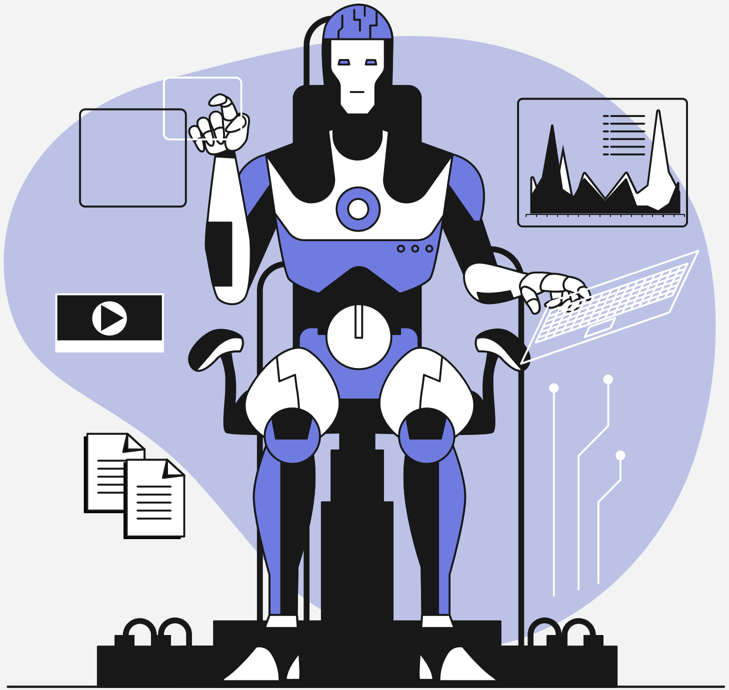
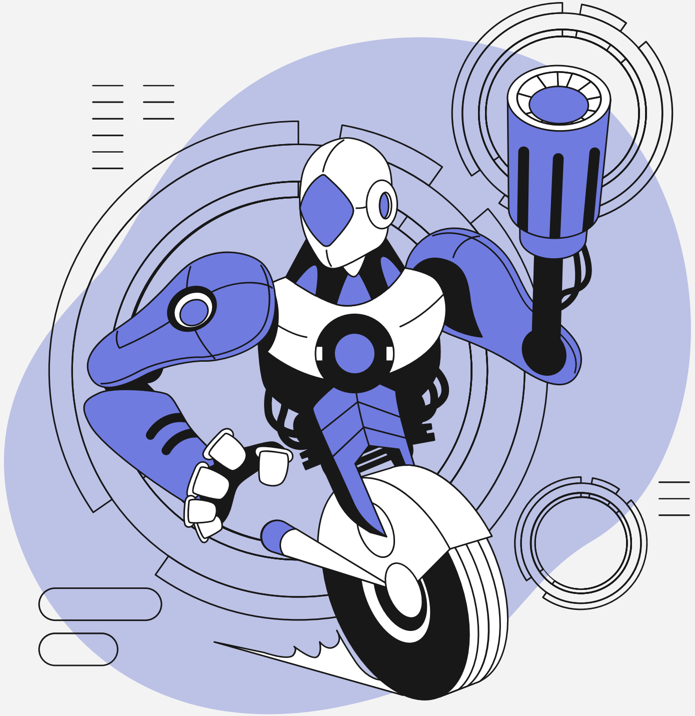
# What AI startups get wrong (and what they get right)



# Leading AI globally, from Dublin, Ireland

- Opening.io – AI first company
- iCIMS Acquisition
- Dublin Site Strategy – Global AI
- iCIMS Acquisitions X 5
- Leadership and Change Management
- GP at Delta Partners



