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# Interactive Dashboard Generation for Analyzing Survival-Changing Patterns and Employee Attrition

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**Abstract**—Employee retention is a major issue for companies. In our previous work [1], we proposed an approach that extracts frequent patterns from employee trajectories to identify those associated with improved retention thanks to survival analysis. Those are called survival-changing patterns. However, the large volume and complexity of these patterns limited their interpretability and practical use by Human Resources (HR) teams. In this paper, we introduce an interactive dashboard that combines sequential pattern mining with survival analysis to support HR decision-making. Our approach refines and visualizes survival-changing patterns, enabling a clearer understanding of attrition dynamics. The dashboard provides a global view of retention trends, an identification of at-risk employees, and a simulation of targeted interventions. Our contributions include the definition of HR personas and use cases, a method for selecting representative pattern of a sequence, the design of tailored visualizations for employee trajectories, and a real-world illustration of how the tool works in practice.

**Index Terms**—sequential pattern mining, dashboard, survival analysis

## I. INTRODUCTION

Employee attrition is a major challenge for companies, particularly in IT firms, where turnover rates are sometimes as high as 25% according to some reports [2]. This phenomenon entails significant costs. However, most recent work in the field of data analysis applied to attrition often neglects the temporal dimension, such as the history of changes experienced by employees. To better understand this temporal aspect, our recent research has combined sequential pattern mining and survival analysis techniques, enabling us to identify sequential patterns impacting survival, called survival-changing patterns [1]. However, the large volume of extracted patterns and the lack of proper visualization make it difficult for non-technical users to fully exploit these results. In our opinion, the most appropriate way to make the most of these results is to develop interactive dashboards. Our choice to use interactive dashboards is motivated by their ability to meet the specific

needs of human resources management, particularly in terms of tracking attrition. Compared to other tools such as static reports or machine learning algorithms accessible only to data scientists, dashboards should enable HR users to interact autonomously and directly with the data, explore scenarios, and adjust their actions without requiring advanced technical skills.

Our approach lies at the intersection of data visualization, survival analysis, and pattern mining, with a specific focus on employee attrition. Unlike generic business intelligence tools, our dashboard is tailored to HR needs, combining sequential pattern mining with survival analysis to support both macro-level insights and micro-level decision-making.

By enabling the identification of at-risk employees and simulation of interventions, our tool goes beyond traditional dashboards, serving as a decision-support system for HR managers. Existing tools often emphasize pattern discovery or trajectory summarization, but rarely integrate survival analysis or HR-specific visual interactions.

Our main contributions are as follows:

- 1) We define key personas and HR use cases related to employee attrition, guiding the design of our solution.
- 2) We introduce a method for selecting the most representative survival-impacting patterns for individual trajectories.
- 3) We propose a dashboard architecture that integrates sequential pattern mining and survival analysis, tailored to each employee's profile.
- 4) We demonstrate the practical relevance of our approach through a detailed real-world use case.

The remainder of this paper is structured as follows. Section II presents related works on interactive dashboards and their relevance to pattern mining and survival analysis in the context of employee attrition. Section III introduces the main use cases and target user personas that guide our design. Section IV details our method for selecting the most representative pattern for each employee. Section V describes the structure and functionalities of the interactive dashboards,

illustrated through three concrete scenarios. Finally, Section VI concludes the paper and discusses future work.

## II. RELATED WORKS

Dashboards have become indispensable tools for synthesizing voluminous and complex data into usable visualizations, facilitating understanding and action [3]–[5]. This section discusses previous work on interactive dashboards, their relevance to our specific use case, and their use in combination with pattern mining and survival analysis. The aim is to justify our choice of dashboards as a tool for managing employee attrition, and to highlight the limitations of current approaches that our work aims to overcome.

There is no common definition of what a dashboard is [6]. The best-known definition comes from Stephen Few, one of the most influential authors in the field, who says: “A dashboard is a visual display of the most important information needed to achieve one or more objectives that has been consolidated on a single computer screen so it can be monitored at a glance” [7]–[9]. This vision is essential for framing our approach: to enable a rapid and useful understanding of the situation of employees within the company.

