesian network” OR “Bayesian belief network”) and publication years 2020–2025. The search was

not restricted to a specific document type or language, although only four documents were not in English. This search returned 5993 accessible records. Records were screened in two stages: first by title/abstract and then, where needed, by full-text inspection. Papers were retained as relevant when they presented, applied, learned, or evaluated a BN in a concrete methodological or applied setting. Papers were excluded when they did not use BNs in this sense, were inaccessible, duplicated another record, used “network” terminology in an unrelated way, or were meta-studies/review papers without a concrete BN application or structure learning analysis. The latter group included review articles, bibliometric studies, methodological overviews without an applied BN model, and network meta-analyses not involving BNs.

Before coding individual papers, we grouped reported structure learning approaches into the following families: (i) constraint-based methods, (ii) score-based methods, (iii) hybrid methods, and (iv) fixed- or restricted-topology BN classifiers, such as naive Bayes, TAN, and related variants. Using this coding framework, an initial screening process was conducted to extract methodological features from each paper. A dataset was developed in Microsoft Excel to facilitate consistent data entry and tracking of key features across studies. Each paper was reviewed and assigned binary or categorical values across predefined variables: presence of a dataset, availability of a dataset link, use of score-based learning, constraint-based learning, or hybrid learning approaches, fixed- or restricted-topology BN classifiers, reliance on expert knowledge for network construction or modification, mention of bootstrapping techniques, specific learning algorithm used, and the scoring metric applied during model training.

Each paper was analyzed, and attributes were recorded either as binary values (e.g., 1 = present, 0 = absent) or as text entries where appropriate (e.g., algorithm name or score type). For example, if a paper employed a score-based algorithm such as K2 in conjunction with the BIC, the following entries would be recorded: 1 under “score-based,” K2 under “specific learning approach,” and BIC under “score used for training.” If more than one structure learning method was used in a single paper, multiple fields could be populated. Expert knowledge was noted if the network structure was manually derived from expert surveys, if structural constraints such as required or forbidden edges were imposed, or if a learned DAG was subsequently modified based on expert feedback. Soft expert input, such as variable selection, was not coded as expert knowledge.

To determine whether bootstrapping was employed, each document was searched for the term “bootstrap” using the text search functionality within the PDF viewer. If any results were returned and the context confirmed the use of a bootstrapping method, a 1 was entered under the bootstrapping column.

Once all available papers were annotated, the compiled data were imported into R for analysis. Descriptive statistics were used to summarize the distribution of structure learning methods and associated features across the literature. To assess the representation of different academic domains, research fields were extracted from each paper and categorized. Fields represented by fewer than 30 papers were aggregated into a single “Other” category. A figure was generated to illustrate the distribution of BN applications across research areas.

A separate list of datasets was also compiled. This included only datasets with direct, functional links, either in the Supplementary Information or embedded in the body of the paper. This criterion was applied to evaluate reproducibility and accessibility across BN studies. Datasets without an accessible URL or repository reference were excluded, regardless of whether the data were described in the text.

To further explore trends in methodological preferences, totals were calculated for each major method family and for normalized named approaches, including both widely used

algorithms (e.g., PC and K2) and less common techniques. These counts were summarized to identify the most frequently reported methods in the literature.

3. Results

A total of 5993 papers were included in the review. Of these, 3661 were retained as relevant papers for analysis of how BN structures were built or learned. The remaining 2332 papers were excluded, including 1239 meta-studies. The percentages in this section use the 3661 relevant papers as the denominator, unless otherwise stated.

3.1. Use of Expert Knowledge

Expert knowledge was used in 2059 of 3661 relevant papers (56.2%; Figure 1). Of these, 1785 papers (86.7%; 48.8% of all relevant papers) relied on expert knowledge without an algorithm or fixed/restricted-topology classifier, whereas 274 papers (13.3%; 7.5% of all relevant papers) combined expert input with such methods. Among the 274 papers, expert input was used mainly as pre-learning structural constraints or assumptions (229/274, 83.6%); fewer papers used expert knowledge for DAG construction alongside these methods (42/274, 15.3%), and explicit post-learning expert modification was rare (3/274, 1.1%). The residual “neither” category (496/3661, 13.5%) for which neither expert knowledge nor a structure learning algorithm or fixed/restricted-topology classifier was coded may reflect fixed structures, parameter learning or inference studies, simulation/theoretical work, or limited reporting, rather than poor practice (Table 1).

