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Pacific-Basin Finance Journal

DOI:
https://doi.org/10.1016/j.pacfin.2023.102011

Published: 01/06/2023

Publisher's PDF, also known as Version of record

Pacific-Basin Finance Journal 79 (2023) 102011

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

Modernising operational risk management in financial institutions via data-driven causal factors analysis: A pre-registered study

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ARTICLE INFO

JEL classification codes:
G20
G32
D81
C44

Keywords:
Risk management
Operational risk
Data analytics
Firm value
Financial institutions
Insurance

ABSTRACT

In an effort to contribute a quantitative, objective and real-time tool to proactively and precisely manage the factors underlying and exacerbating operational risks, this pre-registered study executes the empirical methodology approved in the associated pre-registered report (Cornwell et al., 2023). The application of the Bayesian network-based approach to an Australian insurance company shows that integrating a financial institution's loss and operational data in this way can effectively model the probability of an operational loss event within its interconnected operational risk environment. Further insights and efficiencies are gained by modelling multiple operational loss events together, rather than in isolation. A novel two-module framework derived specifically for causal factors analysis from the resulting operational risk model helps to highlight the relative importance of causal factors, their collective effects and critical thresholds requiring proactivity. These insights derived from the framework are expected to be strategically valuable in helping an organisation design intentional and targeted controls for and monitoring of operational risks. Given existing knowledge of the improvements quantitative risk management tools make to risk management effectiveness and subsequently firm value, the enhanced risk management and the operational efficiencies this tool seeks to afford should ultimately contribute to driving financial performance and firm value.

1. Introduction

The omnipresence of operational risks across all business units within financial institutions (FIs) is resulting in substantial financial losses, reputational damage and adversity for customers and employees, albeit direct or indirect (e.g., Operational Riskdata eXchange Association, 2022). The complexity and rate of change of operational risks is not waning, so it is the effectiveness of FIs' operational risk management (ORM) practices that must improve to maintain a safe and sustainable financial system for society. It is well understood that proactive, preventative management from the root cause is most effective. Yet most existing ORM tools in FIs are reactive, relying on manual reviews of past incidents and infrequent, point-in-time qualitative risk and control self-assessments. This study is motivated by this discrepancy within ORM between the underlying risks' dynamics and monitoring, as well as previous studies demonstrating the positive relationship between quantitative risk management tools, risk management effectiveness and firm value creation (Braumann, 2018; González et al., 2022; Huang et al., 2020). Please refer back to the companion pre-registered report

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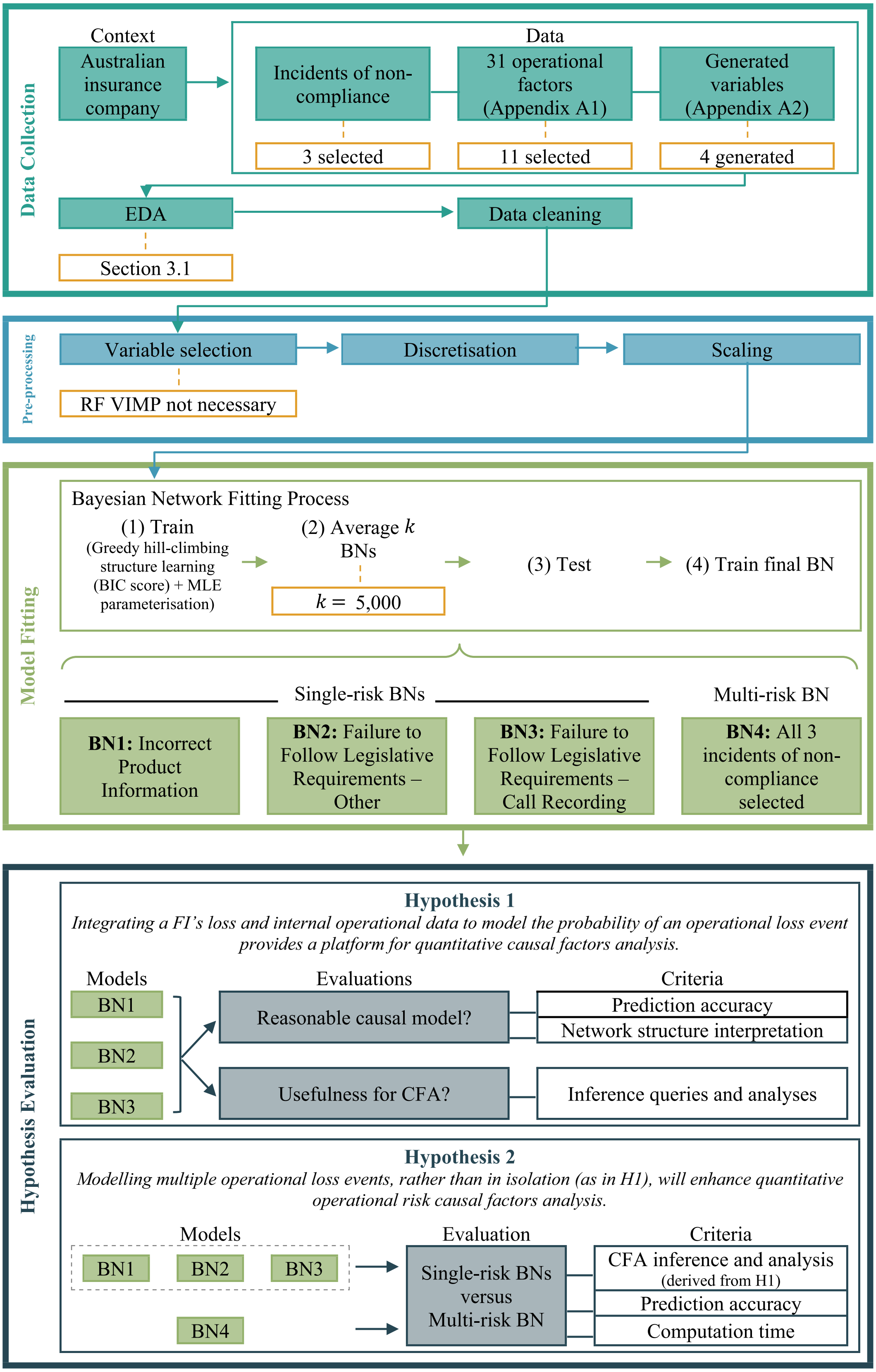
https://doi.org/10.1016/j.pacfin.2023.102011
Received 20 December 2022; Received in revised form 28 February 2023; Accepted 15 March 2023
Available online 21 March 2023
0927-538X/



(caption on next page)

Fig. 1. Overview of empirical design of study.

(Cornwell et al., 2023, p. 6) for the full review and discussion on these empirical relationships underlying this study. To address this puzzle, the study provides a novel application of Bayesian networks (BNs) for an interpretable and data-driven approach to causal factors analysis (CFA) for operational risks.

Our method's feasibility and value in gaining an improved understanding of an FI's operational risk causal factors are demonstrated in a real-world application with data from an Australian insurance company. In doing so, the following two hypotheses are investigated.

H1. : Integrating a FI's loss and internal operational data to model the probability of an operational loss event provides a platform for quantitative CFA.

H2. : Modelling multiple operational loss events, rather than in isolation (as in H1), will enhance quantitative operational risk CFA.

The analysis investigating these hypotheses leads to the contribution of a novel two-module framework of metrics and analyses specifically for CFA from an operational risk BN model. Based on prior literature (e.g., Braumann, 2018; Huang et al., 2020), the insights gained are expected to be strategically valuable for a FI's ORM practices. They aim to aid the design of *smart* controls and monitoring processes that could more efficiently allocate limited resources and more closely align to risk appetite and the overall operational and strategic objectives.

This paper constitutes Phase 4 of the PBFJ pre-registration publication process (Faff, 2022), executing the study outlined in our approved pre-registered "Engagement & Impact" report (Cornwell et al., 2023). Please refer to Cornwell et al. (2023) pre-registered report for the full background and motivation of the study. As per Faff (2022) guidelines, the remainder of this paper is structured as follows. The next section (Section 2) provides a summary of the empirical design fully detailed in the pre-registered report. Section 3 outlines the results from the empirical analysis, followed by a discussion of the results (Section 4) and concludes with the study's key contributions to research and practice (Section 5).

2. Pre-registered report articulation

In executing this study, the method outlined in the approved pre-registered report (Cornwell et al., 2023) was followed. Refer to the pre-registered report for full details on the hypothesis development, data and method. As a summary, Fig. 1 visualises the empirical design from data collection to hypothesis evaluation. The orange boxes note the specific design choices made and implemented throughout the execution of the study.

The data provided by an Australian insurance company relates to the occurrences of 19 different types of incidents of non-compliance over a 2.5 year period. As planned in Cornwell et al., 2023, exploratory data analysis (EDA) and discussions with the insurance company's executives led to the selection of three incident types that have a sufficient frequency of occurrence in the data set and are also of strategic importance to the company. The three selected for analysis in this study are:

- 'Incorrect Product Information' (IPI) – providing customers with incorrect or incomplete information about products, services and processes;
- 'Failure to Follow Legislative Requirements – Other' (FTFLRo) – failing to read the relevant legislated scripting accurately and at the appropriate time, not relating to call recording or payment card industry data security standards; and
- 'Failure to Follow Legislative Requirements – Call Recording' (FTFLRcr) – failing to read the relevant legislated scripting accurately and at the appropriate time, relating to call recording.

All three incidents relate to requirements under various regulation and state and national legislation, including the Corporations Act, Fair Trading Act and Australian Securities and Investments Commission (ASIC) Act, and thus if breached can lead to severe financial, licensing or reputational penalties for the company.

A total of 15 discrete variables are used to model the three different incidents. They consist of:

- 10 operational factors from the original data set, encompassing organisational structure, social or people and technical system factors (*CallType*, *Country*, *Department*, *Group*, *Tenure*, *RemunerationType*, *Experience_callcentre*, *Experience_insurance*, *Education*, *Gender*);
- a control for time (*Period*), also provided in the sample;
- an indicator for the number of co-occurrences of incidents in a call, generated from the data provided (*Cooccurrence*); and
- three generated variables about each advisor's incident history, including the number of previous incidents (*Recurrence_number*), the length of time since the most recent incident (if any) (*Recurrence_time*) and the type of past incidents (*Recurrence_type*).

The 10 operational factors and control were selected from the initial variable screening process of all 31 operational factors in the data set (Appendix A1), as per the pre-registered report. Highly correlated variables were removed in this process, as well as ensuring the variables included relate to information that would be available and known before an incident's occurrence and thus could be proactively manipulated or controlled. Breiman (2003) random forest variable importance-based variable selection process, as planned in the pre-registered report, was not needed since the initial variable screening sufficiently reduced the number of variables. Appendices A1 and A2 detail the discretisation and scaling conducted (i.e., reducing the number of categories to improve model reliability and computational complexity) for the operational factors and generated variables, respectively.

