Supporting Complaints Investigation for Nursing and Midwifery Regulatory Agencies

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Abstract

Health professional regulators aim to protect the health and well-being of patients and the public by setting standards for scrutinising and overseeing the training and conduct of health and care professionals. A major task of such regulators is the investigation of complaints against practitioners. However, processing a complaint often lasts several months and is particularly costly. Hence, we worked with international regulators from different countries (the UK, US and Australia), to develop the first decision support tool that aims to help such regulators process complaints more efficiently. Our system uses state-of-the-art machine learning and natural language processing techniques to process complaints and predict their risk level. Our tool also provides additional useful information including explanations, to help the regulatory staff interpret the prediction results, and similar past cases as well as non-compliance to regulations, to support the decision making.

1 Introduction

Nurses and midwives play important roles in the healthcare system as they provide highly skilled and often complex care in both hospitals and communities. To protect and prioritise the safety of the public from harmful practices, most countries have specific health professional regulators to set rules, monitor and shape the practice of nurses and midwives. When concerns over a nurse or midwife’s practice are raised, a formal complaint can be submitted to the regulator, and investigations will be performed to decide further actions (e.g., warnings to the nurse/midwife in question, or even suspension of their practice). As the investigation results have significant impact on the practitioners’ career and reputation, processing complaints is highly time-consuming and costly (see (NMC, 2020), p49), hence, the need for effective tools to support investigations is crucial.

In this paper, we present a decision support system to improve the efficiency of complaints investigation for nursing and midwifery regulators, by employing state-of-the-art machine learning and natural language processing (NLP) techniques with a human-in-the-loop. We worked closely with the UK Nursing and Midwifery Council (NMC1), the US Texas Board of Nursing (TBON2), and the Australian Health Practitioner Regulation Agency (AH- PRA3), to understand their requirements for the system and collect data for training the machine learning models. Fig. 1 illustrates the major components and workflow of our proposed system. As new cases arrive, the system processes the corresponding complaints for each case and provides the following results: (i) Risk level prediction: each case is labelled as either high or low risk, along with a confidence score, which allows regulators to prioritise the new complaints. (ii) Explanations of the risk prediction results, by highlighting the most salient words in the complaint texts that led to the prediction. (iii) Similar previous cases, so that users can refer to relevant past cases to make decisions on the current case. (iv) Entries in the regulation code that a new complaint is most related to, that can help the regulators quickly link the allegations in the complaints to relevant requirements in the regulation code.

A major challenge in developing the system is data sparsity. Due to the sensitive nature of the healthcare data and the strict data-sharing policies of the regulators, we had access to a small amount of data (initially 1.2k complaints, later 5.7k complaints) to develop and test our system. To mitigate this problem, we use ensemble methods based

1https://www.nmc.org.uk/
2https://www.bon.texas.gov/
3https://www.ahpra.gov.au/
on both classical and neural models, including an adapted version of BERT (Devlin et al., 2019). In addition, to ensure that the predictions made by our system were gender unbiased, we pre-processed the text appropriately and experimented with several bias mitigation techniques. Experimental results show that the risk predictions made by the system achieved an accuracy of 0.71. An expert user evaluation, initially involving five regulatory staff at one regulator, suggests that the highlighted words and related regulation entries the system provides can not only help the regulators better understand how the predictions are made, but also allow them to provide better justifications for their decisions.

To the best of our knowledge, this is the first NLP system that supports complaints investigation for nursing and midwifery regulators.

2 Related Work

Decision Support Systems. Many NLP systems have been developed to process text data (such as records, reports, scientific papers, and social media posts) to assist in making highly critical decisions, in domains like healthcare (Bampa and Dalianis, 2020; Mascio et al., 2020; Feng et al., 2020; Proux et al., 2009), finance (Kogan et al., 2009; Wang et al., 2013), business and management (Dong and Wang, 2015; Assawinjaipetch et al., 2016; Filgueiras et al., 2019), and legislation (Rabelo et al., 2019; Soh et al., 2019; Shaffer and Mayhew, 2019). Our work proposes the first decision support system to process nursing/midwifery complaints.