Expert knowledge and algorithm/classifier reporting among 3661 relevant papers

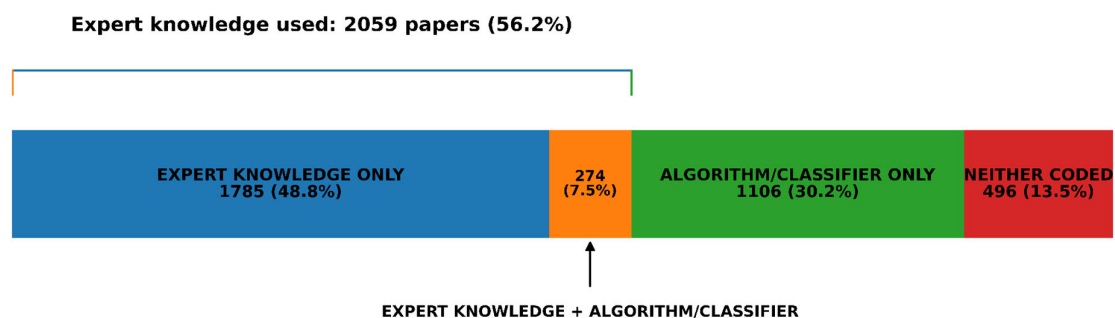


Figure 1. Mutually exclusive categories among the 3661 relevant papers according to whether expert knowledge, an algorithm or fixed/restricted-topology classifier, both, or neither was reported.

Table 1. Summary of main outcomes among the 3661 relevant papers. Expert-only, both, algorithm/classifier-only, and neither are mutually exclusive. Method family and bootstrap indicators are not mutually exclusive.

Outcome	Count	% of Relevant Papers
Relevant papers retained for analysis	3661	100.0%
Open datasets with functional links	129	3.5%
Expert knowledge only	1785	48.8%
Expert knowledge + algorithm/classifier	274	7.5%
Expert knowledge used	2059	56.2%
Algorithm/classifier only	1106	30.2%
Neither expert knowledge nor algorithm/classifier reported	496	13.5%
Score-based methods	950	25.9%
Constraint-based methods	236	6.4%
Hybrid methods	182	5.0%
Fixed- or restricted-topology BN classifiers	164	4.5%
Bootstrapping	223	6.1%

3.2. Structure Learning Methods

Across the 3661 relevant papers, score-based methods were reported in 950 papers (25.9%; Figure 2), constraint-based methods in 236 papers (6.4%), fixed- or restricted-topology BN classifiers in 164 papers (4.5%), and hybrid methods in 182 papers (5.0%). These categories are not mutually exclusive because some papers compared or combined multiple approaches. Among the 1106 papers that reported an algorithm or fixed/restricted-topology classifier without expert knowledge, the corresponding counts were 797 score-based, 194 constraint-based, 143 fixed/restricted-topology classifier, and 131 hybrid papers.

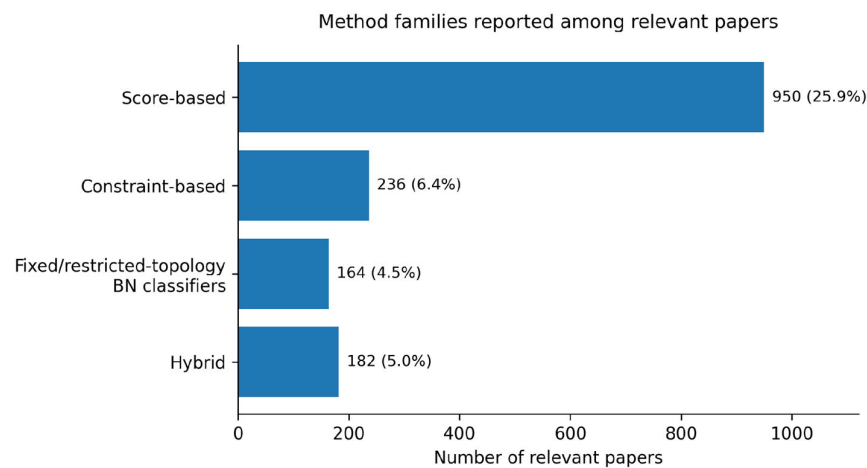


Figure 2. Method families reported among the 3661 relevant papers. Papers may report more than one family.