Four BNs are fit to evaluate the hypotheses – a single-risk BN for each incident of non-compliance selected (BN1-BN3) and one multi-risk BN modelling all three incidents together (BN4). In the BN fitting process, 5000 trained BNs are averaged, substantially more than the target of a minimum of 100 in the pre-registered report given the availability of powerful computing resources, which represents a great improvement on prior BN averaging methodologies implemented in the data-driven ORM literature. Consistent with the pre-registered report and as depicted in Fig. 1, the three single-risk BNs are used to evaluate "if, by applying the proposed BN methodology, a reasonable causal model that measures risk as a continuous probability can feasibly be built for a single operational loss event…[and] how [it] can be used for CFA" (H1) (Cornwell et al., 2023, p. 9). The single-risk BNs are then compared with BN4 using several metrics and analyses to evaluate "if and how the flows of influence change by taking a systems approach, or indeed what efficiencies in understanding the effect of causal factors on loss events can be gained" (H2) (Cornwell et al., 2023, p. 9).

3. Empirical analysis

3.1. Sample descriptive statistics

From January 2019 to June 2021 inclusive, there are data on 13,562 audited calls relating to 531 advisors. Across these, a total of 1039 incidents relating to the three types under investigation were identified, which occur reasonably uniformly over the 2.5 year period. IPI are the most common incident among these, although only occur in approximately 4% of calls audited. FTFLRo and FTFLRcr occur approximately half as frequently, although in similar frequencies to each other (Table 1).

Multiple types of incidents can co-occur in a single call. This happens in 18% of calls that have at least one incident (*Cooccurrence*). Among the three types of incidents of interest, the two relating to failing to follow legislative requirements most commonly co-occur (Table 2).

Approximately 80% of calls involve advisors who have previously had at least one incident of non-compliance (*Recurrence_number*), regardless of if a call has a current incident associated with it. This suggests that an advisor's past incident experience alone is not necessarily representative of an increased likelihood of future incidents.

The calls in this sample predominantly relate to selling new or renewing existing insurance policies (*Department*), including vehicle, building and contents, business liability or third party and other general insurance products (*CallType*) (Fig. 2). In terms of the characteristics of advisors, gender is fairly balanced. The median tenure is approximately two years, with the distribution of advisors with a tenure less than two years relatively uniformly distributed (*Tenure*). Most advisors in the sample are renumerated on a performance-linked variable basis, rather than fixed salary (*RemunerationType*). The typical experience profile of an advisor in this sample is a person with at most a high school or graduate certificate or diploma level of education (*Education*) and no previous call centre (*Experience_callcentre*) nor insurance experience (*Experience_insurance*).

3.2. Main confirmatory analysis (pre-registered)

This section presents the results from the four BN models outlined in the pre-registered report (BN1-BN4 in Fig. 1). Figs. 3 to 6 illustrate the structures learnt from the data for these BNs, and the BN structure formulae encoding these graphs are available upon request.

The three single-risk BNs fit share similar dependence structures (Table 3). Each incident of non-compliance is directly influenced by *Cooccurrence* and indirectly influenced by *Department*. Across BN1, BN2 and BN3, there are slight discrepancies in the arcs that connect operational factors as highlighted in Fig. 7. The differences between BN1 and BN2 generally persist in BN3, such that the BN2 and BN3 structures bear even greater resemblance (Fig. 7(b-c)). This is likely due to the high co-occurrence rate of both failure to follow legislative requirements incidents (Table 2) and thus similar operational risk profile.

When all three incidents are modelled together in a single BN (BN4), the network becomes less dense (Table 3). The dependence structure between the operational factors changes more substantially, despite overall commonalities, as evident in Appendix B comparing the models' parent-child node structures. The flows of influence to each incident in BN4 are consistent with those in the single-risk BNs, although extends two levels of parents beyond *Department*, originating from *Education* (*Education* → *Group* → *Department* → *Cooccurrence* → *Incident*). Additionally, however, FTFLRo is found to directly influence both IPI and FTFLRcr.

Table 4 reports the prediction accuracy measures based on Youden's threshold for the incidents in each BN model. Youden's index is used to select the optimal threshold value to be used as the predicted probability cut-off point for classifying an instance as an

Table 1
Frequency of incidents of non-compliance.

Incident Type	Frequency	Percentage of Calls Audited
IPI	549	4.05%
FTFLRo	277	2.04%
FTFLRcr	213	1.57%
Total	1039	

Table 2
Frequency of incidents of non-compliance co-occurring in a single call.

Occurrence of Incidents in a Single Call			Co-occurrence Frequency
IPI	FTFLRo	FTFLRcr	
✓	✓		19
✓		✓	14
	✓	✓	128
✓	✓	✓	8

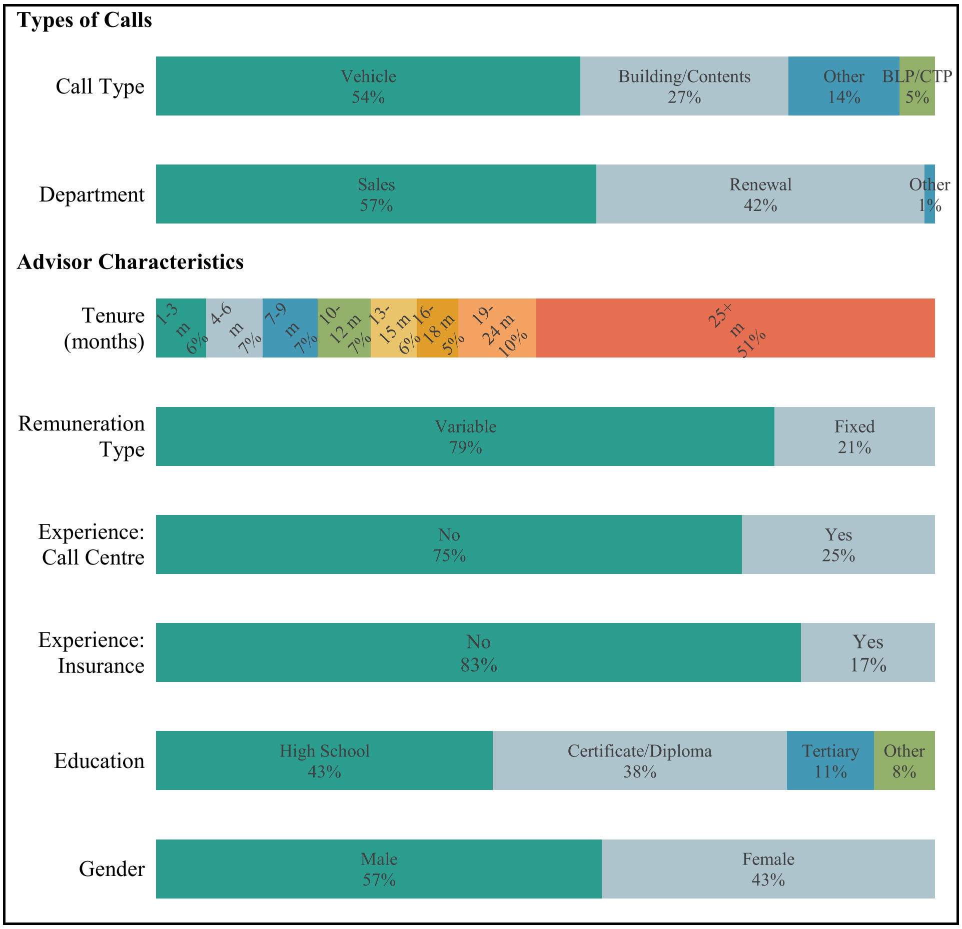


Fig. 2. Descriptive statistics summary of operational factors.

incident or non-incident (Youden, 1950). It adjusts the cut-off point to account for the highly imbalanced sample (i.e., mass of non-incidents compared to incidents (Table 1)), improving the models' sensitivity to correctly predicting incidents (recall prediction accuracy). It results in 100% recall of all incidents from all models. Balancing this with the models' performance in correctly predicting non-incidents (specificity), BN4 consistently outperforms the single-risk BNs across all incident types albeit marginally, as measured by the G-mean. This marginal outperformance is also reflected in the overall out-of-sample prediction accuracy measures, with BN4 providing correct predictions for IPI incidents approximately 86% of the time and approximately 83% of the time for both types of failing to follow legislative requirements.

All four BNs take less than two hours to train their final BN (i.e., step (4) in the model fitting process detailed in Fig. 1 of Section 2) using a Ubuntu 20.04 LTS Focal virtual machine with specifications 32 vCPUs, 64GB RAM and 30GB disk (ARDC Nectar Research Cloud, 2020). There is no substantial difference in the computation time for the single-risk versus multi-risk BN, despite BN4 having two extra nodes.

Several typical (Koller and Friedman, 2009; Scutari, 2010) as well as some novel analyses and inferences are conducted on the BNs learnt in attempt to support operational risk CFA. They are presented in a novel two-module framework, consisting of (1) analyses of the network structure and (2) probabilistic inference queries, with specific analyses and metrics within each. Four main types of insights about the mechanisms of operational risks in FIs result – (i) the collection of factors that influence the probability of operational

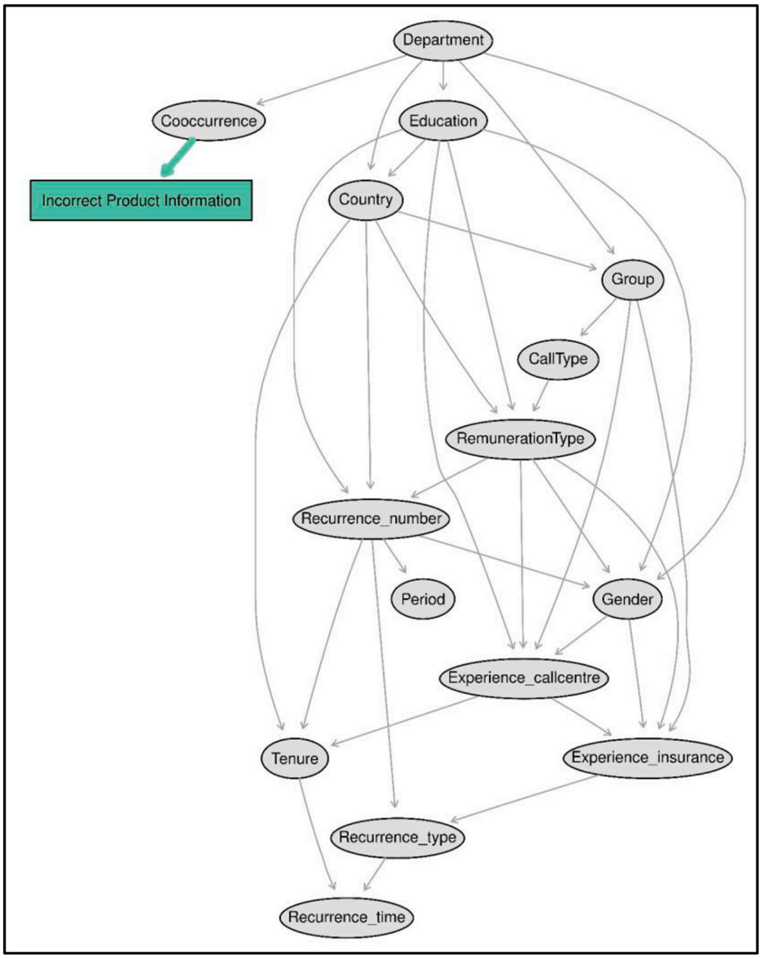


Fig. 3. Single-risk Bayesian network model for 'Incorrect Product Information' (BN1)[11].

loss events, (ii) their relative importance, (iii) compound effects and (iv) the settings or thresholds of factors at which the probability of an incident changes substantially. Table 5 outlines the analyses mapped to their associated operational risk insights. The analyses are conducted across all BNs, however only the results from BN4 are reported for brevity since it is the same principle for BN1 to BN3.