Model Selection & Adaptation. Data sparsity is a common problem encountered by many NLP decision support systems, due to the sensitive nature of the data in certain domains and the high cost of labelling them. Hence, large neural network models do not always outperform classic feature-rich models and careful model selection is often necessary. For example, Filgueiras et al. (2019) found that, in an economic activity classification task, the SVM (Cortes and Vapnik, 1995) with TF-IDF (Salton and Buckley, 1988) representations performed better than an LSTM network (Hochreiter and Schmidhuber, 1997). On the other hand, Assawinjaipetch et al. (2016) and Mullenbach et al. (2018) showed that in complaint and clinical classification tasks, RNNs (Cho et al., 2014) or CNNs (Kim, 2014) with pre-trained word2vec embeddings (Mikolov et al., 2013) outperformed the classic machine learning models with bag-of-words representations. For each functionality in our system, we consider both classic and state-of-the-art neural network models and select the most appropriate one.

Another popular strategy to address data sparsity is to adapt large pre-trained models to an application domain. For example, BioBERT (Lee et al., 2019) and ClinicalBERT (Alsentzer et al., 2019) fine-tune BERT (Devlin et al., 2019) with biological and clinical trial data, to adapt BERT to their respective domains. Feng et al. (2020) performed sepsis and mortality prediction by deploying a hierarchical CNN-Transformer on top of BERT-based models. In our system, we fine-tune BERT with both nursing/midwifery complaints and other relevant data (e.g., MedSTS (Wang et al., 2020)) for downstream tasks (see §3).
**Explainability** is a highly desirable feature for decision support systems, especially in healthcare applications. Different types of information can be presented to users as explanations, including attention distributions (Mullenbach et al., 2018; Feng et al., 2020), similar past cases (Agirre et al., 2012; Rus et al., 2013; Cui et al., 2017; Tran et al., 2019), and salient words in the input text (Ribeiro et al., 2016; Lundberg and Lee, 2017). In the legal domain, to justify a verdict, relevant items in the law are often provided as explanations (Rabelo et al., 2020; Shaffer and Mayhew, 2019). Our method provides explanations in all the aforementioned forms except attention distributions, as it remains unclear whether attention distributions can be reliably used as explanations (Jain and Wallace, 2019; Wiegreffe and Pinter, 2019).

**Gender Debiasing** can help detect and reduce the decision support systems’ biases against certain genders (Sun et al., 2019). Popular gender debiasing methods include gender swapping (Zhao et al., 2018), gender-debiased word embeddings (Bolukbasi et al., 2016; Manzini et al., 2019), and fine-tuning (Park et al., 2018). To detect if there exists systematic biases against certain genders and reduce these biases, we test different gender debiasing methods in our system (see §5).

### 3 Our System

Initially, we used 1,241 real cases from one regulator to develop and test our system. Each case $i$ consists of multiple fields, falling into three categories: the complaint text $t_i$, in which sensitive information is replaced with its corresponding entity type, e.g., all names are replaced with [PERSON]; meta information of the case $(c_{i1}, \ldots, c_{ik})$, e.g., status of the case, and who submitted the complaint; and the investigation results, including the risk level $y_i$ of the case (high or low), and some additional assessment results $(a_{i1}, \ldots, a_{im})$. Preliminary results show that, compared to single-task learning (i.e., training the CNN for predicting only $y_i$), the multi-task learning setup improved the accuracy by about two percentage points. (C) **BERT-base (uncased)**, which was fine-tuned to predict the risk level. (C5) An ensemble which takes case meta information $(c_{i1}, \ldots, c_{ik})$ as input and uses three base classifiers (gradient boosting, AdaBoost, and linear SVM). Logistic regression is then used as a meta-classifier of C5.

For the main stacking model in the ensemble, we also used logistic regression, with the prediction probabilities returned by C1 – C5 as input.

### 3.2 Additional Information

Besides risk level predictions, our system outputs additional information to support the decision-making process of the regulator and help them interpret the prediction results.

| # High/low risk cases | 766/475 |
|-----------------------|---------|
| # Words in each complaint | max/min/avg: 5922/5/280 |
| # Serious harm to patient | 185 |
| # Maternity related cases | 17 |
| # Patient death | 75 |
| # Serious harm to nurse | 5 |

Table 1: Statistics of the dataset, which has 1,241 cases received in 2019-20.
Confidence Scores are provided for each risk level prediction. We used a conformal predictor (Vovk et al., 2005) to produce the confidence scores. When the train and test data are i.i.d., the conformal predictor guarantees that the produced confidence scores are valid: for example, among all predictions with confidence score 0.6, the probability of the prediction being correct is 60%. We applied the conformal predictor to our ensemble model and used 40% of complaints as the calibration set to train the conformal predictor.