The most frequently named or grouped approaches were Hill climbing ($n = 304$, 8.3%; Figure 3), fixed- or restricted-topology BN classifiers ($n = 164$, 4.5%; mainly TAN and naive Bayes), K2 ($n = 129$, 3.5%), PC ($n = 111$, 3.0%), tabu search ($n = 95$, 2.6%), fuzzy BN or fuzzy methods ($n = 72$, 2.0%), MMHC ($n = 72$, 2.0%), and MCMC or structure MCMC ($n = 62$, 1.7%). Among constraint-based or Markov blanket methods, Grow–Shrink appeared in 33 papers (0.9%), IAMB variants in 21 papers (0.6%), PC-stable in 17 papers (0.5%), and MMPC in 15 papers (0.4%). See Table A1 for the frequency of these algorithms among papers that used or did not use expert knowledge.

3.3. Bootstrapping

Bootstrapping, used to estimate model stability and confidence in structural features, appeared in 223 relevant papers (6.1%).

3.4. Reproducibility

Only 129 relevant papers (3.5%) included a readily accessible dataset with a functional link. These links were heterogeneous: 51 were publisher-hosted Supplementary Files or article links, 36 were general open-data repositories, 25 were domain, benchmark, government, or other specialized repositories, nine were code repositories containing data/code, seven were institutional repositories or data portals, and one was another ambiguous web link.

This sparsity limits reproducibility and comparative benchmarking. Without access to the underlying data, it becomes difficult to evaluate the robustness of reported results, replicate findings, or compare algorithmic performance across studies. Supplementary Table S1 lists the links to the datasets in all 129 papers, together with their references and reported methods.