In BN4, we can be most confident in the presence and direction of the following arcs learnt from the data available:

- *Department* → *Cooccurrence* (4.54×10^{-28});
- *FTFRRo* → *IPI* (7.34×10^{-29}); and
- *Experience_callcentre* → *Recurrence_type* (1.99×10^{-32}).

Table 6 summarises the NAFfe and NATe metrics for BN4. The result NAFfe = 2 for FTFLRo incidents suggests that these incidents are likely to influence the occurrence of other incident types, and thus have a risk contagion effect. On the contrary, the result NATe = 2 for both IPI and FTFLRcr indicate these incidents commonly occur with, or are likely to result from the occurrence of, another incident. Reviewing the BN structure as earlier, we identify that the other incident is FTFLRo. Furthermore, from the NAFfe metrics, it appears that the group which an advisor works in (*Group*), followed by an advisor's level of education (*Education*), widely influence the operational environment.

The sensitivity analyses of operational loss events' conditional probabilities to changes in a single operational factor indicate that the factors have different levels of influence on the risk level, relative to their baseline unconditional probability. Summarising the mean and variance of the relative sensitivities for each operational factor offers a general understanding of the most influential factors, according to the BN learnt. As an example from BN4's sensitivity analysis for the IPI incident node, the variance in the incident conditional probabilities for each different value of *Group* relative to the incident's unconditional probability (i.e., $p_{conditional} - p_{unconditional}$) is 0.0188% with an average change from the unconditional incident probability of 0.6796%. The analysis suggests *Cooccurrence* most substantially impacts all incidents. *Group*, *Department*, *Recurrence_type* and *Period* are also in the top five most influential operational factors for each incident type, as measured by the variance of the relative change in the incident probabilities.

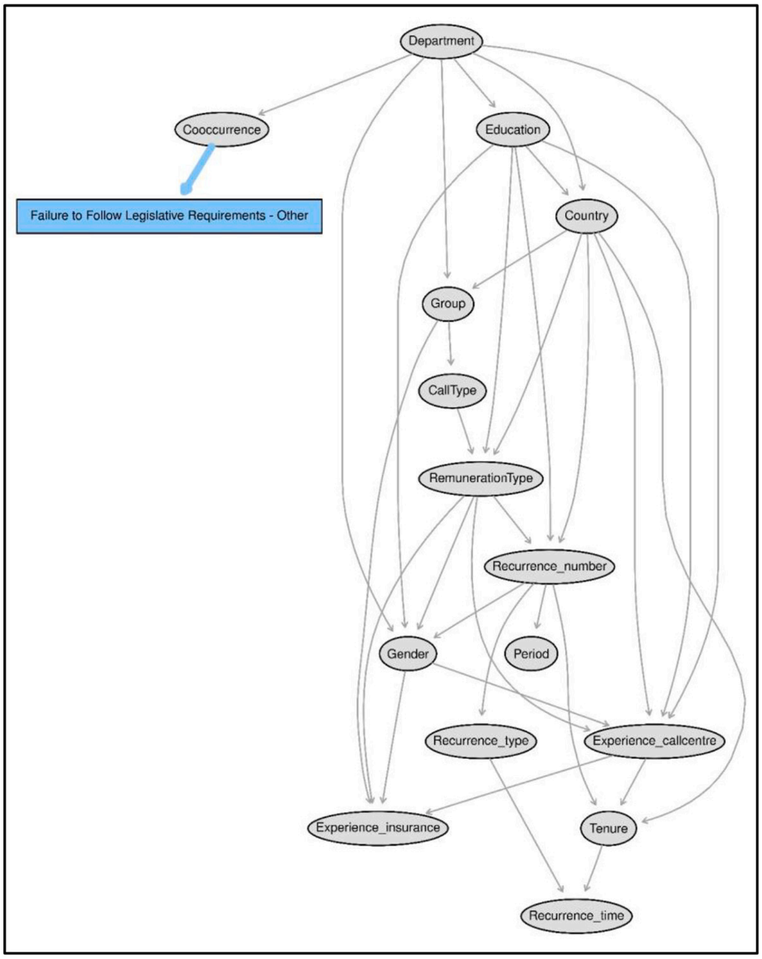


Fig. 4. Single-risk Bayesian network model for 'Failure to Follow Legislative Requirements – Other' (BN2)[1].

When the sensitivities of each individual value of an operational factor are examined, for example in graphical format (Figs. 8–10), a more granular understanding of how each factor influences risks can be gained. For example, overall, *Period* has a relatively high variance of the relative change in incident probabilities (as mentioned above), yet the consistent variability in the incidents' conditional probabilities across the periods in Fig. 8 suggests there is likely no substantial seasonal effect that needs to be managed. This corresponds with the results from the earlier network structure analysis (NAFfe = 0), showing *Period* likely has no influence on other operational factors and incidents.

Several other interesting findings that could be useful for decision-making are identified when the sensitivity analyses for each operational factor are reviewed in detail. Take the sensitivity analysis of *Tenure* illustrated in Fig. 9 for example. The probability of an IPI incident appears to be exacerbated during an advisor's 13 to 18 months post-commencement. By comparison, the analysis indicates there is a heightened risk of FTFLRcr in the first 3 months of an advisor's tenure, and similarly throughout the first 12 months for FTFLRo.

The results from these analyses need to be interpreted with care, however, as the conditional probabilities of some categories of operational factors are estimated from few observations, thus less confidence should be attributed to those results. For example, in Fig. 10, the sample size of the observations across the three *Department* categories with an IPI incident are 389, 152 and 8, respectively. While advisors in departments other than sales or retention (*Department* = ′Other′) appear to have a substantially higher risk profile for this incident, managers are cautioned in being overly confident about this finding given the small sample size of only 8 observations supporting it.

For each incident of non-compliance modelled in BN4, the operational conditions under which each incident is most likely to occur are found to be the same, except for the number of incident co-occurrences (*Cooccurrence*). IPI is more likely to occur on its own than it is with any other type of incident (*Cooccurrence* = ′1 Incident′), while FTFLRo and FTFLRcr are both more likely to occur with another

[1] The grey elliptical nodes are operational factors, and the coloured rectangular nodes are various incidents of non-compliance.

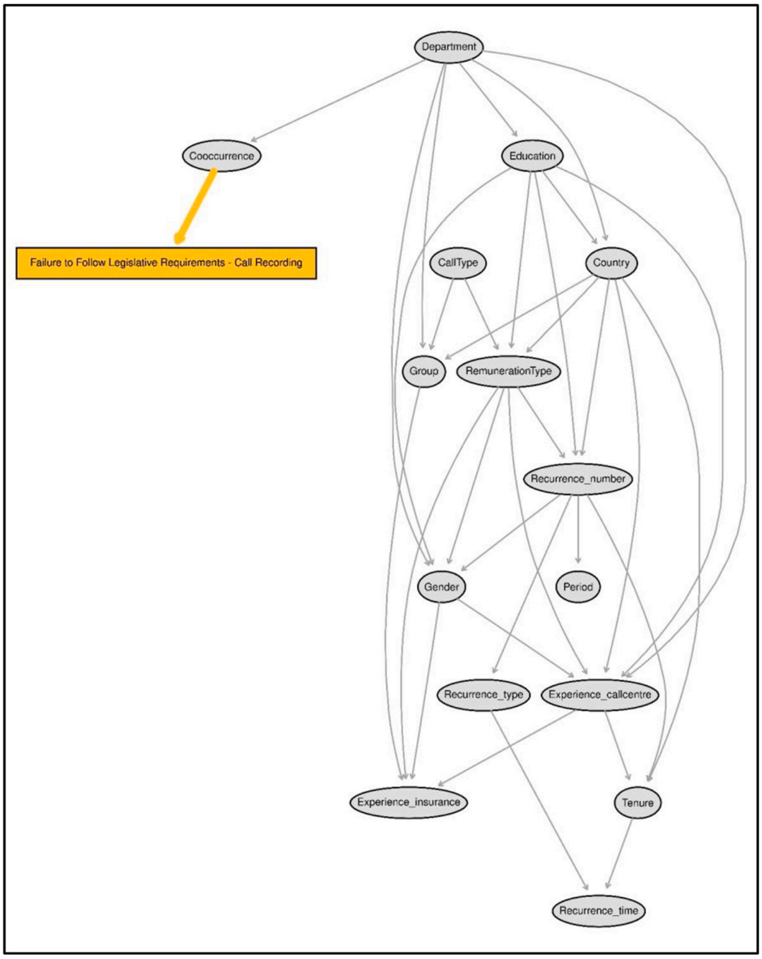


Fig. 5. Single-risk Bayesian network model for 'Failure to Follow Legislative Requirements – Call Recording' (BN3)[1].

incident (*Cooccurrence* = ′2 + Incidents′). This insight from BN4 is validated by the co-occurrence summary statistics presented earlier (Table 2), reinforcing the validity of the BN approach for CFA.