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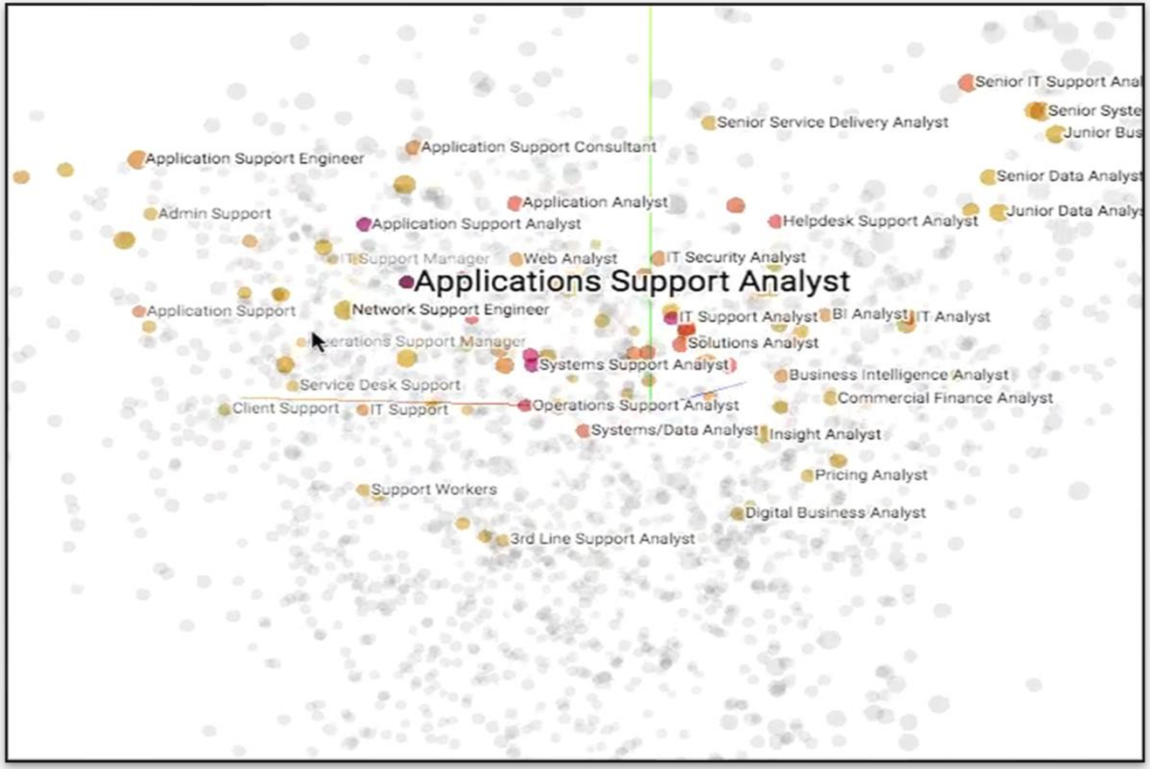
# About opening.io

**Opening.io was an award winning Irish company based in Dublin. The company has been named one of Europe’s 20 super AI, SaaS and enterprise start-ups. Opening.io has built a best in class talent recommender engine for the Talent Management industry.** The AI-first company leveraged machine intelligence on top of existing large-scale recruitment processes: matching & ranking of candidates in relation to jobs, skills inference and recommendations, CV summarising, salary recommendations, parsing and analysis of resumes, information extraction, intelligence around talent pools and the human capital ecosystem at large.

# Deep learning models



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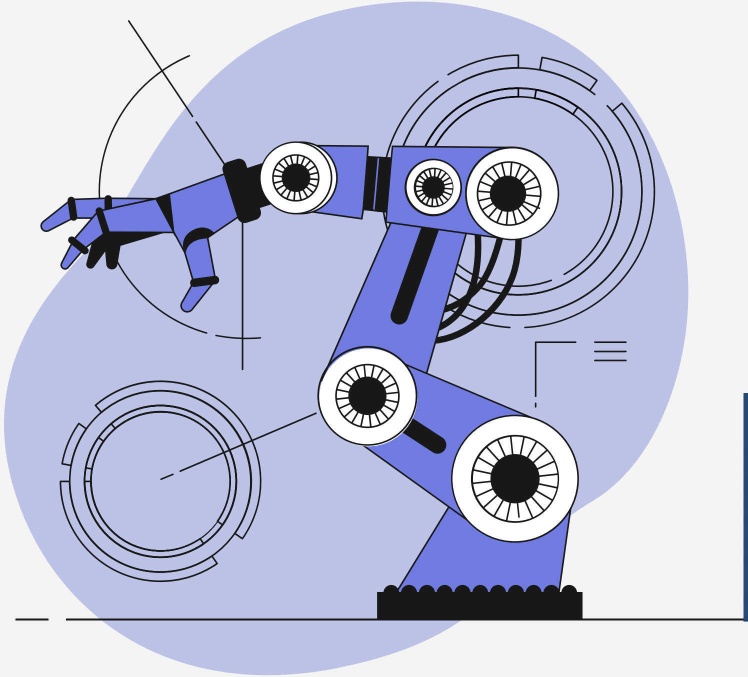
# About iCIMS

