HR LEADERSHIP BRIEFING

Spotting Flight Risk Before It's Too Late

A simple early-warning signal for HR, built and tested on real employee data.

Prepared for: HR Leadership Review

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WHAT WE'LL COVER

Four Things to Walk Away With

01

Who's At Risk

The real headcount, broken into groups — who needs what, and why

02

The Problem

Why we usually find out someone's leaving only when it's too late

03

How It Works

A plain-language look at what we built and how well it performs

04

What To Do Next

Turning a flag into action, what it could be worth, and what's next

What We're Trying to Do

THE PROBLEM

Employee attrition is expensive and hard to see coming. This is demonstrated on IBM's own published HR Analytics Employee Attrition dataset (Kaggle) — 1,470 employees, 237 who left and 1,233 who stayed (16.1% attrition).

THE GOAL

Catch flight risk — the chance that a given employee is likely to leave soon, based on patterns in their work history — early enough to act on it, instead of finding out in the exit interview, when it's already too late.

WHAT ARE WE BUILDING

A simple early-warning tool built from past employee records. Not a person, not magic, and unlike generative AI it doesn't hallucinate — it only reflects real patterns in the data, and it never decides anything on its own.

HOW IT WORKS

It learns what past leavers had in common, then compares today's employees to that pattern and flags the ones who look similar. The next slide shows exactly what that looked like, tested on real data.

16.1% Attrition: Who's At Risk, and What To Do

1,470 real employee records — 237 who left, 1,233 who stayed (16.1% attrition) — from IBM's HR Analytics Employee Attrition dataset (Kaggle). Of the 294 held out for testing, every employee falls into one of four groups:

192 — Quietly Fine

ACTUALLY STAYED · LOW RISK

Intervention: Not needed.

Impact: Confirms the tool isn't over-flagging.

55 — False Alarm

ACTUALLY STAYED · FLAGGED HIGH RISK

Intervention: Possible — a brief, low-key check-in.

Impact: Cheap even when the flag turns out wrong.

18 — Missed Entirely

ACTUALLY LEFT · APPEARED LOW RISK

Intervention: Not possible from this flag — needs a manual safety net for high-value roles.

Impact: The tool's blind spot — 4 in 10 leavers go unflagged.

29 — Caught in Time

ACTUALLY LEFT · FLAGGED HIGH RISK

Intervention: Needed and possible — retention conversation within days.

Impact: Retaining even 1 in 3 (~10 people) could avoid ~$290K–$1.1M in replacement cost (avg $57K/yr pay, SHRM's 50–200% benchmark).

We Usually Find Out Too Late

The 47 departures on the previous slide are the norm, not the exception: the clearest signal that someone was a flight risk usually arrives in the exit interview — the one moment it's too late to act on it.

The Cost of Finding Out Late

- Replacing an employee typically costs half to two times their annual salary (SHRM)
- By the time it shows up in a quarterly report, the decision to leave was already made
- HRBPs are working off instinct, not an early, data-backed signal

The Opportunity

- HR already holds the information needed to see risk coming — it's just not connected
- An early signal, even an imperfect one, turns an exit interview into a retention conversation
- The question this deck answers: can a simple tool actually do this, honestly?

Source: SHRM, cost-to-replace-an-employee benchmark.

03

A Plain-Language Early-Warning Signal

No new systems, no new data collection — just a different way of looking at information HR already has.

1

Look at the past

We looked at employee records — income, tenure, overtime, time with their current manager — for people who stayed and people who left.

2

Find the pattern

The tool learns what past leavers tended to have in common, without anyone hand-writing the rules.