3.3. Additional exploratory analysis (unregistered)

Some extra modelling and analysis of interest to investigate H2 was conducted. This includes two additional multi-risk models (BN5-BN6 in Table 7). They model pairs of the incidents under investigation, offering further comparisons in evaluating the effect of modelling different subsets versus the 'entire' operational risk system (BN4). Given the dependence structures among the operational factors differ between the single-risk BNs and BN4, it is interesting to examine if such structural differences persist when combinations of two risks are modelled in a single network, adding to the robustness of the study. The same pre-registered model fitting and evaluation process was followed for BN5 and BN6, such that these models are very minor additions to the original pre-registered analysis.

The graphical structures and results for these "unregistered" models are presented in Figs. 11 and 12 and Table 8. Overall, the results from BN5 and BN6 do not differ substantially from those of the pre-registered models. The same dependence structures between the incidents in BN5 and BN6 are reflected in that of BN4 when all incidents are combined. There is slight variation in the dependence structure among the operational factors in BN5 and BN6 as compared to BN1 to BN4 – the parent-child relationships are generally a combination of those in the single-risk and BN4 models (Appendix B), reflective of the combination of the types of incidents modelled. BN4 remains marginally superior in terms of prediction accuracy for each incident of non-compliance. BN5 and BN6, however, take more than double the computational time to train, further diminishing any comparative advantage of these models.

4. Discussion

The following discussion reviews the results with respect to the hypotheses defined in the introduction.

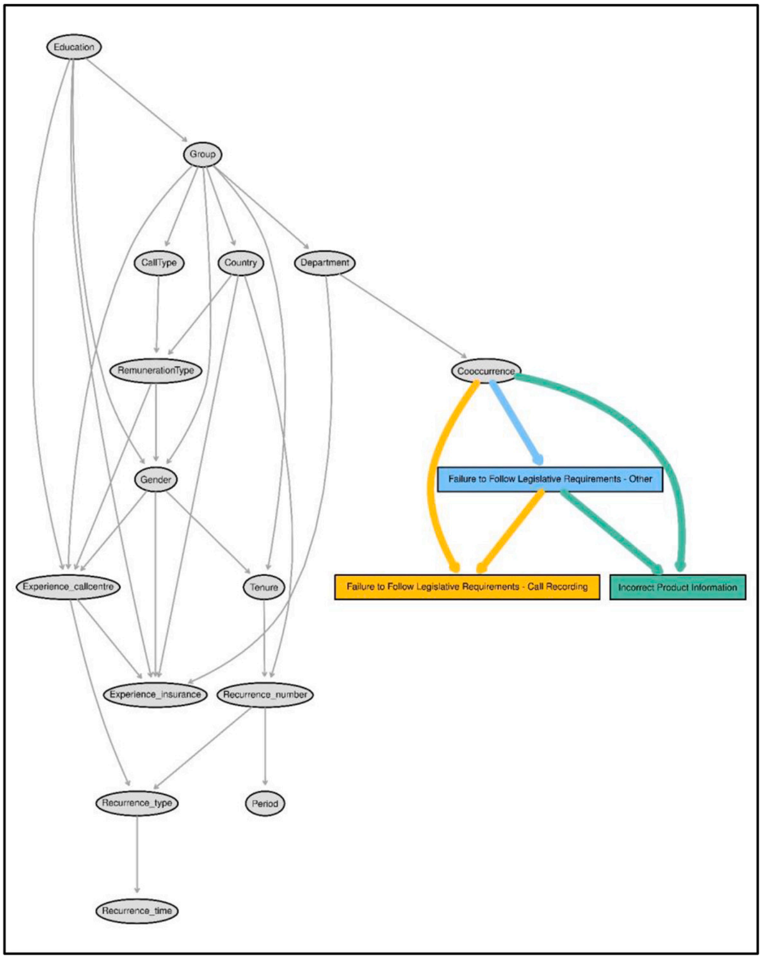


Fig. 6. Multi-risk Bayesian network model for 'Incorrect Product Information', 'Failure to Follow Legislative Requirements – Other' and 'Failure to Follow Legislative Requirements – Call Recording' (BN4)[1].

4.1. Hypothesis 1

Overall, the analysis of the three single-risk BNs (BN1-BN3) support H1. The results (from three dimensions, as explained below) show that applying the BN-based methodology using historical incident and operational data produces a reasonable model that measures operational risks as a continuous probability with respect to changes in operational causal factors.

4.1.1. Prediction accuracy

Each single-risk BN reasonably accurately predicts both incidents and non-incidents, indicating the models are relatively effective in reflecting the relationships that exist in the Australian insurance company's operational risk environment. It should be noted that risk prediction is not the primary objective of the model developed, rather exploratory analysis about the casual risk relationships is the focus, and hence further research involving various hold-out sets would be needed to focus on improving the predictive ability of the models.

4.1.2. Network structure interpretation

Generally, the interpretations of the flows of influence captured in each BN structure are reasonable and broadly consistent with discussions from experts from the insurance company that provided the data. For example, the direct influence on each incident type is *Cooccurrence*, which is not unexpected given the *Cooccurrence* variable itself is somewhat correlated with the incident occurrence variables (i.e., in cases where none of the 19 categories of non-compliance occur, *Cooccurrence* = 0 and any incidents being modelled will also be zero). It also supports past risk analysis (e.g., Embrechts et al., 2018; Hajakbari and Minaei-Bidgoli, 2014). *Department* also influences the probability of each incident, albeit indirectly, which is consistent with past literature (e.g., Embrechts et al., 2018; Wang et al., 2018), global operational risk standards (Basel Committee on Banking Supervision, 2006, p. 3) and also sensible with some internal knowledge of the company's operations. Advisors in the sales and retention departments are specialists in their respective

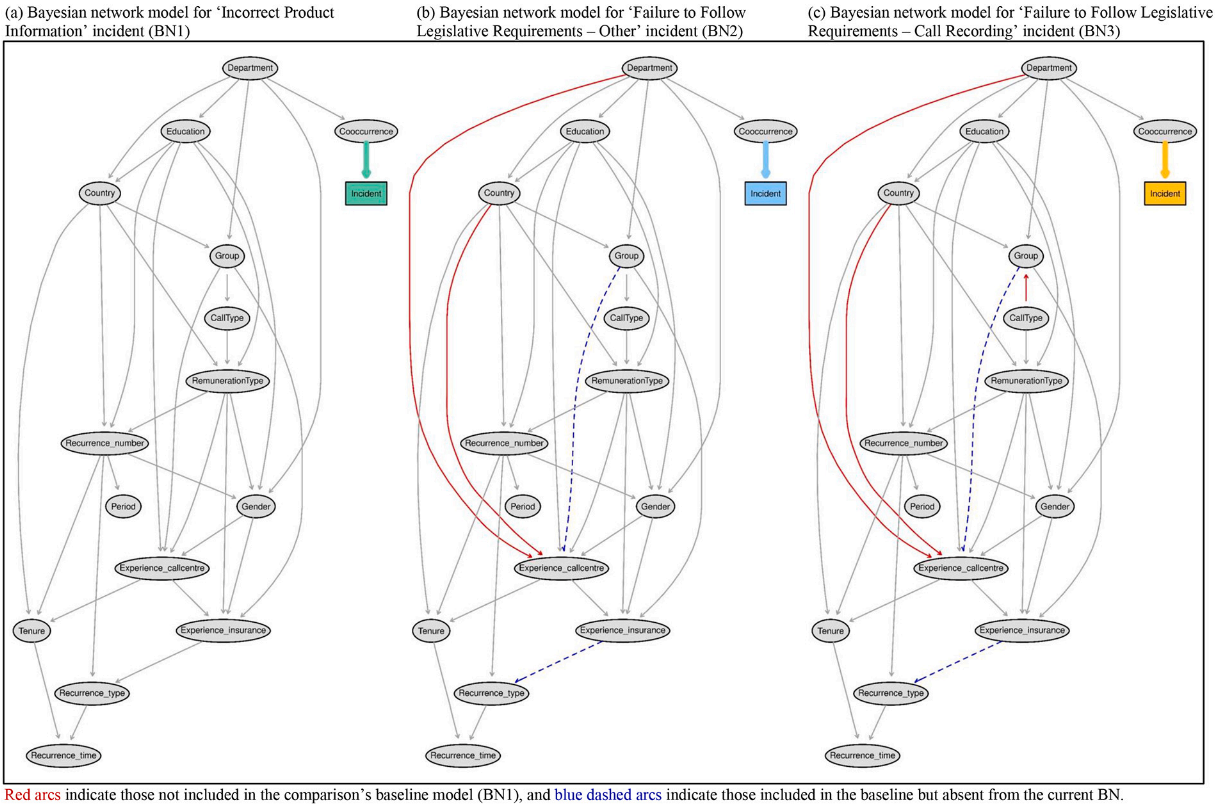


Fig. 7. Comparison of single-risk Bayesian network structures (BN2 and BN3 compared to BN1).
Red arcs indicate those not included in the comparison's baseline model (BN1), and blue dashed arcs indicate those included in the baseline but absent from the current BN.

Table 3
Summary statistics of Bayesian network structures.

Model	Number of Nodes	Number of Arcs	Average Arcs per Node
BN1	16	34	2.13
BN2	16	34	2.13
BN3	16	34	2.13
BN4	18	32	**1.78**

areas (i.e., sales advisors only field sales related customer calls and vice versa for retention), while advisors in the other departments are generalists (i.e., they take calls relating to sales, retention and other customer service enquiries). Therefore, the heightened risk for advisors in the other departments (Fig. 10) is likely explained by the greater breadth of topics the customer calls may relate to and thus the advisors must be proficient in. In comparison, sales and retention advisors have a smaller subset of relevant information and processes to learn, and in turn a greater concentration of on-the-job practice.

In evaluating the reasonableness of the network structure, limitations in terms of the data available for this study should be noted, with several important implications:

- Relative benchmark – it is difficult to validate the 'true' accuracy of the network structures learnt from the data, given the complex nature of the problem and limitations of current qualitative root cause analysis methodologies (see Cornwell et al., 2023). A future study could contrast the causal outputs from the data-driven approach with that of traditional approaches, although it would defeat some of the advantages of data-driven approaches, surrounding identifying highly complex and potentially unknown interdependencies and circumventing the limitations of human biases and cognitive processing ability.
- Data quantity – the amount of data available limits the level of confidence in the accuracy of both the presence and direction of arcs in the BNs, as measured by the arc strength (Section 3.2). It is, therefore, imperative that humans remain 'in-the-loop' when implementing the data-driven approach to CFA in an FI. Future work could investigate the role of a feedback loop to the BN training process upon review and interpretation of the model by domain experts (e.g., correcting illegitimate or erroneous dependencies or probability estimates that were possibly estimated from low sample sizes).