Enterprise hiring platform trusted by the largest global brands



| | | |
|---|---|---|
| 570M+<br>candidate profiles | 25%<br>of the Fortune 500 use iCIMS | 282%<br>average potential ROI |
| 3M+<br>global platform users | 800<br>partners in the iCIMS ecosystem | 5.5M+<br>hires last year |

# iCIMS Talent Cloud AI – Built From Dublin

## iCIMS TALENT CLOUD AI

| ATTRACT & ENGAGE | HIRE | ADVANCE |
|---|---|---|
| Personalize & streamline the candidate experience at scale | Automate recruiting workflows with confidence | Accelerate internal mobility & growth |

**AI/ML-Powered Experiences**

| ATTRACT & ENGAGE | HIRE | ADVANCE |
|---|---|---|
| • AI Chatbot<br>• Job Matching<br>• Job Search<br>• Job Recommendation | • Candidate Ranking<br>• Talent Discovery<br>• Talent Match | • Employee Skills Profile<br>• Career Pathing |

**Platform Meta data**

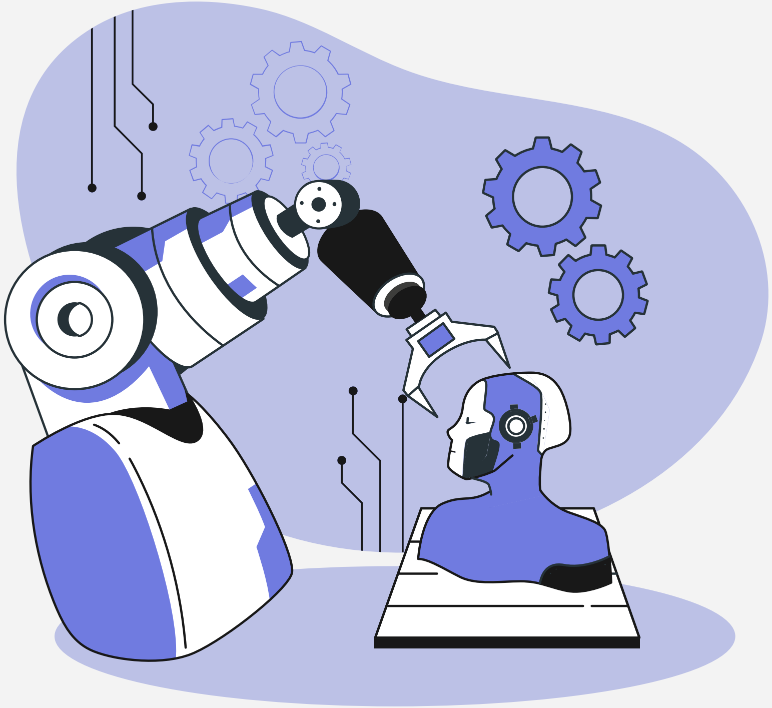
Job Titles taxonomy | Skills Cloud | Skills to Jobs baseline

**NEW Generative AI Experiences**

Interview Question Guide | Job Description Optimization | Career Path Navigator

# We Built AI Responsibly

- Accountability
- Bias and Fairness
- Data Quality
- Robustness
- Explainability
- Privacy and Security

