



Individual Coursework Submission Form

Specialist Masters Programme

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| MSc in: Business Analytics | Student ID number: 240046745 |
| Module Code: SMM750 | |
| Module Title: Digital Technologies & Value Creation | |
| Lecturer: Philippe Blaettchen | Submission Date: 09/04/2025 |
| Declaration: By submitting this work, I declare that this work is entirely my own except those parts duly identified and referenced in my submission. It complies with any specified word limits and the requirements and regulations detailed in the coursework instructions and any other relevant programme and module documentation. In submitting this work, I acknowledge that I have read and understood the regulations and code regarding academic misconduct, including that relating to plagiarism, as specified in the Programme Handbook. I also acknowledge that this work will be subject to a variety of checks for academic misconduct. We acknowledge that work submitted late without a granted extension will be subject to penalties, as outlined in the Programme Handbook. Penalties will be applied for a maximum of five days lateness, after which a mark of zero will be awarded. | |
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In accordance with French labor law and the constraints outlined in the SFB Lyon office closure case, RCCs (rupture conventionnelle collective) must be offered to objectively defined groups rather than to individuals. To develop such groupings in a legally compliant and operationally strategic manner, I structured employees into groups based on two core variables: Department (HR, Sales, and Research & Development) and Salary Tier (Low, Medium, High). This yielded nine employee groups, each reflecting a unique combination of organizational function and compensation level.

These groupings were selected for their clarity, interpretability, and practicality. Departmental divisions align with the internal structure of the firm, enabling targeted offers based on functional relevance and redundancy. Salary Tiers, segmented via quantiles, reflect financial exposure and potential cost savings. Together, these attributes provide a balance between actionable segmentation and respect for employee rights. The simplicity of this framework also facilitates communication with stakeholders and implementation by HR.

Alternative grouping criteria were explored, including tenure bands (e.g., early career vs. senior staff), overtime status, attrition probability tiers (e.g., high-risk leavers), and job role. While these offer more granularity or predictiveness, they introduce additional complexity, increase the number of variables, and may inadvertently reflect protected characteristics.

While our model utilized historical data and focused on objective variables such as Department and Salary Tier, it is important to recognize that even seemingly neutral data can reflect underlying structural biases. As highlighted in recent academic research, “AI systems can inadvertently perpetuate existing biases present in historical data, potentially leading to discriminatory practices in hiring and performance assessments” (Mask & Pearl, 2024). This insight underscores the need to carefully evaluate our grouping methodology, particularly in the absence of direct demographic indicators.

The size of employee groups significantly influences the effectiveness of the RCC offer strategy. Smaller groups allow more precise targeting, potentially increasing efficiency in achieving cost savings while minimizing disruption to critical teams. However, smaller group definitions may introduce legal risk if not based on transparent, objective criteria. They may also

raise perceptions of favoritism or discrimination. Larger groups, conversely, are easier to justify legally and are more inclusive, but they dilute precision and may lead to over-offering, resulting in higher-than-necessary severance payouts or loss of critical talent.

One major issue is the risk of algorithmic bias. AI systems are trained on historical data, which may reflect existing prejudices or discriminatory practices. If not properly managed, these biases can be perpetuated or even exacerbated by AI technologies, leading to unfair hiring practices or skewed performance evaluations (Mask & Pearl, 2024).

To ensure the group definition is non-discriminatory, the methodology includes evaluating demographic diversity (if available) across groups and comparing representation to the full workforce. Although the Lyon dataset lacks explicit demographic indicators such as age, gender, or ethnicity, proxy checks can be applied using department, salary, or tenure distributions. If available, cross-tabulations or Gini coefficients can be calculated to assess whether any demographic group is disproportionately represented in the targeted groups. Additionally, group definitions were grounded solely in job-relevant variables—departmental assignment and salary—ensuring alignment with business necessity and mitigating the risk of indirect discrimination.

Optimization Model Formulation and Solution

The objective of the optimization model was to minimize the total severance cost while satisfying organizational and legal constraints. The model was implemented in Excel Solver using a binary decision framework.

Each of the nine employee groups defined by Department and Salary Tier was assigned a binary decision variable. A value of 1 indicated that the group would receive an RCC offer, while a value of 0 meant that no offer would be extended. This group-level binary approach respected the legal prohibition on individual targeting.

The objective function minimized the total expected severance cost. For each group, this cost was estimated by multiplying the predicted number of employees expected to accept the RCC (based on the sum of individual attrition probabilities) by the group's average severance cost. Severance costs were modeled as a combination of legal minimum entitlements and an

enhancement of three months' salary, in line with company precedent and market practices. These estimates were generated from the enhanced prediction dataset. Severance costs were computed using 1/4 month of salary per year of service for the first 10 years and 1/3 month per year thereafter. Additionally, I calculated enhanced RCC scenarios with 2-month and 8-month severance bonuses to support decision flexibility. These formulas were encoded directly in Python to ensure consistent and replicable cost projections for all employees.