Interactive dashboard design approaches are often based on principles such as the Schneiderman’s mantra [10]: “Overview first, zoom and filter, details on demand”. This foundational concept was later extended and refined by Keim [11] into the “Visual Analysis Mantra”: “analyze first, show the important, zoom/filter, analyze further, details on demand”. These principles are perfectly suited to the visualization of attrition data, where analysis needs to be carried out at different levels of granularity, from an overview of attrition rates by department to detailed analysis of at-risk employee paths. These different visualizations enable HR managers to move from a macro view of attrition problems to a micro analysis of potential solutions.

Building interactive dashboards can be achieved in several ways, including automatically [12], but these approaches often neglect the integration of sequential patterns. Sequential pattern mining and survival analysis are central to our approach. While many pattern mining dashboards focus on visualizing complex event sequences to uncover hidden trends [13], [14], our method uniquely combines them with survival analysis to support strategic HR decisions.

Guo et al. [13] propose a design framework to categorize sequence visualization tools along four axes: data scale, analysis technique, visual representation, and interaction. Our dashboard is positioned as follows: (i) Sequence Collection, analyzing full trajectories and subsequences; (ii) Inference, evaluating survival-impacting patterns; (iii) Chart and Timeline-based views for KPIs and trajectories; (iv) Segment and Filter/Query interactions. Our focus lies in Prediction and Recommendation, a rarely covered analytical task in the surveyed tools.

No existing tool matches this exact combination. CoCo [15] shares some similarities (sequence collections, timeline views, interactive filters) but focuses on pattern discovery and cohort comparison, not inference or prediction. Similarly, DPVis [16]

uses inference and rich visualizations, but targets summarization, while our dashboard aims at actionable recommendations.

Yeshchenko et al. [14] further contrast information visualization and process mining. Our approach falls into their timeline-based category but emphasizes interpretable, actionable insights rather than abstract process models.

Therefore, in conclusion, our review highlights a clear gap in tools that combine sequential pattern mining and survival analysis in an interpretable and actionable way for HR professionals. To address this gap, we now present the concrete use cases and user personas that shaped the design of our interactive dashboards.

## III. USE CASES

The dashboards will be used by a consulting firm operating in several countries, with a total of over 11,000 employees. Hence the need to monitor and analyze attrition. The following paragraph describes the functions of users who will be using the dashboards. The main users of dashboards are HR managers, who can be grouped into several personas according to their functions:

- **Managers/Directors:** These users need a simplified version of the dashboard, enabling them to quickly see key performance indicators such as attrition rates. This will help them make strategic decisions on actions to be taken at departmental level. An initial use case could therefore be a fairly general one, enabling the evolution of attrition to be tracked for different groups of employees.
- **HR analyst:** These users are also in charge of tracking global trends. They also analyze key performance indicators, but are also responsible for identifying groups containing the most at-risk employees. A second use case for dashboards could therefore be to filter by employee group and identify which employees within these groups are most likely to resign in the short or long term.
- **HR in charge of employee follow-ups and/or interviews:** This type of user is directly involved in exchanges with employees. They are in charge of employee satisfaction. His role is to conduct regular (annual or bi-annual) interviews to better understand employee concerns and identify those at risk of leaving the company. A final use case for the dashboard would be to be able to visualize employee career paths, track employee retention probabilities over time, and be able to simulate a specific intervention (promotion, change of mission, etc.) in order to visualize the effect of this decision.

## IV. IDENTIFICATION OF THE RELEVANT PATTERN FOR EACH EMPLOYEE

Our previous work [1], has produced several results on survival-changing patterns. However, for these results to be exploited in a relevant way and applied effectively to each employee, an additional step is necessary: for each employee we need to identify, among the patterns included both in his sequence and in our results, the one that best represents this sequence (or this employee).

Selecting the most representative pattern in a sequence is essential, as our results concern only frequent patterns, not the complete employee sequences. It is therefore necessary to define objective criteria to prioritize these patterns and identify the one that best represents the events specific to each employee.

Note that the data used in this paper and our dashboards are entirely fictitious. They have been created from scratch and in no way reflect the reality of the company in order to comply with the GDPR laws. Thus, all values and information mentioned should not be interpreted as representing real situations within the company.

For example, assuming the employee has the following sequence (replacing events with letters):  $\langle (Age35 - 39, Male, L5), C, J2, C \rangle$  with  $L5$  representing location,  $C$  a change in salary and  $J2$  a change in position within the company. In our fictitious dataset, of all the frequent patterns extracted that have at least one survival-changing pattern, 8 are contained in this sequence. So the aim is to determine which of these 8 patterns the user should use to simulate future interventions.

