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# EMPLOYEE PERFORMANCE PREDICTION MODELS USING MACHINE LEARNING IN BANKING AND ITES

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## ABSTRACT

Predicting employee performance is one area where machine learning can play a significant role in HR. Of course, this will only be possible if there are defensible metrics, sufficient past records and suitable transferability of findings between firms. In this article, we set out a general approach to this problem, focusing on the Banking and ITES sectors. After reviewing the relevant literature, we outline a prospective study drawing on employee capability, historic performance, job attributes and firm-level variables. We discuss a range of ML approaches, including regularized models, tree-based methods and ensemble learning. Shared and distinctive features of the two industries are identified; e.g. error rate, quality of customer contact in Banking and QAP, SLA attainment in ITES. We describe key steps to avoid look-ahead bias, test transportability over time, explain model outputs and understand where the model fails. Through formulae and illustrative cases, we explain the metrics to assess performance, make class predictions and identify variable importance. Finally, we argue that a suite of criteria beyond just the predictive power of a given model is required, and distinguish performance forecasting from the identification of causal drivers of improved employee performance. Overall, our aim is to provide a starting point for the use of ML in a context that allows for continued employee growth, but preserves the role of line managers. Further testing on real-world datasets is required before any robust statements can be made regarding which models or variables predict best.

**Keywords:** Employee performance prediction; machine learning; banking; ITES; workforce analytics; random forest; gradient boosting; explainable artificial intelligence; human resource management.

## 1. INTRODUCTION

As discussed earlier, employee performance will have implications for service, process, customer and competitive standing. For employees working in Banking and ITES, performance will also determine the outputs from the technology-enabled processes that they contribute to.

There will of course be some differences between Banking and ITES on the basis of what is expected from each role. Banking positions could include but are not limited to: transacting, servicing customers, evaluating credit risk and performing key control functions. ITES positions could include but are not limited to: servicing customers, BPO, transacting, providing IT support etc. Any model developed for one industry may therefore have limited applicability to the other.

Conventional approaches typically rely on a mix of target achievement and rater judgement. While this will generate an organization's "internal" view of its workforce, such measures can suffer from variability, lag and differences between raters. By applying machine-learning, we can seek to establish associations between past attributes and actions of employees and future measures of interest.


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That said, if the starting point for measuring 'performance' is flawed, then no matter how precise our algorithm, the resulting system will continue to incentivize undesirable behavior or perpetuate prior judgements. An alternative concern is whether a model trained to predict existing performance metrics, based on data produced by those metrics, has any true predictive power.

**Marler and Boudreau (2017**) argue that HR Analytics should be seen as a rigorous and trustworthy form of management practice. This provides justification to explore the link between data-driven activities and useful, validated HR decision-making.

Here, we propose a general approach to estimating future employee performance, using only pre-existing data. Key considerations include defining appropriate performance indicators for Banking and ITES, rigorously testing the models and ensuring that they yield transparent results suitable for informing improvement efforts.

## 2. REVIEW OF LITERATURE

### 2.1 Human resource analytics and evidence-based management

HR analytics enables organizations to apply workforce data to specific business questions. It requires identifying a suitable question, defining robust metrics, and implementing corresponding actions based on the results.

**Marler and Boudreau (2017)** consider the current literature on the use of analytics in the workplace, cautioning against the notion that more advanced methods will invariably lead to better practice. In the context of predicting staff quality, one might ask whether a model offers any benefit over current processes or even back-testing against past periods alone.

### 2.2 Algorithmic approaches to human resource management

**Cheng and Hackett (2020)** collate the existing literature on algorithmic techniques within HRM, noting the disparity between the growth in commercial uptake and the slower progression of scholarly investigation. This allows some reflection on the implications of embedding algorithms into people management.

Here again, we should consider what a given predictive target tells us about the nature of the job in question, and whether it reflects managers' implicit views of good performance. Alongside assessing the predictive power of any technique, its applicability to particular problems of interest needs consideration.

### 2.3 Random forests

Random forests comprise multiple decision trees, each constructed with some degree of randomness. By combining the outputs from all trees, they provide a means to learn potentially non-linear patterns.

