

Applied Researchers of Colcrane



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Colcrane's applied researchers specialise in advanced customer analytics and behavioural science, with deep expertise in predictive customer base and behavioural modelling.



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***Mastering Customer Value:
Predicting what Lasts,
Deciding & Acting on What
Matters***

Intuition



Customer



Email



AI Model



Decision



Future

2026 2027 2028 2029 2030 2031 2032 2033 2034

Intuition



2026 2027 2028 2029 2030 2031 2032 2033 2034



**HOW MANY DIFFERENT
PEOPLE WILL CLEO INTERACT
WITH DURING HER LIFETIME?**



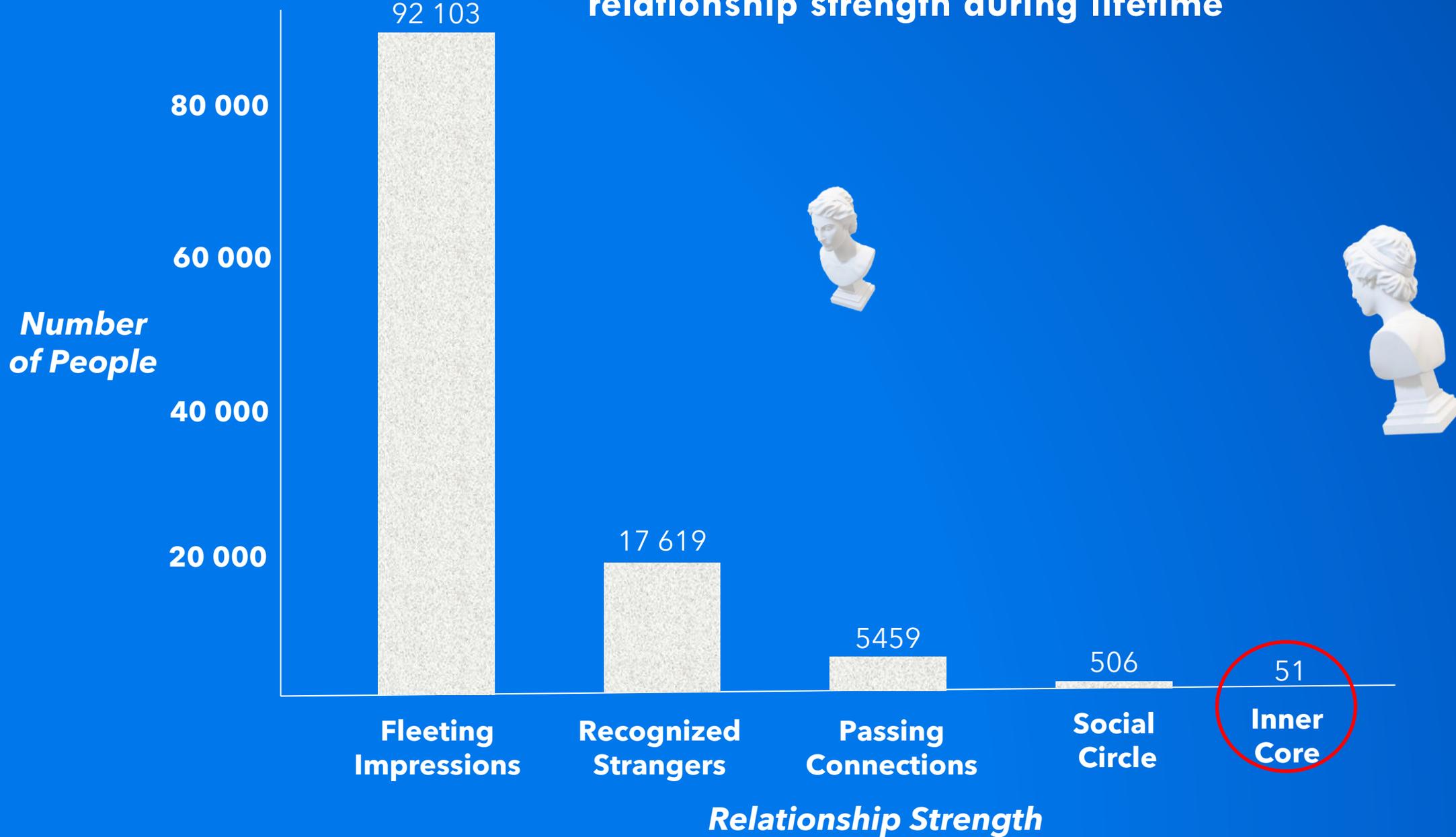
**HOW STRONG WILL HER
RELATIONSHIP BE WITH
THESE PEOPLE?**



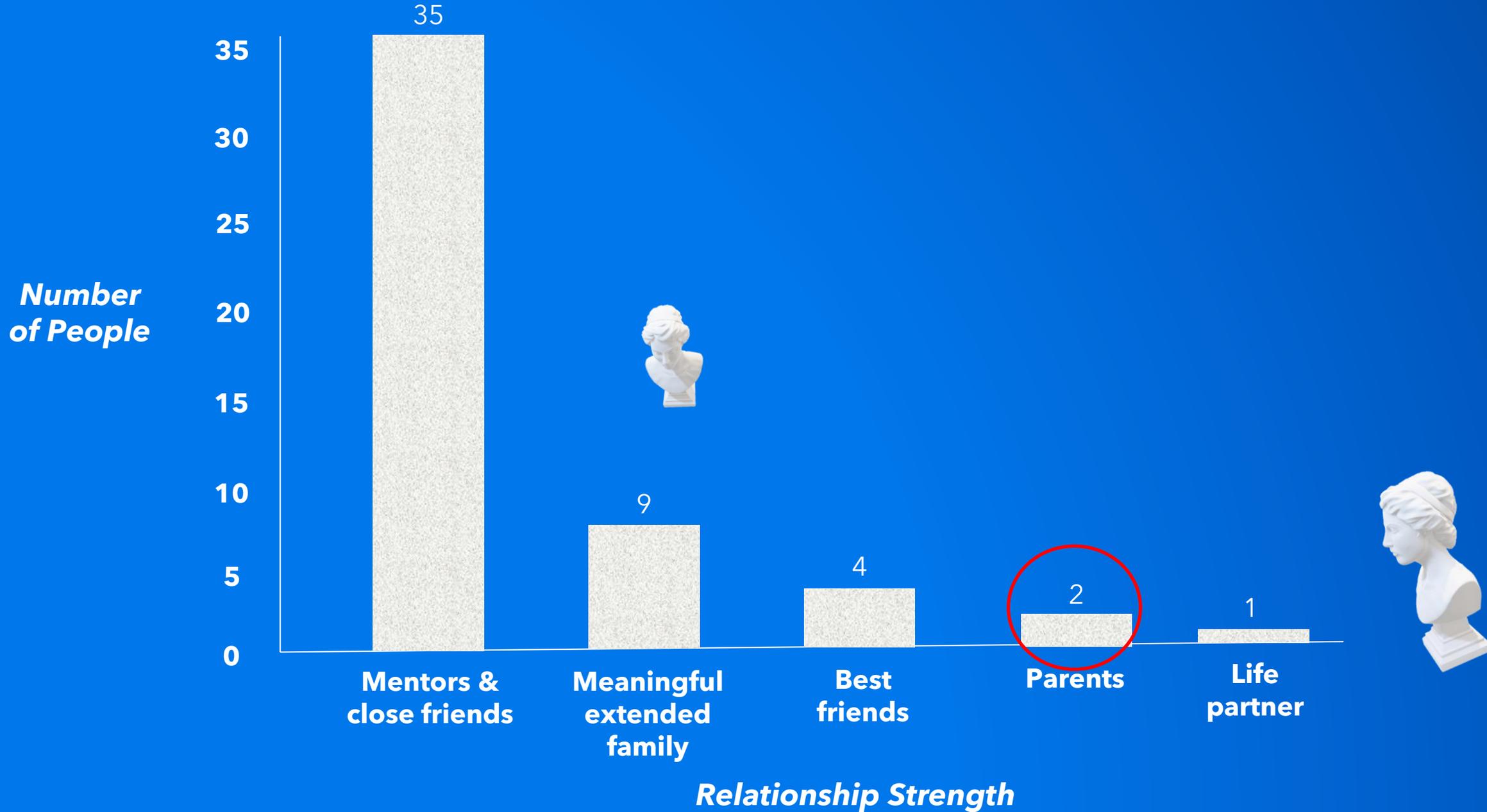
1 1 5 7 3 9



Number of people Cleo will interact with and relationship strength during lifetime