Table 4
Prediction accuracy results (overall accuracy, G-mean, recall, specificity, AUC) for each Bayesian network based on Youden's threshold.

Model	Incident Prediction Accuracy (%)								
	IPI			FTFLRo			FTFLRcr		
BN1	85.21	91.97		-			-		
	100.00	84.58	93.59						
BN2	-			81.39	90.00		-		
				100.00	81.00	95.50			
BN3	-			-			82.28	90.55	
							100.00	82.00	96.87
BN4	**85.62**	**92.20**		**82.87**	**90.84**		**83.16**	**91.05**	
	100.00	**85.02**	**94.50**	100.00	**82.51**	**95.68**	100.00	**82.89**	**97.39**

The five prediction accuracy measures for each model-incident pairing are reported together – overall accuracy (top-left) highlighted in orange, G-mean (top-right) highlighted in teal and recall, specificity and area under the curve (AUC) reported underneath respectively.
Prediction accuracy values are **bold** for those that correspond to the model that has the best prediction performance for a given type of incident and as measured by a given accuracy measure.
Any incident types that are not applicable to a model, and thus not predicted, are marked '-' (e.g., BN1 only predicts IPI incidents and hence the prediction performances of the other types of incidents are not reported).

Table 5
Framework for operational risk causal factor analyses from Bayesian networks.

Causal Factor Analysis		Operational Risk Insight
Network Structure Analysis	Arc connection interpretation	Collection of factors that directly and indirectly influence operational losses
	Arc strength	Confidence that a given factor influences its connected factor
	Number of arcs from a factor or event node (NAFfe)	Breadth of influence of operational factors and loss events
	Number of arcs to an event node (NATe)	Complexity of operational loss events
Probabilistic Inference	Conditional probability query (CPQ) sensitivity analysis for each operational loss event	Impact of changing a single factor to probability of an operational loss event ⇒ Level of influence of operational factors and loss events
		States of operational factors that most greatly influence the probability of an operational loss event
	Maximum a posteriori (MAP) assignment for each operational loss event	Most probable combination of operating conditions an operational loss event may occur under
	Investigative scenario analysis	Impact of changing multiple factors to probability of an operational loss event ⇒ Collective influence of combinations of operational factors

Types of Operational Risk Insights
(i) Collection of factors (ii) Relative importance (iii) Compound effects (iv) Critical settings

Despite these limitations, the BNs' fits and results are reasonable representations of the subset of the Australian insurance company's operational risk environment investigated, as per the main analysis in Section 3.

4.1.3. CFA inference queries and analyses

The two-module framework for operational risk CFA from BNs (Table 5) and the results from these metrics and analyses showcase the types of insights that can be extracted from a model. Many of these translate directly into proactive mitigation actions that could help to reduce the frequency and severity of incidents. For example, targeting operational factors identified with larger values of the NAFfe metric (i.e., those with more connections and so supposedly broader influence) potentially provides a more efficient and

Table 6
NAFfe and NATe network structure analysis results for BN4.

Node		NAFfe	NATe
Incident	FTFLRo	2	1
	IPI	0	2
	FTFLRcr	0	2
Operational Factor	Group	6	–
	Education	4	–
	Country	3	–
	Gender	3	–
	Cooccurrence	3	–
	Department	2	–
	RemunerationType	2	–
	Experience_callcentre	2	–
	Recurrence_number	2	–
	CallType	1	–
	Tenure	1	–
	Recurrence_type	1	–
	Period	0	–
	Experience_insurance	0	–
	Recurrence_time	0	–

Any analyses that are not applicable to a node are marked '-' (e.g., NATe is only calculated for loss event nodes, and hence is not applicable for operational factors).

widespread mechanism to control the operational risk environment.

Similarly, analysing the sensitivity of the operational loss conditional probabilities to different values of each operational factor seeks to highlight factors that most greatly influence the probability of an incident (i.e., valuable levers to pull), as well as particular operational settings that increase or decrease the incident's probability the most (i.e., which direction to pull the levers for the desired outcome). This information is likely valuable to managers of FIs in developing proactive mitigation strategies that target problem areas to reduce the likelihood, and ultimately frequency, of non-compliance (Aven and Flage, 2020; Peters et al., 2018). This may include *training by design* or *advisor rotations by design*, meaning advisors' training or rotation schedules are intentionally planned to proactively pre-empt foreseen issues. For example, the finding that IPI incidents and incidents relating to failing to follow legislative requirements have different high risk tenure profiles (Fig. 9) would suggest more comprehensive training on the process and importance of following legislative requirements for new advisors is needed; however, to address the heightened risk of an IPI incident for advisors with tenure between 13 and 18 months, greater oversight and perhaps a specific refresher training around the 12 month anniversary should be implemented. As mentioned, vigilance is needed when interpreting and making decisions based on the sensitivity analysis since some results may be inferred from small sample sizes. Future research should investigate adjusting the model and visualisations to account for this and to ensure the end user is appropriately informed of such cases.

Furthermore, the MAP assignment identified for each operational loss event in a BN outlines the features of the most probable highest risk scenario based on the data. This information could be used by an organisation to implement targeted monitoring or offer additional guidance and support to advisors of a certain high risk profile, seeking to optimise the allocation of finite resources to where there is greatest risk or differential from risk appetite (KPMG US and The Risk Management Association, 2018).

It is interesting to note the commonalities and differences of the influential relationships and factors identified from the various BN CFA analyses and metrics. Summarising these results as in Table 9 for BN4 not only highlights the importance of operational factors that are frequently identified as influential across the analyses (e.g., *Cooccurrence*, *Department* and *Group*), but also highlights factors that are identified as influential by a single analysis or metric (e.g., *Period* or *Tenure*). Let us also reflect for a moment on the results presented for *Period* and *Tenure* in Section 3.2. In the sensitivity analysis summary, *Period* was indicated to be highly influential, yet the detailed graphical depiction of the sensitivity analysis told a different story. In comparison, *Tenure* was only recognised as an important operational factor to manipulate from the detailed sensitivity analysis graph. Clearly, all analyses in the multi-faceted framework are needed to pinpoint different effects of different strategic value for risk managers.

Moreover, while the network structure metrics, NAFfe and NATe, directly support the graphical depictions of a BN structure, and thus may seem superfluous, they are useful in focussing attention to key operational factors that warrant more detailed review. These simple and easy to rank metrics are expected to be particularly valuable when a larger remit of an FI's operational risk environment is modelled, which may result in extremely large and complex BN structures.

Overall, the suite of inference queries and analyses derived for BNs enables the models to be used for CFA, which should ultimately help to inform the intentional and targeted design of controls and mitigation. In light of past empirical analyses showing the financial and operational enhancements of effective risk management which is often supported by quantitative tools (Braumann, 2018; González et al., 2022; Huang et al., 2020), such *smart* control design and monitoring should facilitate closer alignment to a FI's risk appetite and achievement of overall operational and strategic goals with a more efficient allocation of resources.

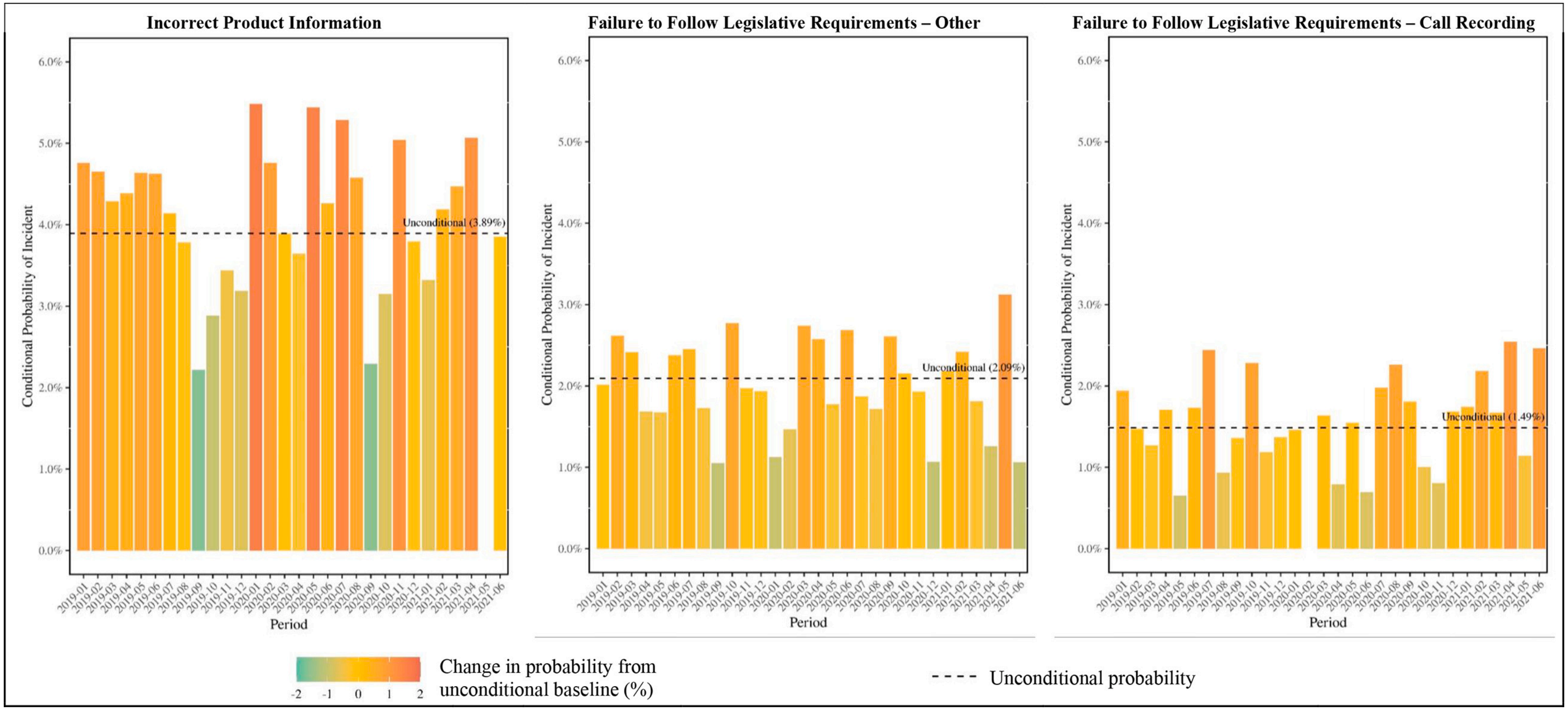


Fig. 8. Sensitivity analysis of incident probabilities in BN4 conditional on different *Period*.