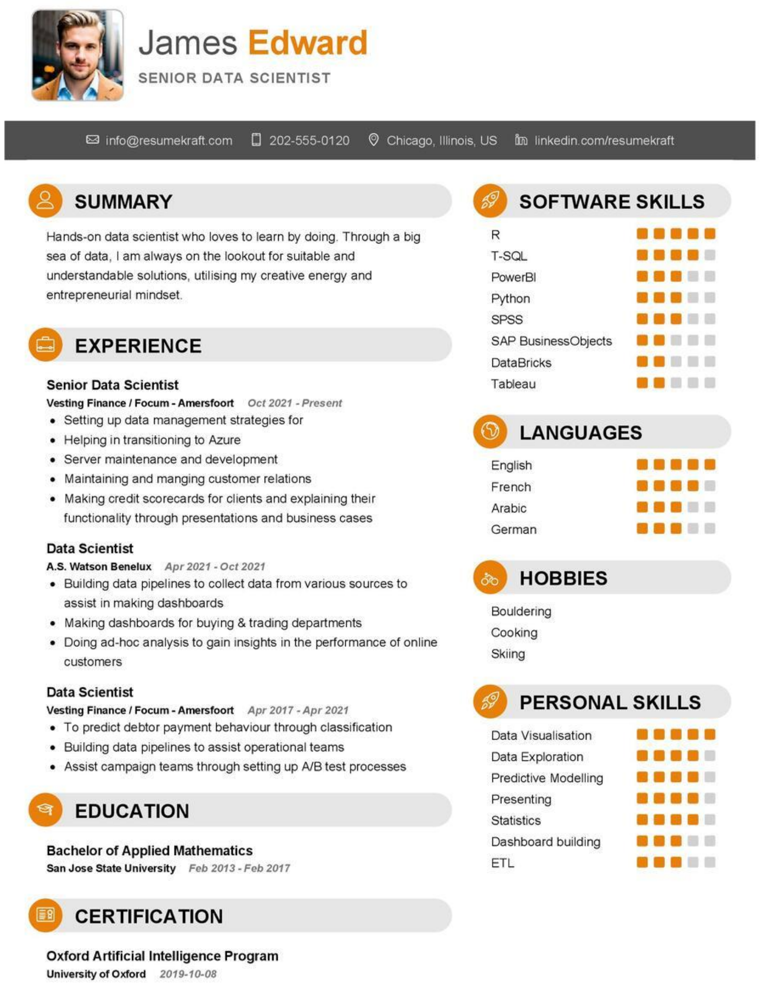


# Lessons Learned (or unknown unknowns)

# 1. Data is the Bedrock

- Proprietary, compounding data = defensibility.
- If you don’t own/enrich data, you’re building on rented ground.

- ***What I learned:*** *In my own company, every feature was also a data-collection engine (or an explainability feature). After the acquisition, I saw how global enterprises prioritise data ecosystems as the backbone of their AI roadmaps. Build for this from the start.*


James Edward
SENIOR DATA SCIENTIST

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**SUMMARY**

Hands-on data scientist who loves to learn by doing. Through a big sea of data, I am always on the lookout for suitable and understandable solutions, utilising my creative energy and entrepreneurial mindset.

**EXPERIENCE**

**Senior Data Scientist**
Vesting Finance / Focum - Amersfoort *Oct 2021 - Present*
- Setting up data management strategies for
- Helping in transitioning to Azure
- Server maintenance and development
- Maintaining and manging customer relations
- Making credit scorecards for clients and explaining their functionality through presentations and business cases

**Data Scientist**
A.S. Watson Benelux *Apr 2021 - Oct 2021*
- Building data pipelines to collect data from various sources to assist in making dashboards
- Making dashboards for buying & trading departments
- Doing ad-hoc analysis to gain insights in the performance of online customers

**Data Scientist**
Vesting Finance / Focum - Amersfoort *Apr 2017 - Apr 2021*
- To predict debtor payment behaviour through classification
- Building data pipelines to assist operational teams
- Assist campaign teams through setting up A/B test processes