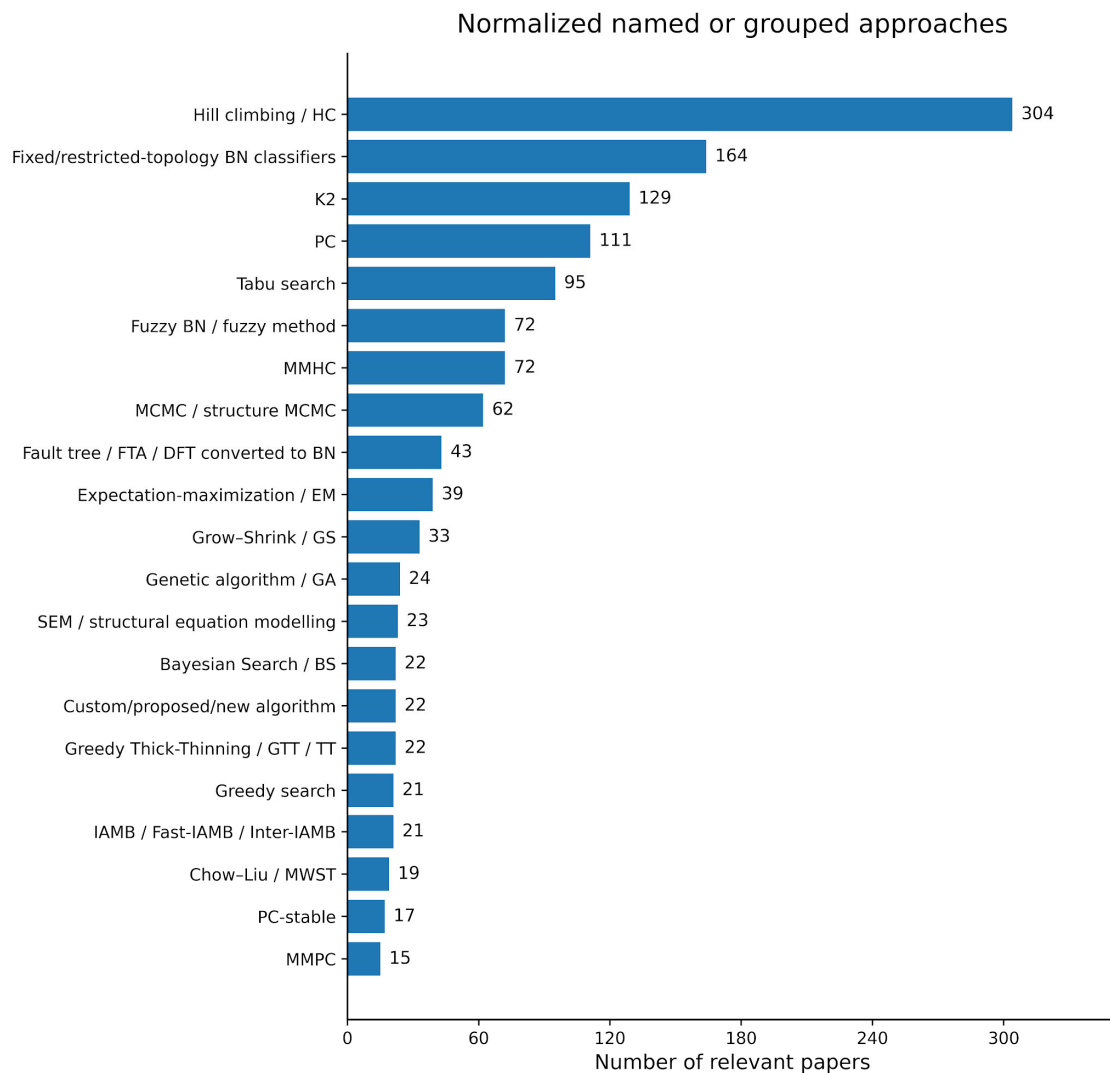


Figure 3. Counts of normalized named or grouped approaches reported in at least 15 of the 3661 relevant papers.

3.5. Disciplinary Breakdown

Among the 3661 relevant papers, engineering was the largest field (1004; 27.4%; Figure 4), followed by computer science (718; 19.6%). Science and technology—other topics (275; 7.5%), environmental sciences and ecology (245; 6.7%), and automation and control systems (221; 6.0%) accounted for smaller shares, while general and internal medicine represented 30 papers (0.8%). The remaining 1168 papers (31.9%) were grouped as “Other.”

Field-level cross-tabulations showed substantial disciplinary variation (Table 2). Expert knowledge was especially common in engineering (786/1004, 78.3%) and automation/control systems (145/221, 65.6%). Score-based methods were proportionally common in computer science (239/718, 33.3%) and science and technology—other topics (91/275, 33.1%); the small general and internal medicine group had the highest proportion (16/30, 53.3%). Functional dataset links remained sparse across all large fields, including engineering (20/1004, 2.0%) and computer science (13/718, 1.8%).