3

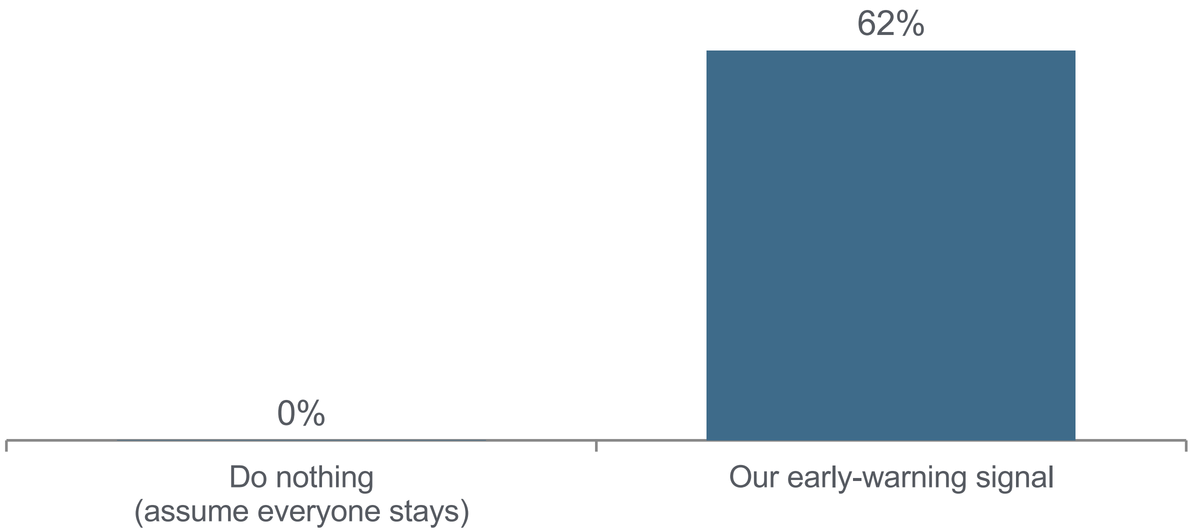
Flag today's employees

It compares today's employees to those patterns and flags the ones who look similar to people who left before — this is how we got the numbers on the opening slide.

This was a proof of concept on a public HR research dataset, ahead of trying it on our own workforce data.

How Good Is the Signal, Really?

A smoke detector that never goes off is “right” almost every day — and useless. The same trap applies here.

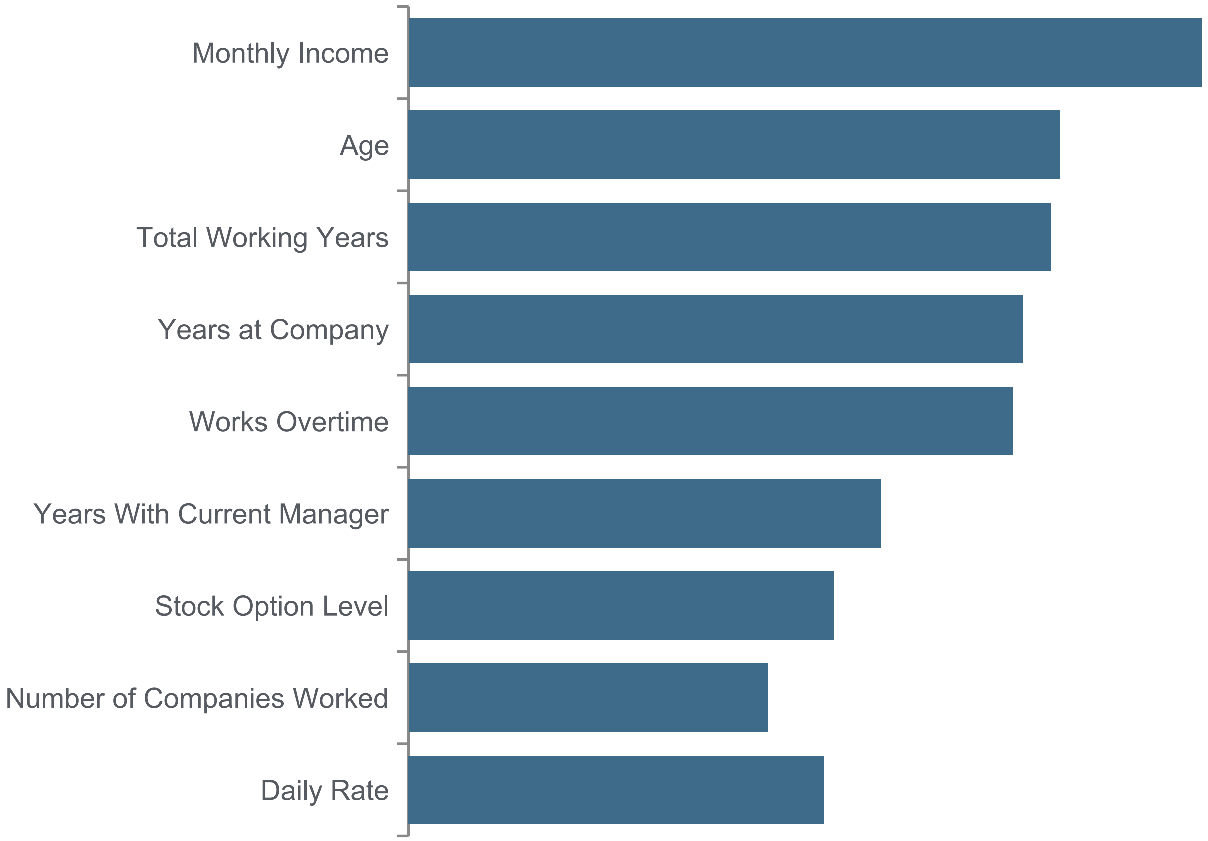


What this means

- Doing nothing “looks fine” 84% of the time, because most employees stay anyway — but it warns you about nobody.
- Our signal catches roughly 6 in 10 people who actually leave, before they leave.
- In exchange, about 1 in 3 flags turns out to be a false alarm — a fair trade for catching real departures early.