**EDUCATION**

**Bachelor of Applied Mathematics**
San Jose State University *Feb 2013 - Feb 2017*

**CERTIFICATION**

**Oxford Artificial Intelligence Program**
University of Oxford *2019-10-08*

**SOFTWARE SKILLS**

R
T-SQL
PowerBI
Python
SPSS
SAP BusinessObjects
DataBricks
Tableau

**LANGUAGES**

English
French
Arabic
German

**HOBBIES**

Bouldering
Cooking
Skiing

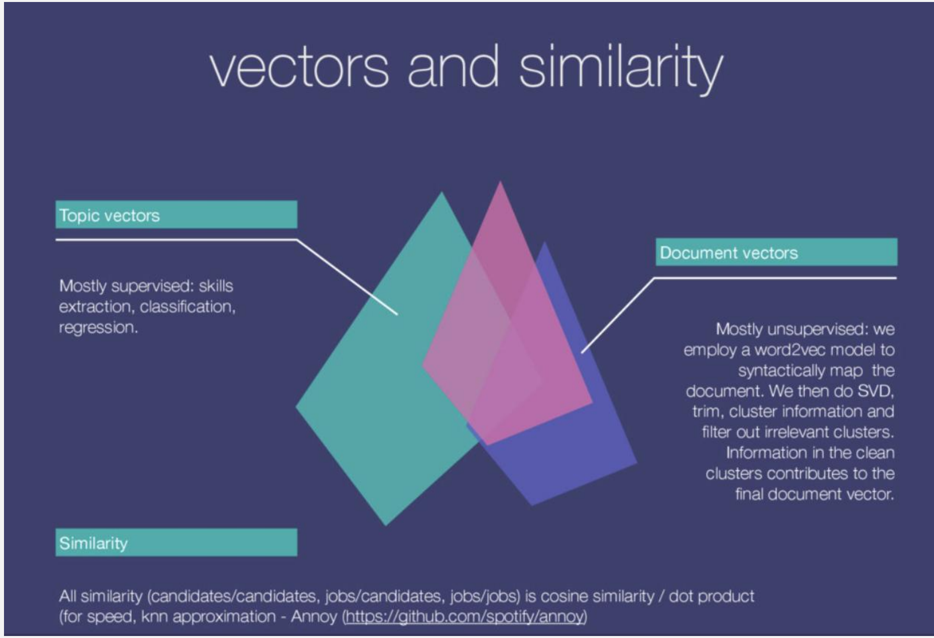
**PERSONAL SKILLS**

Data Visualisation
Data Exploration
Predictive Modelling
Presenting
Statistics
Dashboard building
ETL

# 2. Scaling isn't a "later" problem

- Latency, infra cost, model drift hit sooner than you think.
- First enterprise deal = scale test, not revenue win.

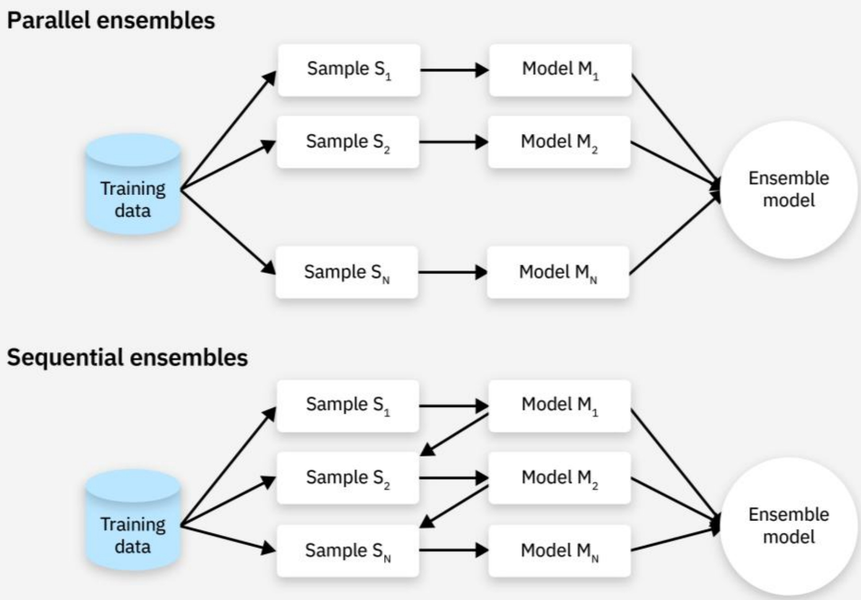
- ***My advice:*** *Don't assume you'll figure out scalability "later." Design for scale early, whether that's custom infra for unique needs (like we did with vector search) or careful orchestration across cloud and edge. These decisions shape how your product performs, and whether it can survive real-world demands.*