They could therefore be applied to study the interplay of factors such as length of service, current demand, prior learning and past staff quality. As always, however, this must be established using real-world datasets.

### 2.4 Gradient boosting

**XGBoost was proposed by Chen and Guestrin (2016**), representing a high-performance implementation of gradient boosted decision trees. The algorithm iteratively updates a model to optimize a target, while penalizing excessive model 'complexity'.


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Gradient boosting is thus one of several potential options for working with tabular data on the workforce. We expect to benchmark it against alternative baselines, using a common set of tests. Again, there is no expectation of it being optimal in every case.

### 2.5 Explainable prediction

**SHAP (Lundberg and Lee, 2017**) produces a measure of the influence of each input variable on a predicted value. This can be used to characterize how a model's estimate compares to a baseline.

With respect to our workforce dataset, we would expect to see which variables drive the predicted level of quality (e.g. historic values, time in position, etc.). Of course, a model's dependence on a particular attribute does not imply that varying it would have a causal effect on the outcome of interest.

### 2.6 Trustworthiness and model governance

A number of properties are recommended in the NIST AI RMF for AI systems. These include: being valid, dependable, interpretable, transparent, and minimizing risks from unfairness. When considering models of workforce performance, we will seek to ensure that the ground truth is fit-for-purpose, disclose known shortcomings, probe the sources of incorrect estimates, and maintain the possibility of human oversight.

### 2.7 Literature synthesis

**Table 1: Literature foundation and research implications**

| Literature | Contribution | Implication for the proposed study |
|---|---|---|
| Marler and Boudreau (2017) | Evidence-based HR analytics | Demonstrate decision value beyond technical sophistication |
| Cheng and Hackett (2021) | Critical examination of HR algorithms | Assess targets, organizational context, and managerial use |
| Breiman (2001) | Random forest methodology | Test nonlinear and interaction relationships |
| Chen and Guestrin (2016) | Scalable gradient boosting | Compare regularized boosting with transparent baselines |
| Lundberg and Lee (2017) | Feature attribution through SHAP | Interpret predictions without making causal claims |
| NIST (2023) | AI risk management | Evaluate reliability, fairness, and accountability |

***Source:*** *Author's synthesis of the cited literature.*

## 3. RESEARCH GAP

A number of papers set out suitable methodologies to forecast employee behavior. However, if a study were to seek to compare banking and ITES employees, further considerations would be required:

Employees will vary across different measures of their output (e.g. sales volume, transaction throughput, customer satisfaction, error rate etc.), so an aggregation of these is unlikely to be appropriate.


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There will also be heterogeneity within each industry. It may not be fruitful to compare e.g. bank Relationship Managers against Bank Operations staff.

Studies that pool multiple observations per individual, randomly allocated between train and test sets, or incorporate future knowledge, risk presenting inflated employee performance.

Models should also be benchmarked against other plausible solutions. If no greater accuracy than the prior period can be achieved, the usefulness of any proposed solution will be reduced.

And of course, knowing the key drivers of performance does not reveal what actions might increase this.

These concerns have been considered in developing a study with multiple periods and differentiated roles.

## 4. RESEARCH OBJECTIVES AND QUESTIONS

### 4.1 Objectives

1. Develop a comparative framework for predicting employee performance in banking and ITES.
2. Identify common and sector-specific predictor categories.
3. Compare transparent statistical models with tree-based machine learning methods.
4. Establish procedures for temporal validation and leakage prevention.
5. Explain how predictions, errors, and feature contributions should be interpreted.
6. Assess the conditions under which predictions can support employee development.

### 4.2 Research questions

1. Do machine learning models improve next-period performance prediction over simple historical baselines?
2. Does predictive performance differ between banking and ITES?
3. Do sector-specific models outperform pooled models?
4. Which predictor groups provide stable incremental predictive information?
5. How do model errors vary across roles, organizations, and employee groups?