The selection of the most representative pattern is based on several criteria, divided into two categories: syntactic criteria (relating to the shape of the sequence) and semantic criteria (relating to the evaluation of the pattern within the dataset).

*a) Syntactic criteria:* This first category aims to favor patterns that resemble as closely as possible the trajectory of the employee under consideration, with the length and positioning of the last event.

The first criterion to consider is the length of the pattern (denoted by  $Length$ ). A longer pattern may capture more information about the employee’s behavior, including successive or non-successive events. Longer patterns are often more descriptive and can contain a diversity of elements reflecting the complexity of the sequence. However, a longer pattern is less likely to be the context of a survival-changing pattern.

A second criterion is the position of the last event in the pattern (denoted by  $Latest$ ), which highlights the importance of recent actions. A pattern including an event at the end of the sequence may be particularly relevant for understanding the last actions influencing employee behavior. To do this, we will count the number of days between the appearance of the pattern’s last element and today’s date.

*b) Semantic criteria:* In a classic way, we also benefit from measures of interest evaluated on the dataset where the sequential pattern was extracted: frequency and mean survival gain.

Firstly, we have the frequency of the pattern (denoted by  $Freq$ ) in the set of frequent patterns, which can be interesting to have as a criterion. In fact, it indicates recurring behavior within the company. A frequent pattern is therefore representative of a typical dynamic for usual interventions.

Secondly, another important criterion is the frequency with which a pattern acts as a context for patterns affecting survival (denoted by  $ContFreq$ ). This allows us to identify patterns that are regularly the basis for identifying patterns that strongly

influence the probability of an employee’s retention or departure.

Finally, the last criterion is the average survival gain associated with a pattern as a context (denoted by  $AvgGain$ ). This measures the extent to which a pattern as a starting point contributes to extending an employee’s retention time. Thus, patterns with a high survival gain are favored, as they indicate that there are patterns that greatly improve this duration.

*c) Score function:* The flexibility of the criteria makes it possible to tailor the selection of patterns to specific use cases. To achieve this, we have set up a multi-criteria score, where each pattern receives a score according to its performance on the different criteria, standardized and weighted according to their importance. More specifically, the score function takes into account pattern length, frequency, final event position, frequency as a context of survival-changing patterns, and average survival gain. The weighting of the criteria is adjusted according to the needs of the analysis, ensuring a consistent solution adapted to each application context.

The score of a pattern  $X$  is computed as a weighted sum of its standardized criteria values:

$$\begin{aligned} \text{Score}(X) = & 0.2 \cdot \text{Length}(X) + 0.2 \cdot \text{Latest}(X) \\ & + 0.1 \cdot \text{Freq}(X) + 0.2 \cdot \text{ContFreq}(X) \\ & + 0.2 \cdot \text{AvgGain}(X) \end{aligned} \quad (1)$$

Table I summarizes the values obtained for each of the candidate patterns for the representation of the sequence  $\langle (Age35 - 39, Male, L5), C, J2, C \rangle$  :

In conclusion, the selection of the most representative pattern in a sequence is a crucial issue for the transposition of global results (frequent patterns) to specific cases (selected employee). Thanks to the score function approach, we are able to adjust our selection according to different performance and relevance criteria, while remaining aligned with business needs and the specificities of the sequences observed.

## V. INTERFACE DESIGN

This section details the tool’s various dashboards. Note that the colors used are those of the company’s visual identity.

### A. Monitoring attrition trends

This interactive dashboard is designed to meet the first use case: monitoring attrition trends for different employee groups. It provides a comprehensive overview of employee attrition according to various criteria. Figure 1 is a screenshot of the dashboard representing this use case.

The dedicated dashboard interface features clear, intuitive visualizations of key performance indicators (Figure 1a), such as overall attrition rate, number of departures or number of employees still active. Filters at the top of the page (Figure 1b) enable users to customize the analysis according to time period, location, age range, and employee gender. This enables them to precisely segment the data according to the specific needs of the analysis.

The interface includes various visual components (Figure 1c) that provide a better understanding of attrition dynamics. For example, the graphs present data segmented by

TABLE I  
EXAMPLE OF SELECTING THE PATTERN THAT BEST REPRESENTS A SEQUENCE.