What Tends to Show Up Before Someone Leaves

The strongest patterns in the data, ranked.



- Pay and stock options matter — both are top signals
- Overtime is the most actionable one — it's a policy lever, not just a data point
- How long someone's been with their manager matters — relationship continuity is a real retention factor

Turning a Flag Into Action

Not an auto-pilot — a way to route the 84 flagged employees to the right level of attention.

Low Risk

Quarterly check-in suggested — no urgency, just logged so nothing falls through the cracks.

Elevated Risk

HRBP prompted to have a retention conversation within two weeks. A person decides what to do, not the tool.

High Risk + High Value

Escalated directly to the manager and HRBP together — this is the costliest kind of miss to allow.

Why a person stays in the loop: the signal gets it right sometimes and misses sometimes — it suggests, it never decides.

What Could This Be Worth? Here's the Model, Not Just a Number

We haven't run real interventions yet, so this can't be a promise — it's a transparent, three-step model anyone in this room can check.

1

237 people leave

Company-wide, that's the real baseline in this dataset — 16.1% attrition, 1,470 employees.

2

~141 we'd catch in advance

Our signal correctly flags about 6 in 10 (59.6%) of them before they leave — the “Caught in Time” group, scaled company-wide.

3

Some fraction we could keep

The one number nobody can measure yet: how many of those 141 an actual intervention would save. We don't guess at a single figure — we use a range.

Why 15–33%, not a single number: 33% (1 in 3) is the same conservative assumption already used for the dollar estimate on the headcount slide; 15% is a more cautious floor. The next slide turns that range into an attrition number and a dollar figure — and into a concrete ask.

The Business Case, and the Ask

Same model, three scenarios — how far attrition could realistically move, and what that's worth.

Scenario	Save Rate	People Retained	Attrition	Avoided Cost
Conservative	15%	~21	16.1% → 14.7% (−1.4 pts)	$0.6M–$2.4M
Likely	25%	~35	16.1% → 13.7% (−2.4 pts)	$1.0M–$4.0M
Matches headcount-slide assumption	33%	~47	16.1% → 13.0% (−3.2 pts)	$1.3M–$5.3M

The Ask: Fund a one-quarter pilot on the flagged high-risk group. Measure the real stay rate against a comparable prior-period cohort, and replace this assumption with a measured number — a stronger case than a static projection alone.

Company-wide figures scale this dataset's real test-set performance (59.6% recall) across all 1,470 employees. Avoided cost uses SHRM's 50–200% of average salary ($57K) replacement-cost benchmark — the same source used on the headcount slide. These are modeled scenarios, not guarantees.

What This Isn't — Said Plainly

Worth being upfront about before anyone treats this as more than it is.

Not a certainty

It's a helpful early signal, not a guarantee. Always talk to the person — never rely on the flag alone.

Not tested on our own data yet

This proof of concept used a public research dataset. Before real use, we'd retrain it on our own employee records.

Not yet checked for fairness

We would check it flags people fairly across age, gender, and tenure groups before any real rollout.

Not a decision-maker

It suggests who might need attention. A person always makes the final call — the tool never does.

If We Wanted to Move Forward

1

Pilot Quietly

Run it alongside one HR team for a quarter — compare its flags to what actually happens before anyone acts on them.

2

Check Fairness

Confirm it flags people fairly across age, gender, tenure, and department before any live use.

3

Set Sensitivity

Decide with HR leadership how cautious or aggressive the flagging should be.

4

Keep It Fresh

Refresh it regularly as new data comes in, and keep checking it still makes sense.

None of this needs new data collection — everything used here already lives inside the systems HR runs today.

CLOSE

Questions & Discussion

- Catches roughly 6 in 10 employees who actually leave, before they leave
- Dataset: 1,470 employees, 237 who left / 1,233 who stayed (16.1% attrition) — IBM HR Analytics Employee Attrition dataset (Kaggle), 294 held out for testing
- Modeled with a measured pilot: attrition could move from 16.1% toward roughly 13–15%, avoiding an estimated $0.6M–$5.3M in replacement cost
- A person always makes the final call — this is a signal, not a verdict
- Full technical detail available from the product & analytics team on request