### 4.3 Testable propositions

- **P1:** Validated competency and work-context variables improve prediction beyond previous performance alone.
- **P2:** Nonlinear models provide incremental predictive value where meaningful interactions exist.
- **P3:** Sector-specific features improve prediction within their corresponding sector.
- **P4:** Model performance varies across organizations, roles, and prediction periods.

These propositions require empirical testing.


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## 5. RESEARCH METHODOLOGY

### 5.1 Research design

The paper combines a structured narrative review with a proposed comparative longitudinal modeling study.

### 5.2 Population and sampling

The proposed population comprises employees in participating banking and ITES organizations.

1. A multistage sampling approach would:
2. Select organizations with suitable historical records.
3. Identify comparable job families within each sector.
4. Include eligible employees across locations, experience levels, and teams.
5. Link repeated observations using pseudonymous identifiers.

Several organizations per sector would improve the ability to distinguish sector patterns from the practices of a single employer. Sample adequacy should be assessed through learning curves, outcome frequencies, organizational clustering, and subgroup coverage.

### 5.3 Unit of analysis and prediction horizon

The primary unit is the employee-quarter.

Predictors are calculated using information available by the end of quarter $t$. The target is performance during quarter $t$+1:

$$\hat{Y}_{i,t+1} = f\left(\boldsymbol{X}_{i\underline{\leq}t}\right)$$

This temporal definition separates forecasting from reproducing an appraisal already completed.

### 5.4 Data sources

**Table 2: Proposed data sources**

| Source | Candidate information | Main measurement issue |
|---|---|---|
| HR information system | Role, tenure, experience, organizational assignment | Record consistency |
| Learning system | Assessment scores, training completion | Completion does not establish learning |
| Operational systems | Workload, errors, processing outcomes | Case complexity and system conditions |
| Quality assurance | Audited service or transaction quality | Sampling and rater consistency |
| Performance records | Historical ratings and component scores | Managerial bias and changing standards |
| Work-context records | Staffing, queue pressure, system downtime | Context may be incompletely recorded |


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Private communications, inferred personality, and unrelated personal characteristics are not necessary to the proposed framework.

## 6. Variable Definition and Performance Measurement

### 6.1 Dependent variable

The primary target should be an independently defined next-quarter performance outcome.

Where a composite is operationally justified:

$$Y_{i,t+1} = \sum_{k=1}^{K} \omega_k \, Z_{ik,t+1}, \qquad \sum_{k=1}^{K} \omega_k = 1$$

Here, $Z_k$ denotes a consistently scaled performance component and $\omega_k$ its prespecified weight.

Weights should be established through job analysis and organizational consultation. They should not be selected merely to make the target easier to predict.

Separate component predictions should accompany any composite because strong productivity may coexist with poor quality.

### 6.2 Sector-specific performance dimensions

**Table 3: Proposed outcome dimensions**

| Dimension | Banking examples | ITES examples |
|---|---|---|
| Productivity | Completed eligible cases or transactions | Resolved cases or completed work units |
| Quality | Transaction accuracy, documentation quality | Quality assurance and rework measures |
| Service | Customer service quality | Customer satisfaction and resolution quality |
| Timeliness | Processing turnaround | Service-level compliance |
| Control adherence | Audited process adherence | Audited process and information-handling adherence |

Raw output should be interpreted alongside opportunity and case complexity. An employee handling difficult cases may produce fewer completed cases while delivering valuable performance.

### 6.3 Independent variables

**Table 4: Candidate predictor groups**

| Predictor group | Examples | Proposed interpretation |
|---|---|---|
| Historical performance | Previous quality and productivity | Persistence of observed performance |
| Competency | Validated technical and job-knowledge assessments | Task capability |
| Experience | Role tenure and relevant experience | Familiarity with work |


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| | | |
|---|---|---|
| | | requirements |
| Learning | Assessment improvement and relevant training | Development history |
| Workload | Assigned volume and complexity | Opportunity and demand |
| Organizational support | Staffing and system availability | Conditions affecting work execution |
| Role context | Job family, process type, branch or team | Differences in work requirements |

Protected characteristics, where appropriately available, can be retained separately for fairness auditing rather than automatically included as predictors. Excluding them does not by itself eliminate bias because other variables may act as proxies.