Candidate patterns	<i>Freq</i>	<i>Length</i>	<i>Latest</i>	<i>ContFreq</i>	<i>AvgGain</i>	<i>Score</i>
$\langle Male \rangle$	500	1	474	213	0.068	2.361
$\langle J2 \rangle$	706	1	232	30	0.102	1.804
$\langle C, J2 \rangle$	641	2	232	18	0.092	1.634
$\langle L5, C, J2 \rangle$	388	3	232	25	0.081	1.338
$\langle L5, J2 \rangle$	426	2	232	32	0.075	1.124
$\langle Male, C, J2 \rangle$	317	3	232	19	0.074	1.064
$\langle (Male, L5) \rangle$	295	1	474	114	0.048	0.864
$\langle (Male, L5), C, J2 \rangle$	186	3	232	6	0.036	0.052

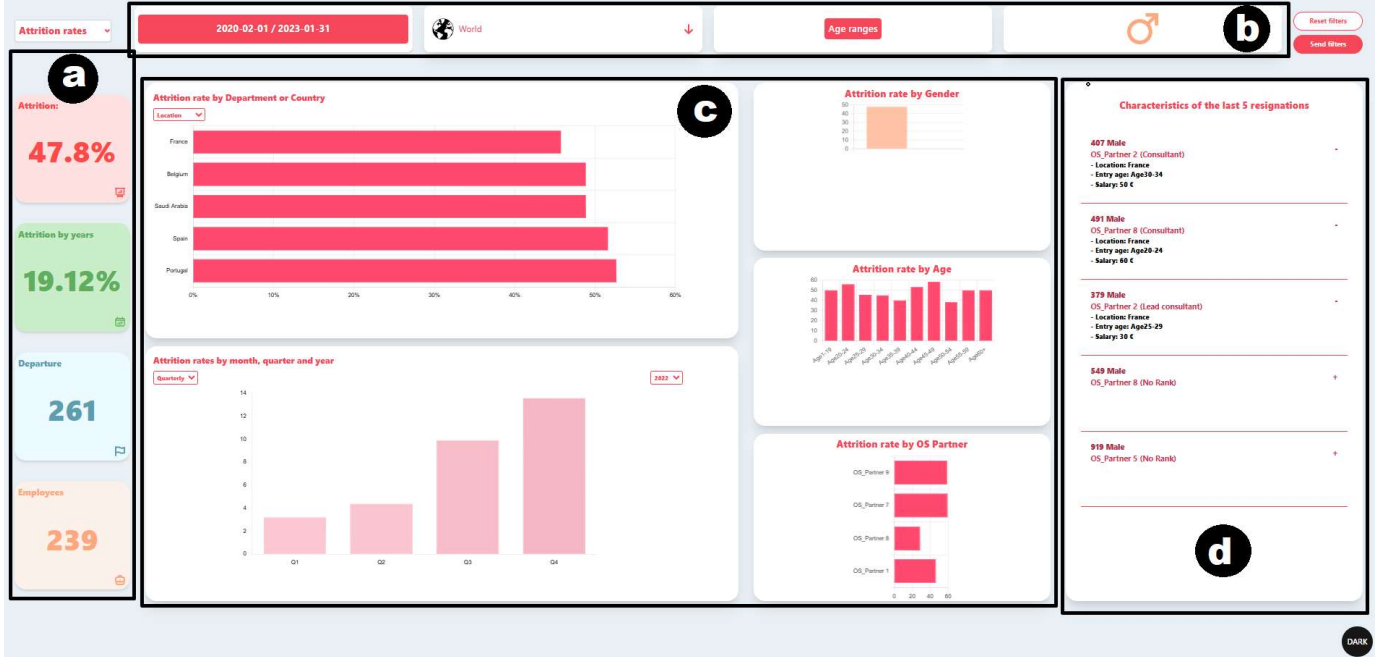


Fig. 1. Dashboard for global attrition monitoring.

department, gender, age group and job type. This makes it possible to identify, for example, which departments or demographic groups have higher attrition rates.

On the right-hand side of the interface (Figure 1d), a list provides detailed information on the last 5 employees to have left the company. This section highlights characteristics such as the employee's gender, position and salary. It enables users to examine the characteristics of recent departures and detect potential trends that may require corrective action.