Explanations. To help regulators understand why the system labels a case as high or low risk, we used LIME (Ribeiro et al., 2016) to provide explanations for each prediction. LIME is a model-agnostic explanation method and does not need additional data for training. It is well suited to our system, which uses the ensemble classifier with different base models and only has access to a limited amount of data. For each case, LIME identifies the tokens that have the largest influence on the prediction probabilities and highlights these tokens as the explanations. Fig. 2 shows an example of the LIME explanation. If the highlighted words agree with the regulator’s understanding of the key words in the text that could explain the risk prediction, then the regulator trusts the prediction results. If the regulator does not agree, then it is an indication that the prediction may not be reliable and hence the regulators need to investigate the case more carefully.

Similar Past Cases. In applications for legal decision-support, users often need to refer back to similar past cases to make decisions for new cases (see the Explainability paragraph in §2). To identify the similar past cases, we first computed the tf-idf cosine similarity scores of each of the past cases with the new case and selected the top 10 past cases with the highest similarity score. We then trained the BERT-base with 800 complaint texts (224k tokens) to create a new language model, fine-tuned the new model on two semantic similarity datasets, STSb (Cer et al., 2017) and MedSTS (Wang et al., 2020), and used the resulting model to further rank the selected past cases.

Initial results showed that the above method was very time-consuming, as, for the ranking, the fine-tuned BERT model needs to compare each sentence from the new case with each sentence from every past case. To reduce the computation time, we used summarisation models to generate a short summary for each case, so we could measure the similarity between cases by their summaries. We used an extractive summarisation model based on LSA (Ozsoy et al., 2011), which selects 1–3 representative sentences from each case to build the summary, and an abstractive summarisation model T5 (Raffel et al., 2020), which generates a few new sentences to summarise each case. We found that T5’s summaries mostly focus on information from the first few sentences in each case. This strategy works well in summarising news articles but ignores much of the useful information in complaints. The LSA-based method, on the other hand, is not biased by the position of sentences and performs better and faster than T5, and hence we used it as the summarisation model.

Non-Compliance to Regulations. To assist regulators to check if the practice of the nurse/midwife, reported in the complaint complies with the regulations or not, our system exploits pre-trained natural language inference (NLI) models to detect non-compliance. Specifically, if we denote the entries in the regulation code as \( R = \{ r_1, r_2, \cdots, r_n \} \) and a complaint as a set of sentences \( t = \{ ts_1, ts_2, \cdots, ts_m \} \), then the task is to determine, for each \( (r_i, ts_j) \) pair, \( i \in [1, n], j \in [1, m] \), if \( r_i \) contradicts \( ts_j \) or not. We used RoBERTa (Liu et al., 2019) fine-tuned on the MNLI dataset (Williams et al., 2018) as the NLI model. To reduce the computation time, we again used the LSA-based summarisation method to reduce the number of sentences in each complaint. The regulation entries \( R \) are from the latest NMC Code (NMC, 2015).

4 System Implementation

Backend. We used Flask 1.0.2, a Python based web development framework, to develop the backend of the system. We used SQLite 3.34.0 to manage the database, SQLAlchemy 1.2.6 for relational mapping, Redis 3.5.3 for internal messaging and caching, Nonconformist for conformal prediction, and WTForms 2.1 to manage forms. The system receives new complaints in real time and can make predictions either in real time or batch so as to minimise the response time.

Frontend. The frontend of our web interface is implemented with Bootstrap 4.1.3 and
Table 2: Performance (mean ± standard deviation) of the risk classifiers, averaged over 10 random splits.

| Model               | Accuracy   | Macro F1    |
|---------------------|------------|-------------|
| Majority Baseline   | 0.617 ± 0.032 | NA          |
| C1: Gradient Boost. | 0.671 ± 0.025 | 0.629 ± 0.025 |
| C2: AdaBoost        | 0.646 ± 0.028 | 0.611 ± 0.034 |
| C3: CNNMultiTask    | 0.668 ± 0.029 | 0.623 ± 0.035 |
| C4: BERT-base       | 0.680 ± 0.038 | 0.658 ± 0.028 |
| C5: Meta info       | 0.662 ± 0.029 | 0.591 ± 0.056 |
| Ensemble model      | 0.708 ± 0.036 | 0.679 ± 0.032 |

To measure to what extent a model is gender biased, two widely used metrics are false positive equality difference (FPED) and false negative equality difference (FNED) (Dixon et al., 2018). The lower the FPED (FNED, respectively) values, it means the gaps between the model’s false positive (false negative, respectively) rates in the gender-specific and overall cases are smaller, hence suggesting lower gender bias of the model. The FPED and FNED values for our ensemble-based risk prediction model are 0.189 and 0.117, respectively (first row in Table 4). Since they are not zero, it suggests that the model does have gender biases.