## 7. Conceptual and Analytical Framework

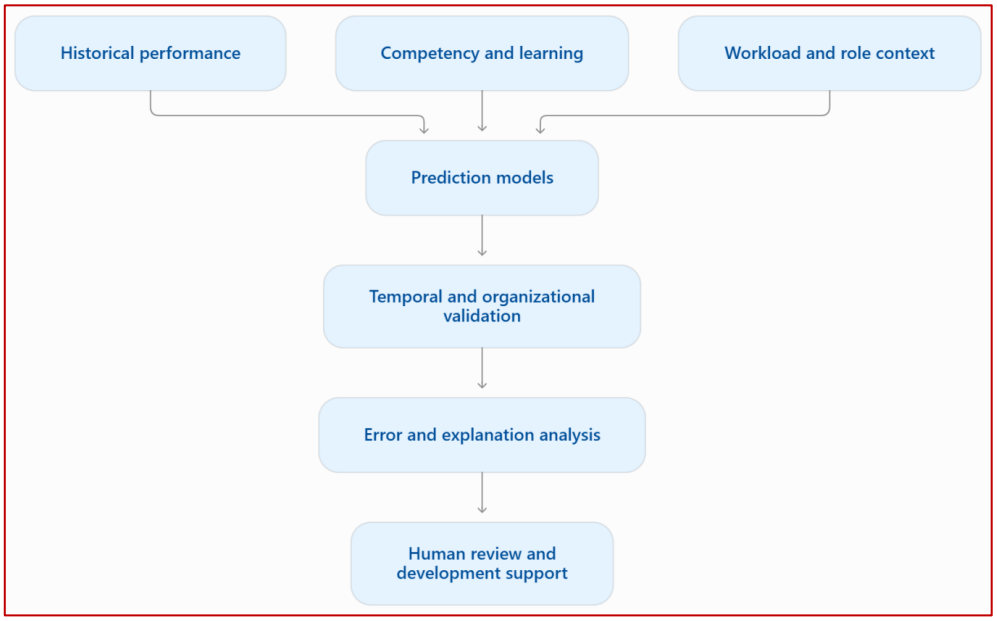



***Figure:*** *Proposed employee performance prediction framework.*

The framework distinguishes three tasks: defining a valid outcome, forecasting that outcome, and deciding whether an intervention is appropriate. Success in one task does not establish success in the others.

## 8. MACHINE LEARNING MODELS

### 8.1 Historical baselines

Two baselines should be evaluated:

$$\hat{Y}_{i,t+1} = Y_{it}$$

and a role-specific historical mean.

These establish whether a more complex model adds value beyond performance persistence and job context.

### 8.2 Regularized linear regression

For continuous performance:


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$$\hat{Y}_{i,t+1} = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ijt}$$

Elastic net estimates coefficients using:

$$\frac{min}{\beta}\left[\frac{1}{2n}\sum_{i=1}^{n}\left(Y_2 - \hat{Y}_i\right)^{2+} + \lambda\left(\alpha\|\beta\|_1 + \frac{1+\alpha}{2}\|\beta\|_2^2\right)\right]$$

This provides a transparent benchmark while controlling coefficient complexity.

### 8.3 Decision tree

A decision tree splits the data based on various cut-off values of the predictors. Non-linearities and interactions can therefore be expressed in an interpretable manner.

The number of levels and minimum number of cases per terminal node must be controlled, otherwise we risk creating a model too fitted to known staff and time periods..

### 8.4 Random forest

For regression:

$$\hat{Y}_{(x)} = \frac{1}{B}\sum_{b=1}^{B} T_b\,(x)$$

where $T_b\,(x)$ is the prediction from tree $b$.

Random forests provide a flexible candidate for mixed workforce variables. Feature importance requires careful interpretation, particularly when predictors are correlated.

### 8.5 Gradient boosting

An additive boosting model is:

$$\hat{Y}_i = \sum_{m=1}^{M} nf_m\,(X_i)$$

where $n$ controls the learning contribution of successive trees.