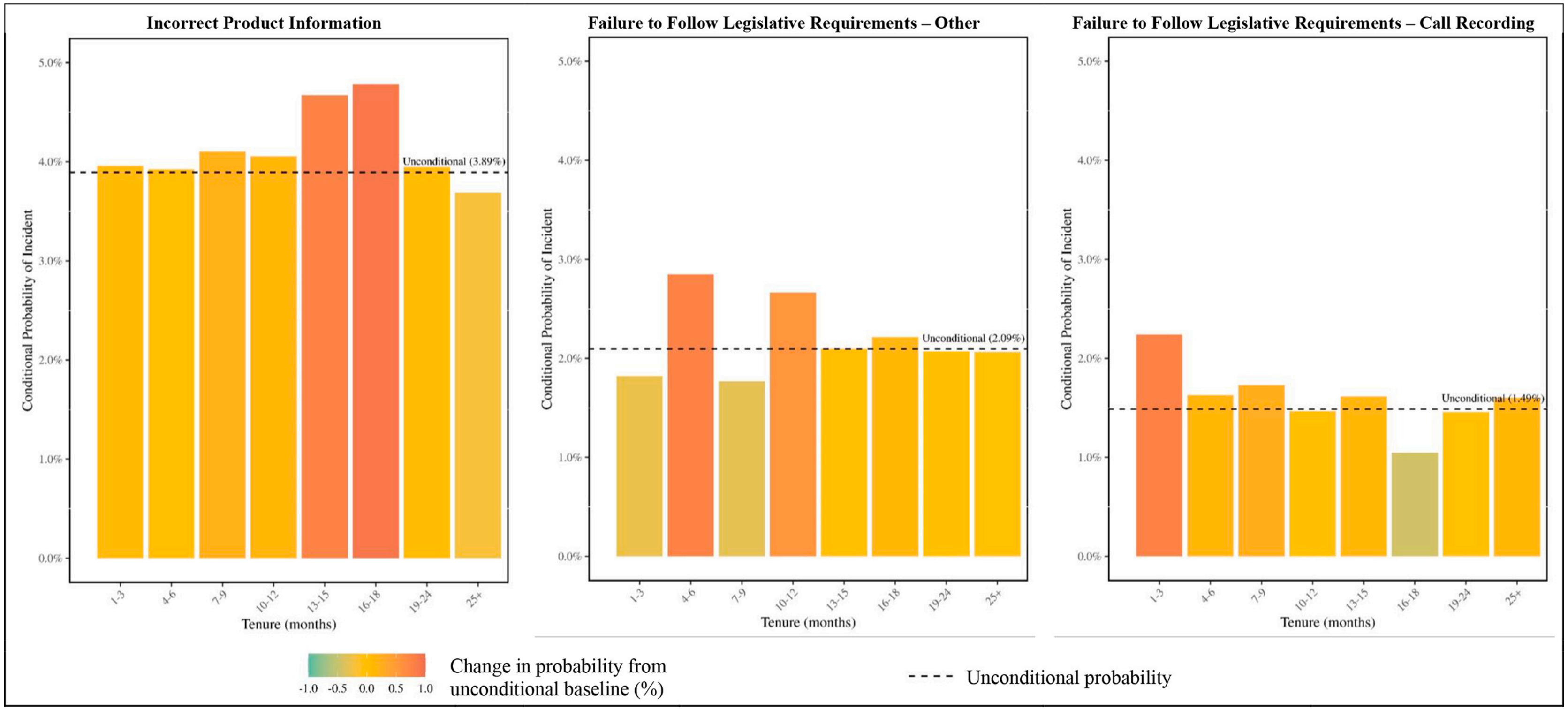


Fig. 9. Sensitivity analysis of incident probabilities in BN4 conditional on different *Tenure*.

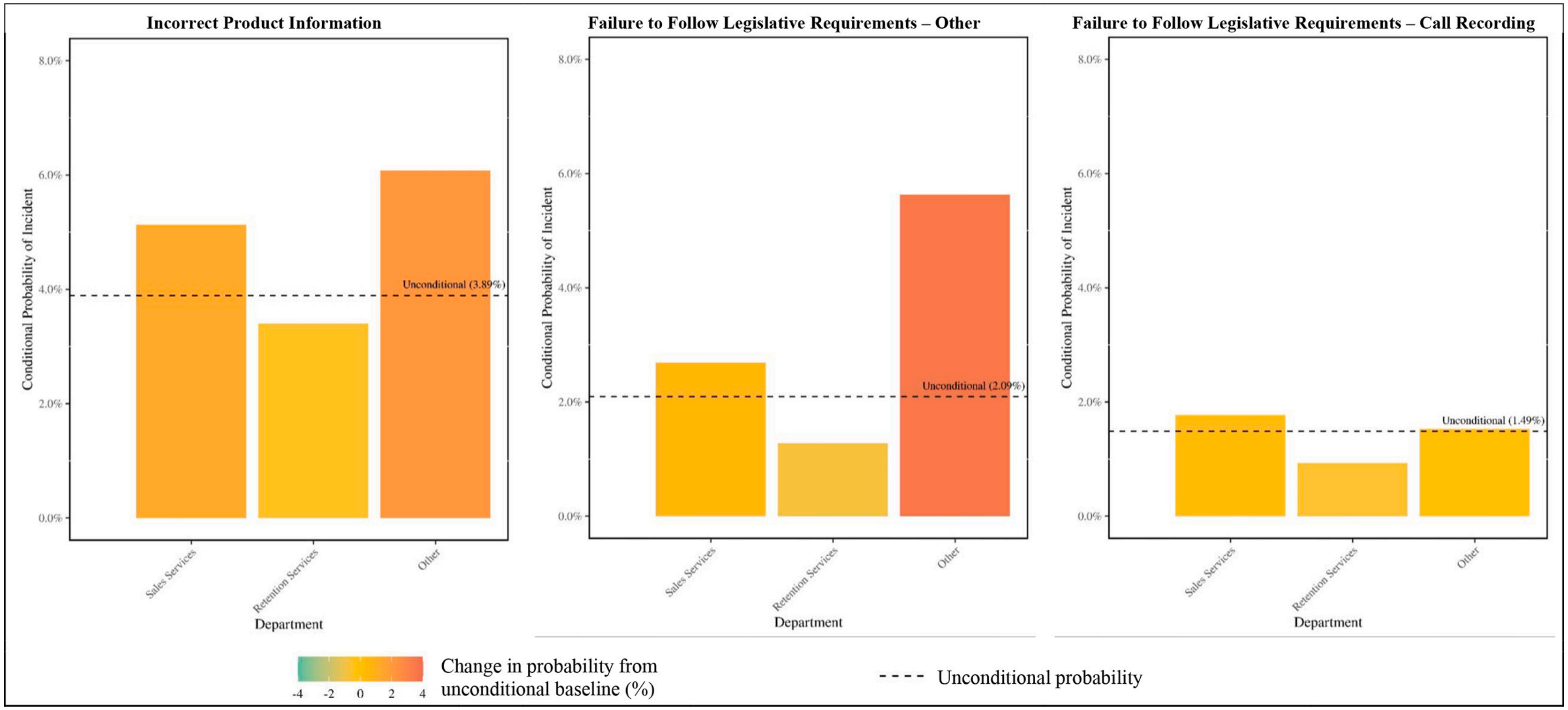


Fig. 10. Sensitivity analysis of incident probabilities in BN4 conditional on different *Department*.

Table 7
Summary of incidents of non-compliance modelled in each Bayesian network.

Model	Incidents of Non-compliance Modelled		
	IPI	FTFLRo	FTFLRcr
BN1	✓		
BN2		✓	
BN3			✓
BN4	✓	✓	✓
BN5*	✓	✓	
BN6*		✓	✓

* "Unregistered" models fit for supplementary exploratory analysis in the evaluation of H2.

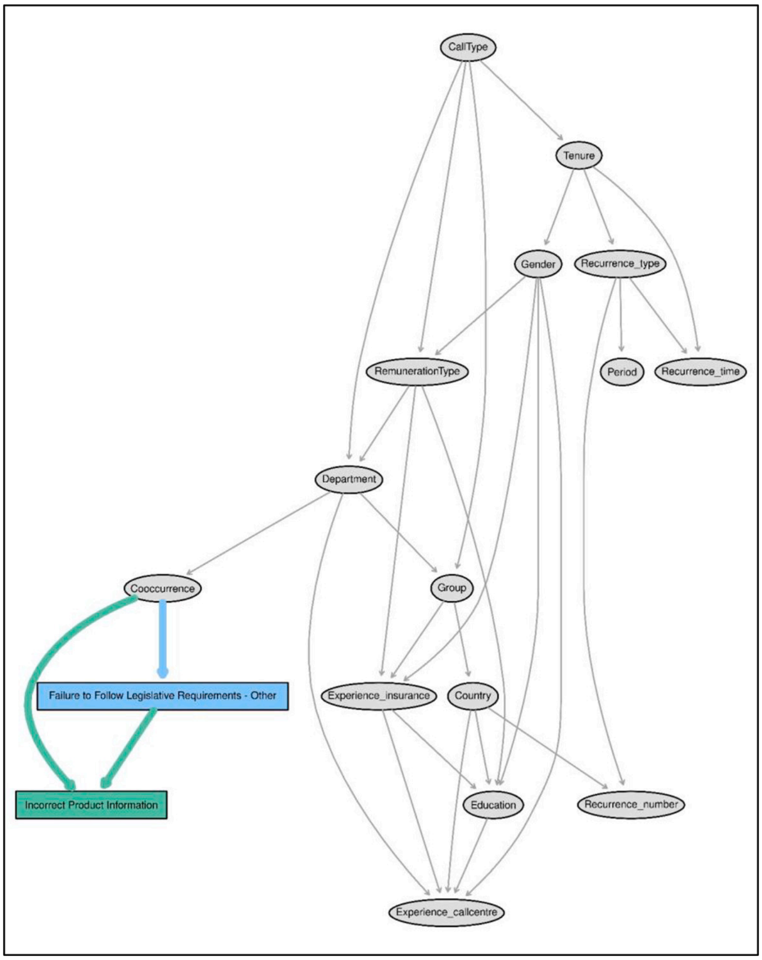


Fig. 11. Multi-risk Bayesian network model for 'Incorrect Product Information' and 'Failure to Follow Legislative Requirements – Other' (BN5).

4.2. Hypothesis 2

The main comparative analysis between the single-risk (BN1-BN3) and multi-risk (BN4) BNs supports H2, and the "unregistered" analysis across BN5 and BN6 compared to BN4 reinforces this. Socio-technical systems theory (Rasmussen, 1997) holds for the BN-based CFA approach presented. Modelling multiple operational loss events together, and in fact larger collections rather than smaller subsets, is more advantageous than modelling each risk in isolation, gaining both an enhanced understanding and practical efficiencies.