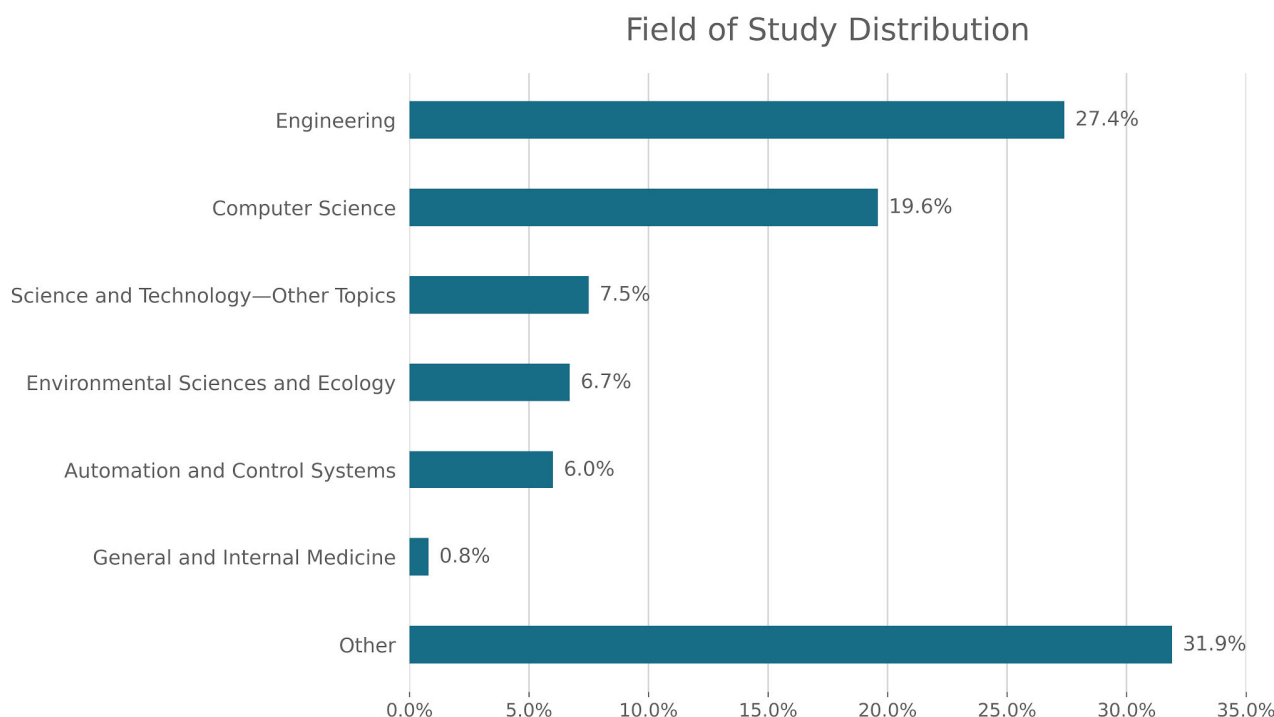


Figure 4. Distribution of the 3661 relevant Bayesian network papers by research field, 2020–2025. Smaller research fields were grouped as “Other”.

Table 2. Field-level distribution of coded BN practices and functional dataset links. The “relevant papers” column is used as the denominator for the percentages.

Field	Relevant Papers	Expert Knowledge	Functional Dataset Links	Score-Based	Constraint-Based	Hybrid	Bootstrap
Engineering	1004	786 (78.3%)	20 (2.0%)	112 (11.2%)	24 (2.4%)	19 (1.9%)	8 (0.8%)
Computer science	718	256 (35.7%)	13 (1.8%)	239 (33.3%)	79 (11.0%)	73 (10.2%)	30 (4.2%)
Science and technology—other topics	275	155 (56.4%)	20 (7.3%)	91 (33.1%)	15 (5.5%)	9 (3.3%)	13 (4.7%)
Environmental sciences and ecology	245	142 (58.0%)	17 (6.9%)	42 (17.1%)	14 (5.7%)	7 (2.9%)	22 (9.0%)
Automation and control systems	221	145 (65.6%)	3 (1.4%)	54 (24.4%)	16 (7.2%)	16 (7.2%)	2 (0.9%)
General and internal medicine	30	9 (30.0%)	2 (6.7%)	16 (53.3%)	2 (6.7%)	2 (6.7%)	2 (6.7%)
Other	1168	566 (48.5%)	54 (4.6%)	396 (33.9%)	86 (7.4%)	56 (4.8%)	146 (12.5%)
Total	3661	2059 (56.2%)	129 (3.5%)	950 (25.9%)	236 (6.4%)	182 (5.0%)	223 (6.1%)

3.6. Temporal Trends

Year-level cross-tabulations showed no strong temporal shift away from expert knowledge or familiar structure learning methods between 2020 and 2025 (Table 3). Expert knowledge appeared in every year, and score-based methods remained the most common algorithmic family throughout the period. Functional dataset links were sparse in all years, although the largest number appeared in 2025. Bootstrapping also remained uncommon, with its highest count in 2025.

Table 3. Year-level counts of expert knowledge, structure learning method families, bootstrapping, and functional dataset links among relevant BN papers.