Throughout this paper, p-values are computed with paired t-test and the significance level is 0.05.
Figure 2: A screenshot of the result page for a fictitious complaint. The page consists of (1) the complaint text (2) the predicted risk level, probability, and confidence (3) word importance scores provided as the explanation by LIME (4) similar past cases (5) non-compliance to regulations (6) the final decision to be given by a case manager.

Table 4: Performance of different gender debias methods. “O” and “D” in the leftmost column stand for original and gender-debiased embeddings, respectively.

| Debias Setting | Accuracy | Macro F1 | FPED | FNED |
|----------------|----------|----------|------|------|
| O unchanged    | 0.718    | 0.688    | 0.189| 0.117|
| remove         | 0.700    | 0.666    | 0.167| 0.105|
| neutralise     | 0.709    | 0.677    | 0.129| 0.085|
| swap           | 0.713    | 0.682    | 0.154| 0.080|
| D unchanged    | 0.705    | 0.674    | 0.186| 0.117|
| remove         | 0.699    | 0.664    | 0.191| 0.082|
| neutralise     | 0.707    | 0.675    | 0.190| 0.101|
| swap           | 0.708    | 0.676    | 0.186| 0.117|

rather than guiding the AI to act fairly (Caliskan et al., 2017). Hence, in real deployment, our system will only perform gender swapping and use the resulting data to train the ensemble model.

Human Evaluation. We invited five regulatory staff from NMC to use and evaluate our system. Each case manager was provided with four complaints randomly sampled from our test set. They were asked to use our system to assist them in their investigation of the complaint. A questionnaire was provided to them after the test was completed, requesting their ratings (5-point Likert scores) and comments on different aspects of the system.

All participants found the usability and responsiveness of the system highly satisfactory, with average scores at 4.4 and 4.2, respectively. With respect to the quality of the risk predictions, explanations (i.e., the highlighted words), and the identified relevant regulations, participants provided moderate ratings at 2.8 for each of them. However, lower ratings (1.8) were given on the similar cases found by the system: for example, a complaint mentions that the nurse has a strong odour of alcohol on her breath and the experts want the system to find other cases about nurses who are inebriated or unfit to practice, but the system found cases with words like alcohol or odour, even though the words were used in very different contexts (e.g., used alcohol as disinfectant). We believe this is a highly challenging task as it requires not only domain knowledge but also common sense knowledge to capture the nuances in the complaints. We leave further investigation of this problem to future work.

As for the explanations (i.e., words highlighted by LIME), the participants reported that the highlighted words in the high-risk cases were often sensible and useful, while the words highlighted in the low-risk cases were sometimes stopwords and hence difficult to interpret. We believe the reason for this is that our models rely on the appearance of certain keywords (e.g., injured, died) to identify the high-risk cases, which are absent in the low-risk cases and hence the model picks up some spurious words to make the predictions. We note that, while highlighting the stopwords makes it difficult for the regulatory experts to interpret the explanations, it helps the system designers and machine learning experts better understand the problems with the system and hence allows them to improve the system accordingly. In the next version, we plan to hide stopwords highlighted by LIME from the regulatory experts to avoid confusion, but we will show them to system designers in order to help them improve the model.
6 Conclusion

In this work, we have presented the first system to support complaints investigation for nursing and midwifery regulators. The system exploits state-of-the-art text classification, summarisation, semantic similarity measurement and NLI techniques, and provides different types of information to assist the regulators, including risk level assessment, similar past cases, and non-compliance to regulations. In addition, explanations (in the form of highlighted words) are provided to improve the transparency of the system, and gender debiasing operations are performed to reduce systemic gender biases. Feedback received from domain experts confirmed the system’s usefulness and potential.