This dashboard focuses on attrition monitoring, offering clear, interactive and granular visualizations to analyze user-defined subgroups. Thanks to its dynamic filters, it helps identify groups with abnormally high attrition rates.

### B. Identifying employees at risk

This interactive dashboard is designed to meet the second use case: identifying employees at greatest risk of leaving the company. Figure 2 is a screenshot of the interface representing this use case.

The main section of the interface (Figure 2(a)) presents a list of employees ordered by decreasing departure probability. Each row of the table provides detailed information on each employee, such as identifier, probability of departure, rank, department, gender, age of entry into the company, and country. This information enables HR analysts to better understand the context and characteristics of at-risk employees. Just above the left-hand side of the list, interactive filters allow selection of the number of employees to be displayed and the calculation period for the probability of departure. This makes it possible to detect employee departure risks at an early stage.

The filters at the top (Figure 2(b)) are the same as those in Figure 1.

This interface is designed to provide a clear and precise visualization of the employees most at risk, enabling HR managers to prioritize their actions and intervene proactively. Based on this interface, users can identify employees requiring special monitoring and plan appropriate interviews or interventions, in order to reduce the risk of departure and improve



Fig. 2. Dashboard for identifying employees at risk.

retention within the organization.

### C. Simulation of interventions on an employee

This latest dashboard has been designed to address the third use case, which involves simulating an intervention on an employee to see how this affects retention. It is specifically geared towards the detailed analysis of an individual employee, enabling users to test different actions and understand their potential impact on retention. Figure 3 is a screenshot of the dashboard representing this use case.

The interface of this table is made up of several sections that provide a complete overview of the employee’s characteristics. This includes basic information such as ID, position, salary, department and geographical location (Figure 3(a)). This static data is used to contextualize simulation results.

A graph representing the employee’s sequence of events is displayed to visualize the employee’s trajectory within the company (Figure 3(b)). This visualization makes it possible to track the various changes the employee has undergone along the way, facilitating understanding of the context before applying a specific intervention.

Just below (Figure 3(c)), we have the list of potential frequent patterns best representing the employee’s trajectory (see section IV) ordered by descending score. For each of these patterns, in addition to the score, we find their area under the survival curve (AUC) as well as their average gain as a survival-changing pattern context.

In the upper right-hand section of the interface (Figure 3(d)), survival-changing patterns are proposed, based on the best representing pattern that has been chosen in Figure 3(c), to be applied to the employee’s sequence. By clicking on a survival-changing pattern, the user can visualize the impact of this survival-changing pattern on the employee’s retention curve, using the survival graph on the right of the interface (Figure 3(e)). For example, the red curve represents the current retention curve, while the green curve shows the new retention curve after the pattern has been added.

Finally, the interface displays an estimate of the probability of retention after the intervention (Figure 3(f)), with a comparison between the current value and the new value following the addition of the survival-changing pattern. This component is essential for immediately visualizing the potential impact of an intervention, enabling HR managers to adapt their retention strategy accordingly.

This interface enables HR managers to simulate different actions and observe their effects in real time, while providing

a detailed analysis at the level of each individual employee. It is a simulation tool that can be used to test various hypotheses, such as the potential impact of a salary increase on the probability of an employee leaving the company. These features not only help to understand the current situation, they also facilitate informed decision-making based on simulations of future scenarios. In this way, the dashboard contributes to proactive, optimized management of employee retention within the company.

### D. Running example

We present a step-by-step example showing how a user can interact with the dashboards to obtain a global then detailed view, thus facilitating strategic decision-making in human resources management. The user, an HR manager in charge of employee tracking, starts by using the first dashboard (Figure 1) to identify the countries with the highest attrition rates. He then switches to the second dashboard to select one of these countries (e.g. Spain) and filters out employees at high risk of immediate departure. A list of the 5 employees most at risk, sorted in descending order, is then displayed. The user sees that employee 161 is the most female at risk immediately (Figure 2).

The user then clicks on employee 161 to access the latest dashboard to visualize the employee’s trajectory, obtain detailed information, and select the most representative pattern. The dashboard will then display the survival curve and the associated survival-changing patterns, enabling different strategies to be tested for retaining the employee. In Figure 3, the set of events  $\langle\langle J2, J3 \rangle\rangle$  is simulated as a survival-changing pattern, enabling the probability of survival to increase from 0.202 to 0.354.