Year	Relevant BN Papers	Expert Knowledge	Score-Based	Constraint-Based	Hybrid	Bootstrapping	Functional Dataset Links
2020	551	326	146	35	28	26	20
2021	623	378	156	38	27	33	12
2022	678	394	185	42	42	37	26
2023	702	452	185	46	29	41	20
2024	337	205	83	22	16	14	12
2025	662	245	166	44	31	72	39
Unassigned publication year in Web of Science export	108	59	29	9	9	0	0
Total	3661	2059	950	236	182	223	129

4. Discussion

BNs capture conditional dependence through DAGs and support probabilistic reasoning and, with additional assumptions, causal interpretation. Structure learning seeks graphs that best explain observed independencies or optimize a fit-complexity criterion, with three main families—constraint-based, score-based, and hybrid—each offering different theoretical and practical trade-offs [32,58].

Across disciplines, the use of BNs was broad but uneven. Among the 3661 relevant papers, engineering accounted for 27.4% and computer science for 19.6%, with smaller shares in science and technology “other” topics, automation and control, environmental sciences and ecology, and general and internal medicine. This pattern reflects BN versatility in technical decision-making and signals growth opportunities in underrepresented areas such as psychology, economics, and public health.

Data availability remains the central barrier to comparability and cumulative progress. Only 129 relevant studies (3.5%) provided working links to the underlying datasets, limiting external validation, cross-paper benchmarking, and reuse. In this review, we therefore compiled a dataset index with direct links; this resource lowers search costs, supports immediate replication, and facilitates standardized benchmarks and teaching use. We also defined strict inclusion criteria for that table—only datasets with functional links in the paper or supplement were retained—to promote reliable reuse. Community experience in machine learning shows that artifact policies and reproducibility checklists can improve transparency and research quality [59,60], and the dataset index is intended to serve that role for Bayesian network structure learning.

Expert knowledge was used in 56.2% of the relevant papers, and 48.8% relied on expert knowledge without an algorithm or fixed/restricted-topology classifier. While expert constraints can improve interpretability and shrink the search space, they can also introduce bias and hinder replication unless the elicitation protocol and exact structural constraints are reported. These descriptive counts do not establish predictive or causal superiority of automatic methods. Rather, they highlight an underused reporting practice: including an automatic, data-driven baseline alongside expert-informed models when study data are available [56,58,61].

Methodologically, score-based methods were the most common, whereas constraint-based methods, hybrid methods, and fixed- or restricted-topology BN classifiers were much less frequent. The named-method distribution suggests that the field relies heavily on a small subset of familiar algorithms and software-accessible workflows. Hill climbing, fixed- or restricted-topology BN classifiers, K2, PC, tabu search, MMHC, and MCMC

accounted for much of the named-method reporting, whereas many exact, metaheuristic, continuous optimization, and Markov blanket approaches appeared only sporadically. This concentration may suggest that applied BN research is shaped not necessarily by algorithmic performance but by familiarity, implementation availability, and reporting conventions. To improve interpretability and comparability, algorithmic BN studies should report the chosen score, hyperparameters, search settings, and, where applicable, any expert constraints [35–37,40,44].

Fixed- or restricted-topology BN classifiers were separated because their structures are fixed or strongly templated rather than freely learned over DAG space. Naive Bayes, TAN, and weighted variants remain active methods, valued for interpretability, simplicity, and stable baselines, with recent weighted and correlation-adjusted variants showing continued methodological development [62,63].

Bootstrapping appeared uncommon, with only 6.1% of the relevant papers using resampling. Such analyses can be useful, but their results require careful interpretation. Bootstrap and Bayesian methods assess uncertainty across complete network structures, while reported edge frequencies usually describe each connection separately. A graph assembled from several high-frequency edges therefore does not necessarily represent a well-supported network and may not have appeared in any resampled model. These frequencies are best interpreted as measures of uncertainty about individual connections, not as confidence in the displayed graph as a whole [64–66]. For prediction or causal analysis, uncertainty should ideally be carried through across complete models rather than reduced to a single consensus graph [67].