Three constraints were embedded into the model. First, the projected salary reduction had to exceed €3 million. This was calculated by multiplying the attrition probability for each employee by their annual salary and summing across selected groups. Second, the total predicted number of leavers had to be at least 40, reflecting the minimum headcount reduction required. This was also calculated by summing the attrition probabilities for all employees in the selected groups. Third, the model enforced departmental retention, ensuring no department fell below 80% of its initial headcount. This constraint was operationalized by estimating the expected number of leavers per department and verifying that the retained count met the threshold.

The solution obtained selected four groups to receive RCC offers: Research & Development – Low Salary, Research & Development – Medium Salary, Sales – Medium Salary, and Sales – High Salary. The remaining five groups, including all HR tiers and the lowest salary group in Sales, were excluded from the RCC offer. This configuration achieved a projected 53.41 leavers, exceeding the 40-person requirement. It also delivered a total annual salary reduction of €3,147,079, surpassing the €3 million target. The total severance cost was €285,736.83. Departmental headcounts post-offer remained compliant: HR experienced no reductions, R&D retained 285 of its 347 employees, and Sales retained 135 of 168—all above the 80% retention threshold.

This final allocation adhered strictly to all constraints while achieving the lowest severance cost possible under the scenario. The strategy ensured that high-risk and high-cost groups were addressed without overextending offers to departments or compensation bands where voluntary exits were unlikely or disruptive.

Pros, Cons, and Assumptions of the Prediction and Optimization Approach

This prediction-and-optimization approach presents several strategic advantages. First, it enables data-driven decision-making, leveraging historical attrition patterns and financial information to guide RCC offerings. This reduces reliance on subjective judgment or political negotiation, aligning with Kusha's emphasis on transparency and analytical rigor. Second, the use of objective, interpretable groupings facilitates legal defensibility under French labor law. Third, the optimization ensures efficient resource allocation, minimizing severance costs while meeting headcount and budgetary goals.

Despite its strengths, the approach involves key limitations and assumptions. One central assumption is the stability and accuracy of predicted probabilities. Employee decisions in response to RCC offers may deviate from model forecasts due to factors not captured in the data, such as sentiment, market conditions, or peer influence. The model also assumes uniform behavior within each group, which may mask individual variation in acceptance likelihood. Additionally, employee decisions are assumed to be independent, whereas real-world behavior may reflect social dynamics or strategic interactions. Another limitation is the singular focus on severance costs; qualitative dimensions such as institutional knowledge, leadership potential, or cross-functional expertise are not directly incorporated. This could lead to unintended organizational consequences if high-value individuals disproportionately exit. Additionally, the prediction model was trained using employee data from a previous office closure (`employee_attrition_previous_closure.csv`). This dataset provided a rich foundation for estimating voluntary attrition behavior in a restructuring context, with the assumption that patterns of acceptance for RCC offers would generalize to the Lyon office.

Finally, the model presumes that severance cost is the dominant decision criterion, excluding considerations such as team morale, replacement costs, or long-term productivity impacts. These factors must be weighed alongside the quantitative outcomes. Therefore, while the model offers a robust foundation for action, it must be supplemented by managerial discretion and post-model review to ensure a balanced, responsible restructuring strategy.

Although the grouping strategy was based on objective business-related factors (Department and Salary Tier), no formal proxy checks were implemented in the current version of the model. In future iterations, it would be advisable to assess whether these groupings might

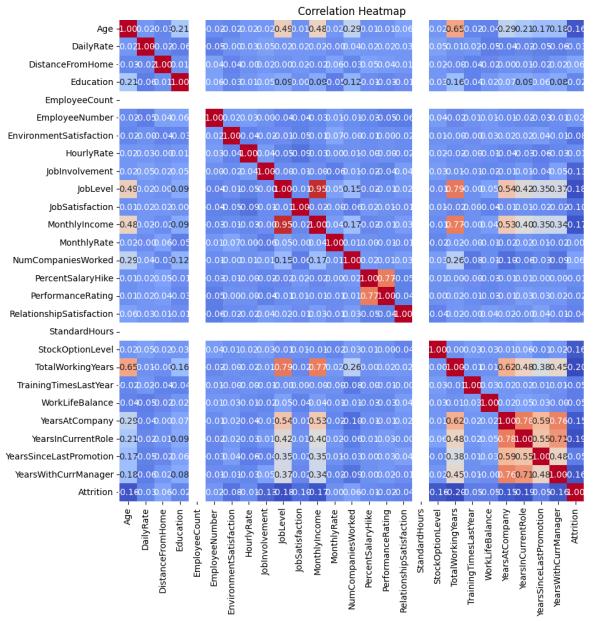
indirectly capture protected characteristics such as age or gender, especially in the absence of direct demographic data.

