PACE in Scotland: Utilising machine learning to assess the importance of patient and clinician engagement in HTAs in SMC.

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01. Introduction

The Scottish Medicines Consortium (SMC) assesses new medicines for the National Health Service (NHS) in Scotland, using Health Technology Assessments (HTAs). As part of the HTA process, Detailed Advice Documents (DADs) are published on the SMC website.

As part of the decision-making process for some medicines for end of life and/or rare or ultra-rare conditions, a Patient and Clinician Engagement (PACE) meeting can be convened. This allows patient groups and clinicians an additional opportunity to input into decision making.

For medicines used to treat end of life and/or rare conditions, the SMC offers the submitting company the opportunity to request a PACE meeting, if the draft advice for the medicine is 'not recommended' following evaluation by the New Drugs Committee (NDC).

For ultra-orphan medicines, a PACE meeting is not convened during the initial assessment. If the advice from the NDC is 'not recommended' the pharmaceutical company can choose to request that SMC convenes a PACE meeting.

The key objectives of this research are:

1. Assess the frequency of PACE meetings over the last decade.
2. Build predictive algorithms, using machine learning, that predict HTA outcome (i.e., SMC decision) using the text in DADs.
3. Assess which algorithm yields the best performance.
4. Assess the consideration given to PACE outputs in SMC decision making (i.e., feature importance).
5. Discuss possible methods for future improvements in the predictive algorithms.

02. Machine Learning Process

The key elements of the algorithm building process are outlined in Figure 1, below.

Figure 1: Overview of steps for model algorithms

Data cleaning
- Machine learning problems are highly sensitive to data which is not "clean". (1)
- Necessary step to avoid inaccurate analytics. (1)
- Includes removing duplication, attribute, and relevant errors. (1)

Text pre-processing
- Text mining: seeking or extracting the relevant information from textual data. (2)
- Allows discovery of knowledge from unstructured texts. (2)
- Includes "stop words" removal, stemming or lemmatisation, and Term Frequency-Inverse Document Frequency (TF-IDF). (2)

Train predictive models
- Split data into training and test groups.
- Training data is fed to learning algorithms to train the model (3)
- Test data is used to make predictions. (3)
- Model prediction accuracy accounts for number of wrong predictions on the test dataset (3)

Tune predictive models (oversampling)
- Data imbalances can be encountered when the distribution of classes or labels in a dataset is not uniform. (4)
- This can be solved using resampling methods (oversampling or undersampling). (4)
- Oversampling is performed by increasing the amount of minority class instances. (4)
- This analysis uses Random Over Sampling – where data from minority classes are randomly replicated and added to the original dataset. (5)

03. Predictive Algorithms

Three algorithms were created for analysis, the details of each algorithm is presented in Figure 2.

Figure 2: Predictive algorithms

Gaussian Naïve Bayes (GNB)
- Naïve Bayes – technique of using algorithms based on Naïve Bayes theorem. (6)
- GNB assumes features of a dataset follow a normal distribution. (6)

Random Forest Classifier (RFC)
- RFC uses a simple random sampling of features. (7)
- RFC are generally considered more robust than a single tree model. (7)

Logistic Regression (LR)
- Supervised machine learning algorithm used for classification purposes. (8)

04. Methods

The sample consists of DADs (n=742) from the SMC website between 2015 – 2025. These were collated in Microsoft Excel® for descriptive analysis. A subsample of DADs for full submissions (n=250) from 2021 to 2025 were collated in Python® for machine learning. The text was extracted, a text matrix was produced, and three model algorithms were created to assess the feature importance of PACE in SMC decision making. The process for preparing the data from each jurisdiction is outlined in Figure 3.

Figure 3: Overview of research methods.