There are limitations to this review. Our classification recorded the presence or absence of methods and practices at the paper level rather than effect sizes, head-to-head outcomes, or the quality of expert elicitation, repository metadata, and dataset documentation. Papers using multiple approaches were counted across categories, and fixed- or restricted-topology BN classifiers were grouped separately from score-based, constraint-based, and hybrid structure learning families. The counts therefore represent reported adoption, not algorithmic performance, mutually exclusive methodological pathways, or quality assessments.

Several coding choices may also affect the counts. Bootstrapping was identified by searching for the term “bootstrap” and confirming the context, so studies describing resampling without that term may be undercounted. We did not separately code studies framed primarily as structural causal model identification, including structural equation, intervention-based, and latent variable formulations [68–71], or structure learning methods designed for unfaithful distributions or relaxations of faithfulness [49,72,73]. Field labels with small counts were aggregated. Coding was harmonized by a common author across all records, but the workflow did not involve independent duplicate coding or estimation of interrater reliability; the resulting counts and percentages should therefore be interpreted as descriptive rather than independent reliability estimates.

5. Recommendations

1. Share data and code by default, with stable links or DOIs and metadata.
2. Deposit data in a trusted, domain-appropriate repository that offers persistent identifiers, rich metadata, and long-term preservation—such as Zenodo, Dryad, or Figshare. Where specialist archives exist, prefer the disciplinary option [74–77].
3. Where study data exist, report an automatic, data-driven structure learning baseline, especially when presenting an expert-informed DAG.
4. Document scoring and search settings explicitly (score family, hyperparameters, restarts, tabu, simulated annealing) to enable reproducibility and fair comparison.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/math14152669/s1>. The curated index of 129 papers or studies with functional dataset links is provided as Supplementary Table S1 in Excel format. The table includes dataset name, reference, functional link, method indicators, and reported learning approach.

Author Contributions: Conceptualization, P.R. and H.K.; methodology, H.K., L.C., P.A. and P.R.; formal analysis, H.K., L.C. and P.A.; investigation, L.C., H.K. and P.A.; data curation, L.C.; visualization, L.C.; writing—original draft preparation, L.C.; writing—review and editing, L.C., H.K., P.A. and P.R.; supervision, P.R.; project administration, P.R. All authors have read and agreed to the published version of the manuscript.

Funding: P.R. acknowledges support from an NSERC Discovery Grant RGPIN-2022-05199 NSERC.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: We thank Sam Longdon, Ethan Garrafa, Milo Boccinfuso, Rika Luo, Bennett Warkentin, Hayden James, Ada Fast, Sheraz Ahmad, Maham Taqi, and Izaak Gagnon, who supported the literature review through screening and preliminary assessments of some of the papers.

Conflicts of Interest: The authors declare no conflicts of interest. The funder had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Appendix A

Table A1. Normalized named or grouped approaches with expert knowledge overlap.

Algorithm/Approach	Total	With Expert Knowledge	Without Expert Knowledge
Hill climbing/HC	304	40	264
Fixed- or restricted-topology BN classifiers	164	21	143
K2	129	33	96
PC	111	21	90
Tabu search	95	13	82
Fuzzy BN/fuzzy method	72	49	23
MMHC	72	11	61
MCMC/structure MCMC	62	3	59
Fault tree/FTA/DFT converted to BN	43	26	17
Expectation-maximization/EM	39	16	23
Grow-Shrink/GS	33	3	30
Genetic algorithm/GA	24	6	18
SEM/structural equation modelling	23	2	21
Bayesian Search/BS	22	7	15
Custom/proposed/new algorithm	22	1	21
Greedy Thick-Thinning/GTT/TT	22	4	18
Greedy search	21	1	20
IAMB/Fast-IAMB/Inter-IAMB	21	0	21
Chow-Liu/MWST	19	3	16
PC-stable	17	4	13
MMPC	15	4	11
ISM	14	11	3
DEMATEL	13	13	0
GES/FGES/ARGES/SCCGES	13	4	9
Dynamic Bayesian network/DBN	11	6	5
Bow-tie converted/modelled as BN	10	8	2
Delphi/expert scoring	10	9	1
RSMA2/restricted maximization	10	3	7

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