4.2.1. CFA inference queries and analyses

Given the structural similarities across each single-risk BN, modelling all incident types in the single model brings about efficiencies and a greater understanding about the operational risk environment as a whole. For example, *Cooccurrence* is a parent of (i.e., directly

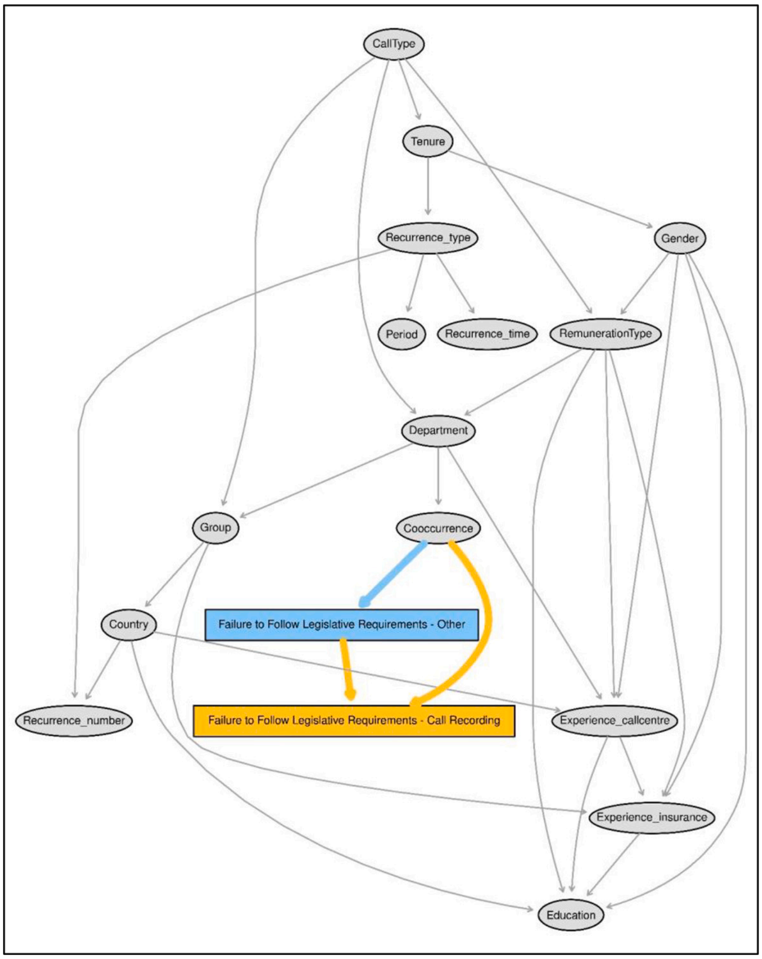


Fig. 12. Multi-risk Bayesian network model for 'Failure to Follow Legislative Requirements – Other' and 'Failure to Follow Legislative Requirements – Call Recording' (BN6).

Table 8
Results for "unregistered" Bayesian network models.

		Model					
		BN5			BN6		
Structure Summary Statistics	Number of Nodes	17			17		
	Number of Arcs	31			31		
	Average Arcs per Node	1.82			1.82		
Incident Prediction Accuracy (%)	IPI	85.33	92.04		-		
		100.00	84.71	93.74			
	FTFLRo	82.70	90.74		82.87	90.84	
		100.00	82.34	96.41	100.00	82.51	95.95
	FTFLRcr	-			83.07	90.99	
					100.00	82.80	96.61

The five prediction accuracy measures for each model-incident pairing are reported together – overall accuracy (top-left) highlighted in orange, G-mean (top-right) highlighted in teal and recall, specificity and area under the curve (AUC) reported underneath respectively.
Any incident types that are not applicable to a model, and thus not predicted, are marked '-'.

Table 9
Summary of key results from operational risk causal factor analyses for BN4.

Causal Factor Analysis			Top Results
Network Structure Analysis	Arc connection interpretations	Direct incident influence	***Cooccurrence***
		Indirect incident influence	*Department*, *Group*, *Education*
	Arc strength		*Department* → ***Cooccurrence*** *FTFRRo* → *IPI* *Experience_callcentre* → *Recurrence_type*
	NAFfe	Incidents	FTFLRo
		Operational factors	*Group*, *Education*, *Country*, *Gender*, ***Cooccurrence***
	NATe		IPI, FTFLRcr
Probabilistic Inference	CPQ sensitivity analysis	Overall (i.e., most varied)	***Cooccurrence***, *Group*, *Department*, *Recurrence_type*, *Period*
		Detailed graph	*Tenure*, *Department*
	MAP assignment		***Cooccurrence***

Influential operational factor nodes common across the causal factor analyses are colour-coded and the most common is **bold**.

influences) all incidents investigated in their respective single-risk BNs, and BN4 more clearly shows this commonality. This more efficient representation of the operational risk environment that the multi-risk BN yields is also reinforced by the fact that it has fewer arcs despite having more nodes than each single-risk BN.

Further, when multiple incident types are modelled together, the notion of incident co-occurrence, or risk contagion, is naturally identified. The NAFfe metric for incident nodes clearly highlights such relationships. For example, in BN4, NAFfe = 2 for FTFLRo yet is zero for the other two incidents (Table 6). It captures the two most common combinations of incidents co-occurring, consistent with the EDA results (Table 2). Such insights gained exclusively from a multi-risk perspective mean risk managers have greater visibility of the likely chain of losses. In practice, this should help in:

- prioritising mitigation efforts toward areas with extensive ripple effects expected;
- highlighting incident types with similar causal pathways and thus potentially sensible groupings for proactively addressing root causes of risks; and
- identifying likely leading indicators of connected incidents for just-in-time intervention or more targeted and thus efficient investigation or audit methodologies.

Contextualising these based on the incident dependencies identified in BN4, the insurance company could:

- indirectly reduce the likelihood of IPI and FTFLRcr incidents by focussing on mitigating FTFLRo incidents;
- design and implement strategies to address the factors found to influence the group of incidents relating to failing to follow legislative requirements; and
- use the knowledge of an occurrence of a FTFLRo incident to attentively limit the likelihood of or actively audit for a FTFLRcr incident.

A multi-risk BN also appears particularly advantageous for sensitivity analysis. It allows examination of the effect of changing one factor across all risks simultaneously, as demonstrated in Figs. 8 to 10. This enables mitigation strategies to be designed that mindfully balance differences in risk profiles and reduce unintended consequences (i.e., even *smarter* control design and monitoring). Taking the earlier example of the different influences of *Tenure* across the three incidents investigated, the analysis indicates different actions are needed to target the different high-risk tenures across these incidents.

4.2.2. Prediction accuracy

The multi-risk BN4 is consistently the most accurate at predicting each incident type, reflective of its more realistic depiction of the operational risk environment. Additionally, there is no notable difference in computation time between the single-risk and multi-risk BN in this setting.

Overall, the evaluation of H2 demonstrates that when implementing our BN-based approach, modelling multiple operational loss events as a holistic system enhances quantitative operational risk CFA.

5. Conclusion

To the author's knowledge, this study is the first that provides a fully data-driven approach to analysing cause-effect relationships of FIs' operational risks holistically and that does so by quantifying these relationships as continuous probabilities. The BN methodology implemented on loss and operational data offers a quantitative, objective, reproducible and virtually continuously updateable tool to quantify and analyse an interconnected operational risk environment. The unique framework for operational risk CFA from BNs presented and applied uncovers insights that are expected to be strategically valuable for risk managers. A multi-risk BN that provides a holistic view of multiple operational risk profiles offers a more efficient, accurate and interpretable mechanism for understanding the interdependencies of operational factors across risks, as well as highlighting the contagion between risks. The superiority of the multi-risk perspective, as compared to modelling each operational risk event in isolation, is consistent with systems theory.

As mentioned, the study is limited by the data available from the insurance company engaged, which has several implications relating to the level of confidence in the models' inferences. Thus, there is scope for future work to verify the BN-based CFA approach in other contexts and with a greater number of operational risks, in addition to exploring alternative techniques. The current study, however, contributes a much-needed benchmark of a data-driven application to the field of research for future research to compare to and improve on.

Additionally, to fully evaluate and seek assurances on the value that the BN-based CFA approach offers as a strategic decision-making tool, a direct empirical comparative analysis of the causal factor findings between our posited approach, traditional qualitative CFA approaches and other established quantitative approaches should be conducted in future research. Further, a longitudinal study investigating the total business and economic impacts (including the direct and indirect effects resulting from incidents mitigated, risk management process and other operational efficiencies gained as well as the financial consequences) of this data-driven CFA approach in practice would also be valuable to rigorously assess its commercial value. A study by Forrester Consulting (Hall, 2022) on the total economic impact of a digital risk tool (Dataminr's real-time alerts of external risks) evaluates these impacts, comparing the benefits across five dimensions (avoiding (a) disruption, (b) reputational damage, (c) remediation costs, (d) security labour hire and (e) labour costs associated with alternative approaches) against the costs (setup, training and licensing). However, the lack of data collected surrounding the true costs and effectiveness of current risk management in organisations may pose difficulties for such a comparison. Certainly, the data constraints for this study did not make such an analysis viable. Beyond the scholarly contributions, discussions with the insurance company engaged in this study to date have aided innovative idea generation about practical steps for the organisation to implement based on the approach's findings. The effectiveness of the study's engagement and impact with industry will continue to emerge with time and we look forward to monitoring this, in line with the impact signals presented in Appendix A2 of the pre-registered report (Cornwell et al., 2023).

More broadly, this study is expected to have enduring practical relevance to FIs in the Asia-pacific region and beyond. The BN-based CFA approach showcased is generic and so could be applied to other organisations. When implemented within a FI, the insights that follow are specific to that FI, helping inform controls and monitoring *by design* – the intentional and strategic design of mitigation activities for more proactive ORM and in a more efficient manner. If such improvements in the effectiveness of ORM and availability of operational capacity ensue from incorporating the approach into ORM processes, it is likely the frequency of costly losses in an organisation will reduce. Given the existing positive empirical relationships between quantitative risk management tools, risk management effectiveness and firm value, the posited approach in this study could ultimately support an uplift in financial performance and firm value, ceteris paribus.