Important tuning parameters include learning rate, tree depth, number of trees, subsampling, and regularization.

### 8.6 Classification models

Where appropriate, the level of performance can be grouped into pre-defined bands (e.g. below, equal to or above the standard). These will need to be determined on an appropriate benchmark. Importantly, they must not be selected with the aim of achieving desirable outcomes from the model.

## 9. DATA PREPARATION AND VALIDATION

### 9.1 Preprocessing

Duplicates, units, proportion of missing values and harmonisation of variables (e.g. job titles, target) will all be part of preprocessing.

Any imputation, normalisation, binning, variable selection or sampling needs to occur inside each train fold, as doing so risks data leakage.


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### 9.2 Leakage prevention

Some examples would be:

1. Any rating completed subsequent to the relevant prediction date.
2. Bonus linked to an end-of-target-period assessment.
3. Quality measures for the target period, to forecast the associated composite.
4. Other admin data revealing the ultimate rating achieved.

Of course, lagged performance can also be an appropriate predictor if known at the prediction date.

### 9.3 Temporal validation

As with all time series, models will be fit to prior data and tested on subsequent periods via a rolling origin. For repeated measures per individual, some deployment scenario must be assumed. It is reasonable to make predictions for incumbent staff based on their past data, but we would expect a distinct result when predicting new, previously-unseen individuals.

### 9.4 Organizational generalization

If there are sufficient number of organizations, leave-one-organisation out cross-validation will assess transferability.

There are three options to consider:

1. Pooled across all sectors on shared variables only.
2. Pooled across all sectors with added sector dummies and interactions.
3. Distinct models for Banking and ITES.

The last two can only be directly compared if the targets are equivalent.

## 10. MODEL EVALUATION

### 10.1 Regression metrics

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Y_i - \hat{Y}_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}$$

$$R^2 = 1 - \frac{\sum_i (Y_i - \hat{Y}_i)^2}{\sum_i (Y_i - \bar{Y})^2}$$

MAE gives us the average of the absolute errors, while RMSE will penalize larger errors more heavily. As discussed above, out-of-sample R_2 can take negative values if the model underperforms against the appropriate mean.

### 10.2 Classification metrics

Classification results should include:

1. Macro-F1 score and mean balanced accuracy.
2. Precision and recall per class.
3. Confusion matrix.


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4. Calibration of predicted probabilities.
5. Additional PR-based metrics if needed for rare cases.

Note that an overall high accuracy may mask poor performance on some classes.

### 10.3 Fairness and stability

These should also be looked at within each sector, job family, geography, company and any other suitable breakdown of employees. In addition to subgroup MAE, one should consider whether there is consistent bias (over- or under-prediction) or inflated number of 'below standard' flags. Confidence limits will be key where sample sizes are low.

## 11. ILLUSTRATIVE ANALYSIS AND INTERPRETATION

The following calculations are hypothetical and do not represent findings from banking or ITES employees.

### 11.1 Regression example

**Table 5. Hypothetical performance predictions**

| Employee | Actual score | Predicted score | Absolute error |
|---|---|---|---|
| A | 80 | 76 | 4 |
| B | 65 | 70 | 5 |
| C | 90 | 86 | 4 |
| D | 70 | 73 | 3 |
| E | 85 | 80 | 5 |

$$MAE = \frac{4+5+4+3+5}{5} = 4.2$$

$$RMSE = \sqrt{\frac{16+25+16+9+25}{5}} \approx 4.27$$

The average absolute error is 4.2 score points. Its practical acceptability depends on score reliability and the intended decision.

If an illustrative baseline MAE were 6.0:

$$Relative\ MAE\ reduction\ = \frac{6.0-4.2}{6.0} \times 100 = 30\%$$

This represents a reduction in prediction error, not a 30% improvement in employee performance.

### 11.2 Classification interpretation

Suppose a hypothetical model flags 40 employees as potentially requiring support, and 25 subsequently fall below the agreed standard:

$$Precision = \frac{25}{40} = 62.5\%$$

If 50 employees actually fall below the standard:

$$Recall = \frac{25}{50} = 50\%$$


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The model identifies half of the relevant cases while incorrectly flagging 15 employees. This illustrates why predictions require contextual review.