## VI. CONCLUSION

We have developed interactive dashboards that can be used to valorize survival-changing patterns, derived from frequent sequential pattern mining and integrating survival analysis. They enable users to gain a global and detailed view of attrition trends, identify employees with a high probability of resigning, and simulate interventions and their effects on employee retention. HR managers can then make informed decisions to optimize retention.

In future work, we plan to extend the tool so that it can be used by non-HR users such as the company management or managers. To do this, we will need to add restitution tools so that HR users can communicate their analyses to non-HR users. We can also improve the score function by adding a

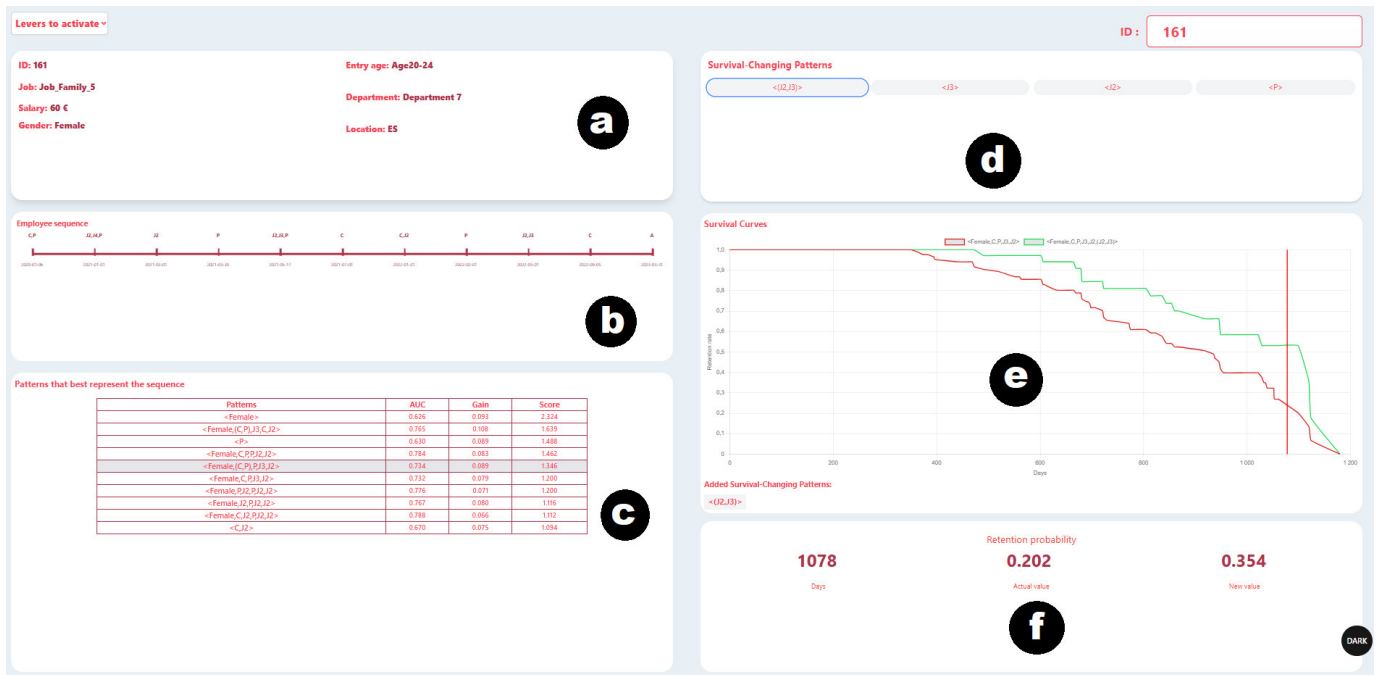


Fig. 3. Dashboard for specific intervention simulation.

new criterion based on the length of time between the first and last event of the pattern under consideration. Finally, we also plan to implement a filter allowing analysis of the attrition evolution of a specific manager’s team.

Given its adaptable design, our dashboard could also be leveraged beyond the context of employee attrition, with potential for applications in other domains involving sequential behaviors and retention issues, such as customer churn or student dropout.

The dashboard is currently being tested by HR professionals within the company to gather initial user feedback. This evaluation will help identify potential improvements and validate its practical relevance.

Here is a practical demonstration of the tool: <https://tinyurl.com/IV-Conference-2025-Demo>

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