# 3. It's never just one model

- You'll run fleets (LLM + classifiers + retrieval).
- Build modularity, swap in/out as tech shifts.

- ***For builders**: Think modular, not monolithic. Build a stack where you can swap models in and out as better ones emerge, or as your use cases evolve.*



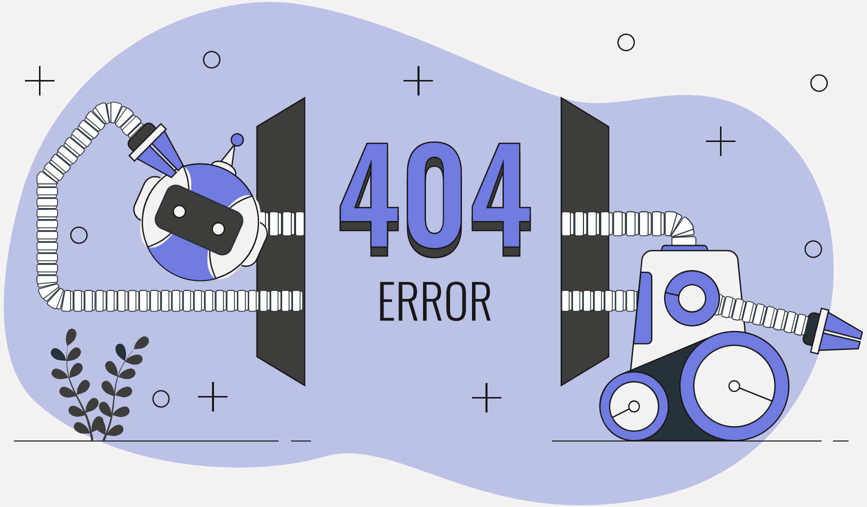
# GEN AI Considerations

## Avoid

- Use cases with notable regulatory impact or oversight requirements
- Applications with no ability to interject human review
- Use cases where accuracy is critical

## Consider

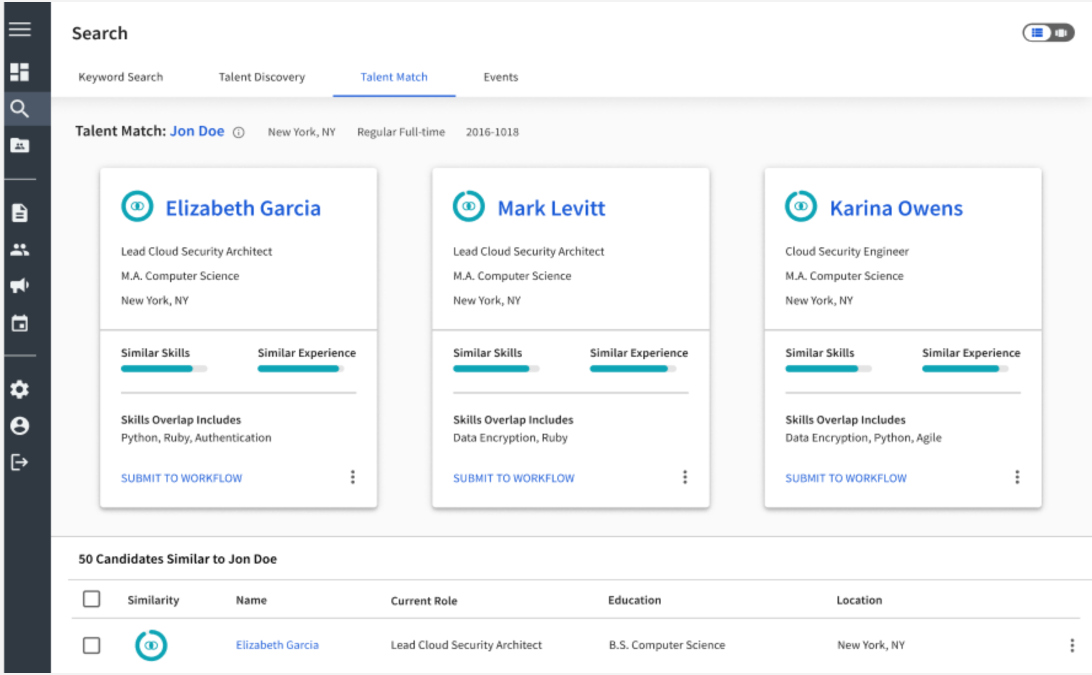
- Productivity tasks
- Use cases involving Text analysis, summarization, or generation
- Information discovery or knowledge mining
- Human in the loop scenarios