We will continue our collaboration with the nursing and midwifery regulatory bodies and collect more labelled data, e.g., relevant case pairs and non-compliance to regulations; this data will help us develop domain-specific sentence similarity measurement and NLI models to further improve the performance of the system. We are considering extending the system with additional functionalities, for example, applying active learning (Klie et al., 2018) to allow the system learn more efficiently from human feedback and thus be constantly updated online. We also plan to perform additional experiments in control groups with domain experts to test the effectiveness of the system, e.g., by comparing the average time consumed to process a case with and without the use of our system.

Regulatory bodies in different jurisdictions face similar problems (e.g., long processing time, high cost, and an increase in the number of cases to investigate) and have similar requirements on the functionalities of the system (risk prediction, similar past cases, non-compliance to regulations). Hence, we hope this work will inspire more AI/NLP-based decision support systems across different jurisdictions, and encourage more collaborations between the NLP researchers and regulatory bodies in the legal, financial and healthcare sectors.

Acknowledgements

We thank our colleagues from the UK Nursing and Midwifery Council (NMC), the US Texas Board of Nursing (TBON), and the Australian Health Practitioner Regulation Agency (AHPRA), for their feedback to the development of the prototype. We also thank Francesco Fildani and Narinderpal Sehra from the CIM IT helpdesk at Royal Holloway, University of London, who helped us deploy the demonstration system. This project was funded by the US National Council of State Boards of Nursing (NCSBN).

Ethical Impact Statements

As our system processed highly sensitive data and its recommendations can have an impact on the person under investigation, we describe the system’s potential ethical impact in different aspects below. Data Collection. All data were collected, redacted and distributed by professionals from the regulatory agencies, strictly following all the related regulations in their respective countries. Institutional Review. This project has been reviewed and approved by each participating institution, in line with their ethical approval process. Expected Beneficiaries. The direct beneficiaries are the regulatory agencies, as the system improves the efficiency of their investigation and reduces the cost. The nursing/midwifery community and the patients will also benefit, as the waiting times will be reduced. Moreover, it will reduce costs which are often passed on to registrants via registration fees. Failure Modes. Our system provides confidence scores and highlighted words to help users make sense of the predictions. Hence, even in the “failure cases” where the system provides imprecise predictions, the users can quickly identify the problems and reject the predictions (see §3). In terms of data security, our system does not edit or modify the original texts, and all texts have backup copies in secure servers; hence, the risk of data contamination or loss is minimised. Biases. We inspected different types of potential biases and employed multiple techniques to minimise biases, as discussed in §5. Misuse Potential. The system will be used by well-trained users from the regulatory bodies strictly inside their organisations, following all guidelines and requirements of the agencies. Hence, we believe that the potential for misuse is very low. Potential Harm to Vulnerable Populations. Our system learns from past decisions to make new predictions. A potential risk is that, if the human decisions on the past cases have strong biases or systematic mistakes, the system may exploit those biases in its decision making. We believe the explanations produced by our system can be used to identify such systemic biases and mistakes. If users find
that certain gender-related words are highlighted, it suggests that the model heavily relies on those words to make predictions, and the regulatory staff can perform further investigations accordingly.

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Appendix

Hyperparameters Selection

Hyperparameters of our models are selected using grid search on 250 randomly sampled cases; results are presented below. For the CNN model (base model C3 in the ensemble), we use three filter sizes (2,3 and 4) and 15 filters for each size. For the
multi-task training (base model C3), the loss function we use is $L_y + 2L_A$, where $L_y$ and $L_A$ are the cross-entropy losses for predicting the risk level and additional assessment results, respectively. To fine-tune BERT (base model C4), we use Adam as the optimiser with fixed learning rate 2e-5, batch size 8 and perform the training for 10 epochs.

**Data Fields**

Fields in the dataset are summarised in Table 5.

| Category          | Data Fields                                                                 |
|-------------------|-----------------------------------------------------------------------------|
| Meta Information  | CreateDate (when the case was created), CurrentStatus (closed, in investigation, or await adjudication hearing), Referrer (who submitted the complaint) |
| Assessment Results| RiskLevel (high or low), RiskOfRepetition (True or False), SeriousHarmToRegistrant (True or False), SeriousHarmToPatient (True or False), BreachOfOngoingRegulatoryIntervention (True or False), MaternityRelated (True or False), PatientDeath (True or False), InvestigationResults (free text) |

Table 5: Fields in the complaints dataset.