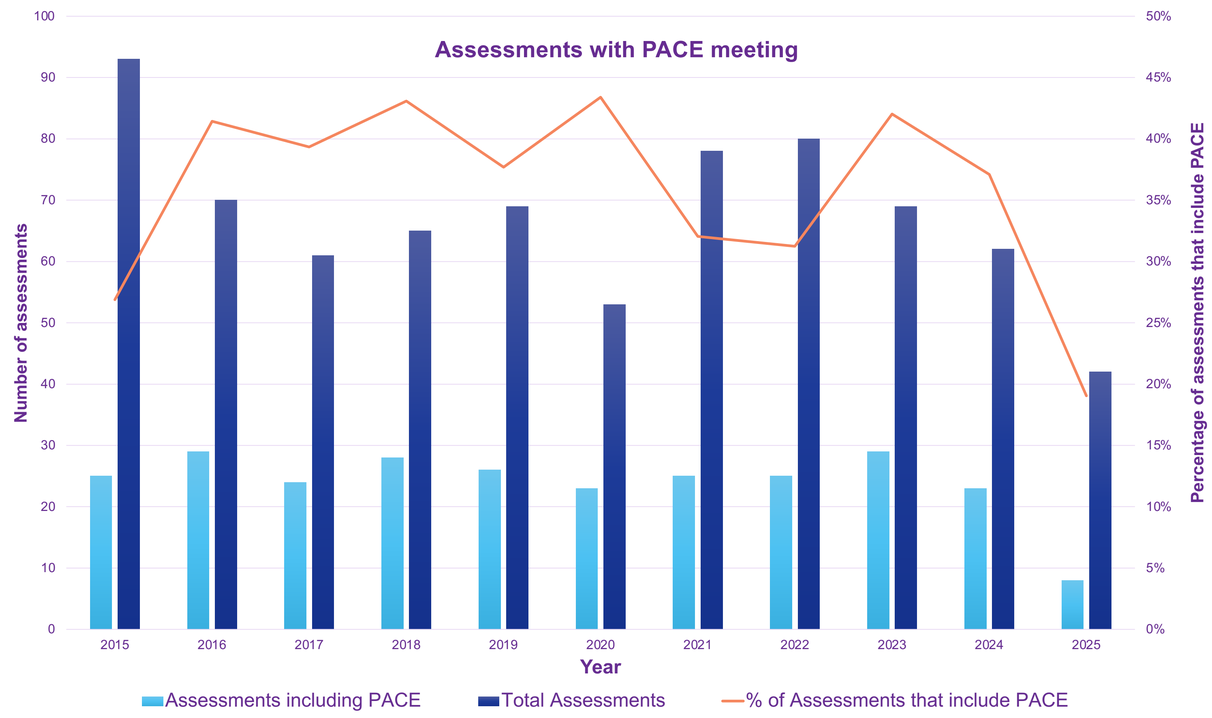
Collate data and perform descriptive analysis → **Extract text from subsample for machine learning** → **Data cleaning and text pre-processing** → **Train predictive models** → **Assess the feature importance of PACE**

05. Results

Frequency of PACE meetings

Between 2015-2025, PACE meetings were convened for 35.71% of SMC decisions (excluding withdrawn submissions and discontinued medicines). The proportion of PACE meetings peaked in 2020 with 43.40% of assessments including a PACE meeting. In the subsample (2021-2025), PACE was mentioned an average of 7.2 times per DAD.

Figure 4: Frequency of PACE meetings



Predictive model accuracy

Using the 2021-2025 subsample, the accuracy, precision, and recall for all algorithms (GNB, RFC, and LR) are shown in Table 1.

Table 1: Model accuracy

	GNB	RFC	LR
Accuracy	0.676	0.705	0.705
Precision	0.93	1.00	1.00
Recall	0.68	0.71	0.71

Table 2: Feature importance

Top 20 Feature Importance	
1	Survival data
2	Age years
3	Disease pd death
4	Disease pd
5	Treatment adult patients
6	Products national local
7	Price PAS
8	Disease management
9	Table results
10	Median age years
11	Statistically significant improvement
12	Accepts medicine use
13	Statistically significant
14	Response evaluation criteria
15	Values based
16	Accepted restricted
17	Case considering available
18	Performed patients
19	Guidelines management
20	Response evaluation

Feature importance of PACE

The RFC algorithm was utilised to assess the feature importance of PACE in SMC decision making, using the 2021-2025 subsample. Table 2 details the Top 20 most important features regarding SMC decision making when a PACE meeting is convened.

The most important features included survival data, price and Patient Access Schemes (PAS), and statistically significant improvements.

In the analysis, PACE was the 126th most important feature out of 333 total features when predicting HTA outcome from SMC.

06. Conclusions

The descriptive analysis shows that SMC consistently convene and consider PACE insights in HTA decision making.

The number of assessments which included PACE meetings has been relatively steady over the last decade. Assessments for 2025 are still ongoing.

Machine learning analysis signals that while the insights from PACE meetings may influence HTA outcomes in Scotland, they are not a primary driver of HTA outcome. However, it is important to recognise the limitations given the current sample size and model development.

Based on the current analysis, stronger considerations for SMC decision making may include, survival data from clinical trials, the price of a medicine, as well as PAS offerings, and improvement in condition or disease management.

Further research is required to continue to improve the predictive algorithms and gather more valuable insights on the consideration given to PACE meetings within SMC decision making. These include, but are not limited to:

Increasing Sample Size
To improve model training, evaluation, and performance.

Adjusting the N-gram count (number of words considered in a singular phrase)
Algorithms can consider longer word sequences when assessing feature importance

Adjusting training and test split
To prevent overfitting and accurately evaluate the algorithm's generalisation ability on unseen data.

References

References for this poster can be found by scanning the QR code below:

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