Predicted probabilities were generated using a logistic regression model trained on historical data and stored in attrition_prediction_model.pkl. These predictions were then applied to the Lyon employee dataset using a Python notebook (prediction.ipynb) and exported to CSV (enhanced_attrition_prediction.csv) for analysis and optimization in Excel (optimization.xlsx).

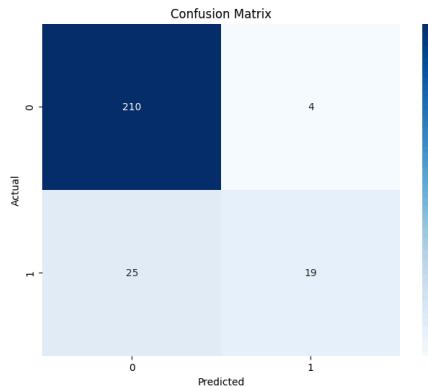
Visualizations

| Group | count | avg_prediction | expected_leavers | avg_monthly_income | avg_severance_cost | expected_salary_reduction | RCC Offer | Total Expected Leavers | Salary Reduction | Severance Cost | | | | | | | | |
|---------------------------------|-------|----------------|------------------|--------------------|--------------------|---------------------------|-----------|------------------------|------------------|----------------|--|--|--|--|--|--|--|--|
| Human Resources - High | 5 | 0.132541679 | 0.662708393 | € 14,502.20 | € 174,026.40 | € 115,329.00 | 0 | 0 | 0 € | - € | | | | | | | | |
| Human Resources - Low | 9 | 0.269037451 | 2.421337063 | € 2,589.11 | € 31,069.33 | € 75,229.00 | 0 | 0 | 0 € | - € | | | | | | | | |
| Human Resources - Medium | 7 | 0.196475001 | 1.375325006 | € 5,756.86 | € 69,082.29 | € 95,011.00 | 0 | 0 | 0 € | - € | | | | | | | | |
| Research & Development - High | 83 | 0.054635938 | 4.534782826 | € 12,518.12 | € 150,217.45 | € 681,203.00 | 0 | 0 | 0 € | - € | | | | | | | | |
| Research & Development - Low | 116 | 0.202493083 | 23.48919765 | € 2,853.23 | € 34,238.79 | € 804,242.00 | 1 | 23.48919765 | € 804,242.00 | € 34,238.79 | | | | | | | | |
| Research & Development - Medium | 86 | 0.141333465 | 12.15467799 | € 5,285.06 | € 63,420.70 | € 770,858.00 | 1 | 12.15467799 | € 770,858.00 | € 63,420.70 | | | | | | | | |
| Sales - High | 59 | 0.1212725705 | 7.181816572 | € 10,252.80 | € 123,033.56 | € 883,604.00 | 1 | 7.181816572 | € 883,604.00 | € 123,033.56 | | | | | | | | |
| Sales - Low | 22 | 0.247397416 | 5.442743147 | € 2,920.50 | € 35,046.00 | € 190,746.00 | 0 | 0 | 0 € | - € | | | | | | | | |
| Sales - Medium | 54 | 0.195986172 | 10.58325327 | € 5,420.31 | € 65,043.78 | € 688,375.00 | 1 | 10.58325327 | € 688,375.00 | € 65,043.78 | | | | | | | | |
| Total Headcount | | 441 | | | | | | | | | | | | | | | | |
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This table summarizes the nine employee groups by Department and Salary Tier. It includes group size, average attrition probability, expected leavers, salary reduction, and severance cost. The “RCC Offer” column indicates which groups were selected in the final optimization. Aggregated totals show the solution meets all constraints: over €3M in salary reduction, more than 40 expected leavers, and compliance with department-level retention thresholds.



This heatmap shows the pairwise correlation coefficients between numerical features in the dataset. Notably, features like TotalWorkingYears, YearsAtCompany, and MonthlyIncome show strong positive correlations with each other, while Attrition has weak negative correlations with most features, indicating limited linear relationships.



This matrix visualizes the performance of the prediction model. The model correctly predicted 210 non-leavers (true negatives) and 19 leavers (true positives), but it misclassified 25 leavers (false negatives) and 4 non-leavers (false positives). This highlights a common imbalance issue where the model is more accurate at predicting those who stay than those who leave.

Citations

Mask, E. and Pearl, J., 2024. *Artificial Intelligence in Human Resources: Ethical Implications and Performance Enhancement*. [ResearchGate]. Available at:

<https://www.researchgate.net/publication/381999512> [Accessed 1 Apr. 2025].