### 11.3 Feature attribution

Suppose a SHAP explanation on the score scale contains:

| Contribution | Score points |
|---|---|
| Reference prediction | 74 |
| Previous quality score | +6 |
| Competency assessment | +3 |
| Workload conditions | −4 |
| Other contributions | −1 |
| **Predicted score** | **78** |

The predicted value from the model is 4 units higher than the reference. The Workload term indicates the extent to which the model relies on the observed workload data, but gives no indication of what gain could be achieved by lowering the workload by 4 units.

## 12. COMPARATIVE DISCUSSION

### 12.1 Banking

There will of course be differences in key performance metrics between the various banking functions. Transaction staff may look to transact volumes and compliance with controls; others will consider the success of their clients and the appropriateness of deals driven. Factors such as branch activity, number of cases presented and IT functionality must also feed into any assessment, given that what an individual achieves will be influenced by these. Models which fail to incorporate them risk unfairly penalizing staff.

### 12.2 ITES

ITES models need to be able to separate productivity from quality. A low handle time could be indicative of both high volume AND poor work being left unresolved. Increased volumes may result in further workload elsewhere in the process. ITES case attributes such as process, language, queuing and IT factors will all influence this. By measuring quality and productivity in isolation, these potential issues will not be masked within an aggregated KPI.

### 12.3 Model selection

A reason to adopt complexity must be based on repeatable improvements. Where regularised models and GBMs give comparable performance, we may want to deploy the former for ease of use. Non-linear approaches may be appropriate if they yield robust improvements with adequate interpretability. We will also need to reflect on prediction error, model calibration, portability within our organization and ongoing model management.

### 12.4 Prediction and intervention

However, this will not show whether further training leads to better subsequent performance. It could be that those chosen to receive the initial training are different in some respect from the rest of the population. Other forms of intervention (e.g. coaching, changing job demands, alternative training) would need to be assessed using appropriate experimentation.


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## 13. MANAGERIAL IMPLICATIONS

This would allow the need for further intervention to be flagged at an earlier point, enable targeted review of employees' training, and prompt enquiry into any contributory working factors.

In applying this tool, the following considerations would apply:

1. Transparent explanation of the intention and caveats behind the model output.
2. The opportunity to consider additional data on employees at a management level.
3. Mechanism to amend erroneous entries for individual employees.
4. Recording of any 'over-rides' made and the resulting actions.
5. Scheduled re-evaluation where employee position, technology and KPIs are updated.

It is important that these outputs drive appropriate action, rather than being viewed as a direct proxy for an individual's capability.

## 14. LIMITATIONS AND FUTURE RESEARCH

The aim of this study is purely methodological. No conclusions can be drawn about the superiority of any given predictive algorithm nor the relative importance of each predictor for the two industries. Data spanning several companies would be required to test these issues, including the robustness of targets, cross-time and cross-firm transferability, levels of prediction uncertainty, and if the use of model-informed interventions yields improved results. The potential for feed-forward loops will also require further attention. As a consequence of applying the models to inform employee development and deployment, observed behavior could be driven at least in part by the change in practice induced by the models.

## 15. CONCLUSION

There is an opportunity to apply machine learning methods to forecast employees' subsequent performance within the Banking and ITES industries, provided we can identify good target variables, obtain sufficient quality data and develop suitable metrics. As will become apparent, some characteristics of the sectors and job roles need to be incorporated directly into the models. In particular, key indicators include accuracy, service levels, output and compliance. Our solution incorporates baseline approaches, penalized regression, RF and GBM with time series splits and interpretability. Importantly, we highlight additional considerations including the degree to which forecasts are well-calibrated and the extent of error in sub-populations, and generalisability across the organisation. We suggest that the principal value of such methods will be to facilitate earlier appraisals and flag any organisational issues for further investigation. Further conclusions as to relative performance of models or impact of actions cannot yet be drawn.

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