# 4. AI/ Agentic UX is its own ballgame

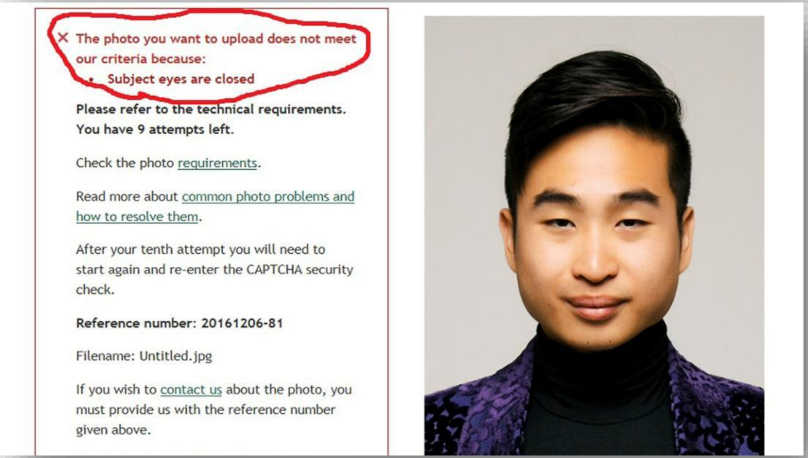
- Trust > features
- Users need control, overrides, explainability
- Bad UX kills good models

- ***My advice:*** *Work with great UX designers early. Build experiences that let users stay in control, even as AI takes on more of the heavy lifting.*



# 5. Responsible AI isn't optional

- Bias, governance, data lineage = table stakes
- Customers + regulators demand it
- "Ethics" is a sales unlock, not a PR move

# Research: Bias Experiments

- Gender: We have taken a set of gendered title pairs (e.g. actor/actress, salesman/saleswoman) and a set of query titles (3 titles associated with seniority - manager, leader, expert, 2 titles associated with gender -man, woman). For each query title and gendered title pair we generated a **'male favorability' score.** This can be interpreted as **'according to our model by how much is the male title preferred to the female title for a given query title?'.**

- Ethnicity: A second experiment was based on the hypothesis that **the origin of a candidate's name or gender specificity of a name can unintentionally influence the matching score**. We knew that it was not the case for our system, and with this experiment we wanted to show it in a clear way using methods available to our customers.

- Gender: In our 3rd experiment we identified pairs of words that defined gender subspaces for the embeddings, such as he-she, or male-female. Next, we determined if our embeddings are biased against one of the genders. **An example of bias would be a case where all the senior roles go to male candidates.**

- Ethnicity: In our 4th experiment we created ethnic subspaces to determine if our embeddings have a bias against a specific ethnicity. An example of ethnic bias would be **a case where all senior and managerial roles go to White candidates, and manual jobs go to Hispanic candidates.**

‘Some people worry that artificial intelligence will make us feel inferior, but then, anybody in their right mind should have an inferiority complex every time they look at a flower’.

**—Sybil Sage, comedy writer.**

# Thanks!

## Do you have any questions?

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