Glossary

Term	Abbreviation (if used)	Definition
Bayesian network	BN	Within the family of probabilistic graphical models, BNs are directed acyclic graphs that concisely capture the conditional probabilistic dependence structure between a set of random variables, represented as nodes (Nagarajan et al., 2013).
Causal factors analysis	CFA	Analysis conducted in the ORM assessment process to identify the causes (direct, indirect or root causes) of incidents (Chapelle, 2018).
Enterprise risk management	ERM	"A systematic and integrated approach to the management of the total risks [operational, financial, strategic and external risks] that a company faces" (Dickinson, 2001, p. 360), in comparison to traditional siloed approach to risk management.
Exploratory data analysis	EDA	The process of conducting initial analysis and investigations on a data set to gain a thorough understanding of patterns and anomalies, as well as checking assumptions, before formal analysis and modelling. It often involves summary statistics and graphical visualisations.
Financial institution	FI	An organisation relating to the service of financial products or advice, including authorised deposit-taking institutions (or banks), insurance companies and superannuation entities.
Financial services	FS	The sector of industries relating to FIs (i.e., banking, insurance and superannuation).
Incident data		Records of event-level incidents (also referred to as loss or risk events) that occurred during core day-to-day operations in an organisation, including information about their timing, type and consequences.
Operational data		The raw data generated and collected from day-to-day business activities and processes in an organisation.
Operational risk		"The risk of loss resulting from inadequate or failed internal processes, people and systems or from external events" (Basel Committee on Banking Supervision, 2006, p. 144), also referred to as non-financial risk. They include but are not limited to legal, regulatory, compliance, conduct, technology, data, reputational and change management risks (APRA, 2022).
Operational risk management	ORM	A continual recurring process involving identification, assessment, mitigation, monitoring, communication and reporting of operational risks to avoid the occurrence of incidents or near-misses (Chapelle, 2018).
Risk and control self-assessments	RCSA	The principal operational risk assessment tool for FIs to evaluate the likelihood and impact of operational risks, as well as assess control effectiveness (Chapelle, 2018).

(*continued on next page*)

(*continued*)

Term	Abbreviation (if used)	Definition
Risk matrix		A two-dimensional matrix (typically 4–6 square) used to rank the likelihood of risks occurring on one axis and the severity of their consequences on the other, leading to an overall risk rating at their intersection.

Funding

This work was supported by KPMG Australia and an Australian Government Research Training Program Scholarship.

CRediT authorship contribution statement

Nikki Cornwell: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Visualization, Funding acquisition. **Christopher Bilson:** Conceptualization, Supervision, Validation, Writing – review & editing. **Adrian Gepp:** Conceptualization, Supervision, Validation, Writing – review & editing, Funding acquisition. **Steven Stern:** Conceptualization, Supervision, Validation, Writing – review & editing. **Bruce J. Vanstone:** Conceptualization, Supervision, Validation, Writing – review & editing.

Acknowledgements

Thank you to the Australian insurance company who provided data for this study.

The authors would also like to make a special acknowledgement of the PBFJ Editorial Board for their commitment to promoting responsible science and thank them for the opportunity to publish via the innovative "pre-registration" pathway. Our thanks extend to the anonymous reviewers for their thoughtful feedback throughout each phase of the process. It was valuable to approach the research and publication process in this structured way with interim input from peer-reviewers.

Appendix A. Variables

A.1. Operational factor variables

The following table details the 31 operational factors in the data provided by the Australian insurance company. The rows highlighted in blue indicate those variables selected for inclusion in the BN models (corresponding to the 'Selected' column).

Variable	**Description**	**Category of Information**	**Class (# categories)**	**Selected**	**Discretised (# categories)**	**Scaled (# categories)**
Date	Date of advisor call audited and incident relates to (if an incident occurred)	Time	Date			
Period	Year and month of call audited and incident relates to (if an incident occurred)	Time	Factor (30)	✓	NA	×
CallType	Type of insurance business call relates to	Technical System	Factor (16)	✓	NA	✓ (4)
Country	Country of location of advisor	Organisational Structure	Factor (3)	✓	NA	×
Workplace	Workplace from where advisor working at time of call (e.g., head office, home)	Organisational Structure	Factor (4)			
Department	Department of advisor in the company	Organisational Structure	Factor (4)	✓	NA	✓ (3)
Group	Group of advisor in the company	Organisational Structure	Factor (25)	✓	NA	✓ (12)
Team	Team of advisor in the company	Organisational Structure	Factor (59)			
HeadDepartment	Reference code of head of department of advisor	Organisational Structure	Factor (34)			
Manager	Reference code of manager of advisor	Organisational Structure	Factor (66)			
TeamManager	Reference code of team manager of advisor	Organisational Structure	Factor (109)			
Role_level	Level of advisor (e.g., team member, team manager, manager, executive)	Organisational Structure	Factor (3)			
Role_duties	Role of advisor	Organisational Structure	Factor (19)			
Employment_start	Advisor's start date of employment	Social/People	Date			
Employment_end	Advisor's end date of employment (if applicable)	Social/People	Date			
Tenure	Tenure of advisor with the company	Social/People	Factor (12)	✓	NA	✓ (8)
RemunerationType	Remuneration structure of advisor	Organisational Structure	Factor (6)	✓	NA	✓ (2)
AnnualLeave_used	Days of annual leave advisor has used throughout employment with company	Social/People	Numeric			
AnnualLeave_remain	Days of annual leave advisor has accumulated throughout employment with company and available to be used	Social/People	Numeric			

Variable	Description	Category of Information	Class (# categories)	Selected	Discretised (# categories)	Scaled (# categories)
SickLeave_used	Days of sick leave advisor has used throughout employment with company	Social/People	Numeric			
SickLeave_remain	Days of sick leave advisor has accumulated throughout employment with company and available to be used	Social/People	Numeric			
StudyLeave_used	Days of study leave advisor has used throughout employment with company	Social/People	Numeric			
StudyLeave_remain	Days of study leave advisor has accumulated throughout employment with company and available to be used	Social/People	Numeric			
LieuLeave_remain	Days in-lieu advisor has accumulated throughout employment with company and available to be used	Social/People	Numeric			
PublicHolidays_remain	Days of leave advisor has accumulated associated with working public holidays throughout employment with company and available to be used	Social/People	Numeric			
Recruitment	Method of recruitment of advisor (e.g., interview, assessment centre)	Technical System	Factor (3)			
Experience_callcentre	Indicator of if advisor has had previous experience working in a call centre	Social/People	Factor (2)	✓	NA	×
Experience_insurance	Indicator of if advisor has had previous experience working in insurance	Social/People	Factor (2)	✓	NA	×
Education	Highest level of education of advisor	Social/People	Factor (10)	✓	NA	✓ (4)
Firstaid	Indicator of if advisor has accredited first aid training	Social/People	Factor (2)			
Gender	Gender of advisor	Social/People	Factor (2)	✓	NA	×

A.2. Generated variables

The following table details the additional 4 variables that were generated from the data provided by the Australian insurance company. The rows highlighted in blue indicate those variables selected for inclusion in the BN models (corresponding to the 'Selected' column).

Variable	Description	Category of Information	Class (# categories)	Selected	Discretised (# categories)	Scaled (# categories)
Cooccurrence	Number of incident types that co-occur in a single call	Risk/Loss/Incident	Integer	✓	✓ (4)	×
Recurrence_number	Total number of previous incidents for advisor	Risk/Loss/Incident	Integer	✓	✓ (7)	×
Recurrence_time	Time (months) since previous incident for the given advisor	Risk/Loss/Incident	Integer	✓	✓ (7)	×
Recurrence_type	Indicator of if the advisor's previous incidents are most frequently of the same or different type to the current incident	Risk/Loss/Incident	Factor (3)	✓	NA	×

A.3. Bayesian Network Model Parent-Child Node Structures

The following table compares the parent-child relationships across the six BN models fit. The contents of the table are the parent nodes for each respective child node in the header row. '-' indicate incident variables not modelled in the BN, whereas blank cells indicate there are no parent nodes to the variable (i.e., root nodes).

	Incidents			Operational Factors														
	IPI	FTFLRo	FTFLRcr	Period	CallType	Country	Department	Group	Tenure	RemunerationType	Experience_callcentre	Experience_insurance	Education	Gender	Cooccurrence	Recurrence_number	Recurrence_time	Recurrence_type
BN1	Cooccurrence	-	-	Recurrence_number	Group	Department, Education		Department, Country	Country, Experience_callcentre, Recurrence_number	Country, CallType, Education	Group, Remuneration Type, Gender, Education	Group, Remuneration Type, Gender, Experience_callcentre	Department	Department, Remuneration Type, Education, Recurrence_number	Department	Country, Remuneration Type, Education	Tenure, Recurrence_type	Experience_insurance, Recurrence_number
BN2	-	Cooccurrence	-	Recurrence_number	Group	Department, Education		Department, Country	Country, Experience_callcentre, Recurrence_number	Country, CallType, Education	Department, Country, Remuneration Type, Gender, Education	Group, Remuneration Type, Gender, Experience_callcentre	Department	Department, Remuneration Type, Education, Recurrence_number	Department	Country, Remuneration Type, Education	Tenure, Recurrence_type	Recurrence_number
BN3	-	-	Cooccurrence	Recurrence_number		Department, Education		Department, Country, CallType	Country, Experience_callcentre, Recurrence_number	Country, CallType, Education	Department, Country, Remuneration Type, Gender, Education	Group, Remuneration Type, Gender, Experience_callcentre	Department	Department, Remuneration Type, Education, Recurrence_number	Department	Country, Remuneration Type, Education	Tenure, Recurrence_type	Recurrence_number
BN4	FTFLRo, Cooccurrence	Cooccurrence	FTFLRo, Cooccurrence	Recurrence_number	Group	Group	Group	Education	Group, Gender	Country, CallType	Group, Remuneration Type, Gender, Education	Department, Country, Gender, Education, Experience_callcentre		Group, Remuneration Type, Education	Department	Country, Tenure	Recurrence_type	Experience_callcentre, Recurrence_number
BN5*	FTFLRo, Cooccurrence	Cooccurrence	-	Recurrence_type		Group	CallType, Remuneration Type	Department, CallType	CallType	CallType, Gender	Department, Country, Gender, Education, Experience_insurance	Group, Remuneration Type, Gender	Country, Remuneration Type, Gender, Experience_insurance	Tenure	Department	Country, Recurrence_type	Tenure, Recurrence_type	Tenure
BN6*	-	Cooccurrence	FTFLRo, Cooccurrence	Recurrence_type		Group	CallType, Remuneration Type	Department, CallType	CallType	CallType, Gender	Department, Country, Remuneration Type, Gender	Group, Remuneration Type, Gender, Experience_callcentre	Country, Remuneration Type, Gender, Experience_callcentre, Experience_insurance	Tenure	Department	Country, Recurrence_type	Recurrence_type	Tenure

* "Unregistered" models fit for supplementary exploratory analysis in the evaluation of H2.

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