Cleo's "Inner Core"

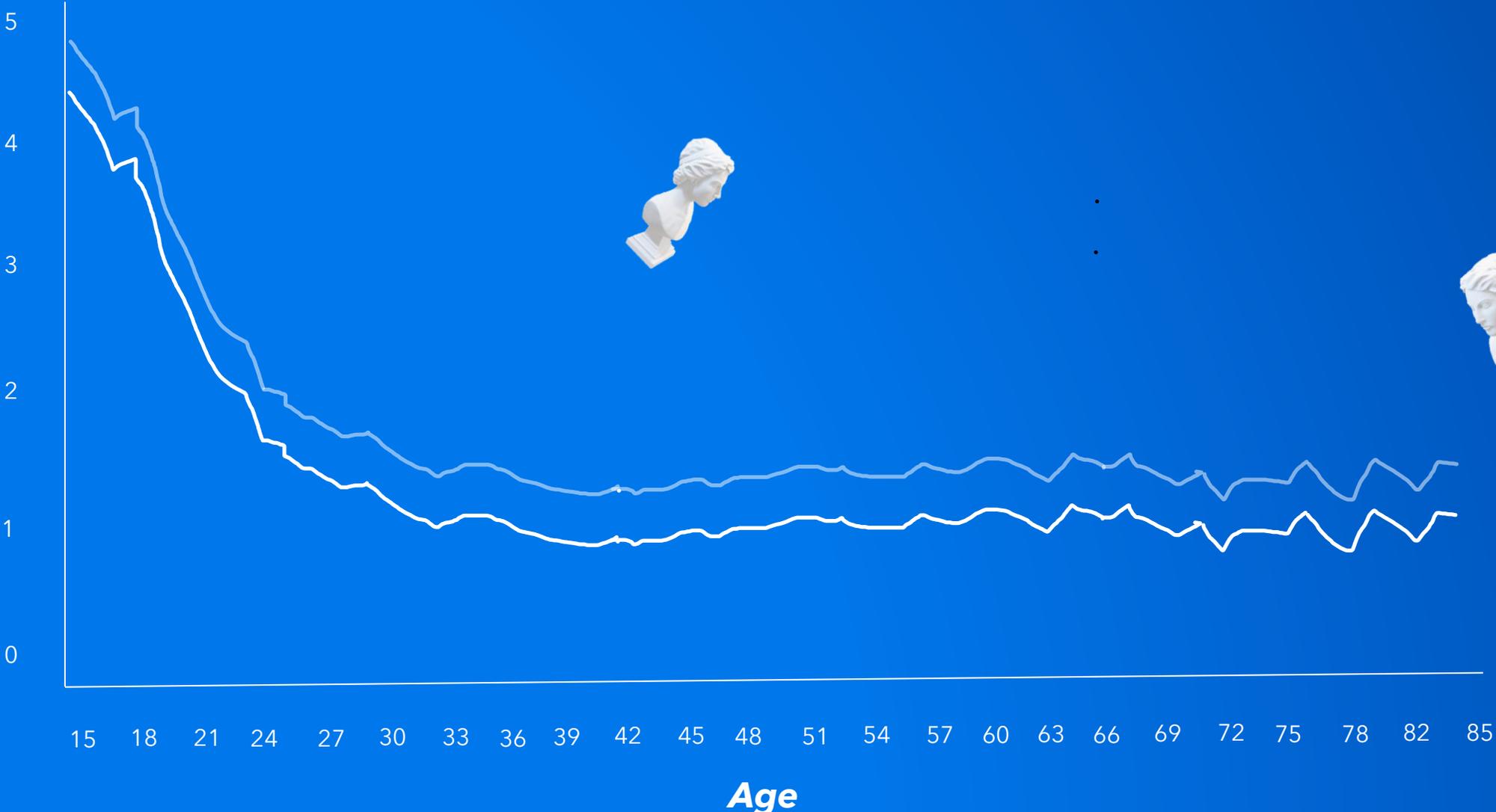


The time Cleo will spend with me during her lifetime

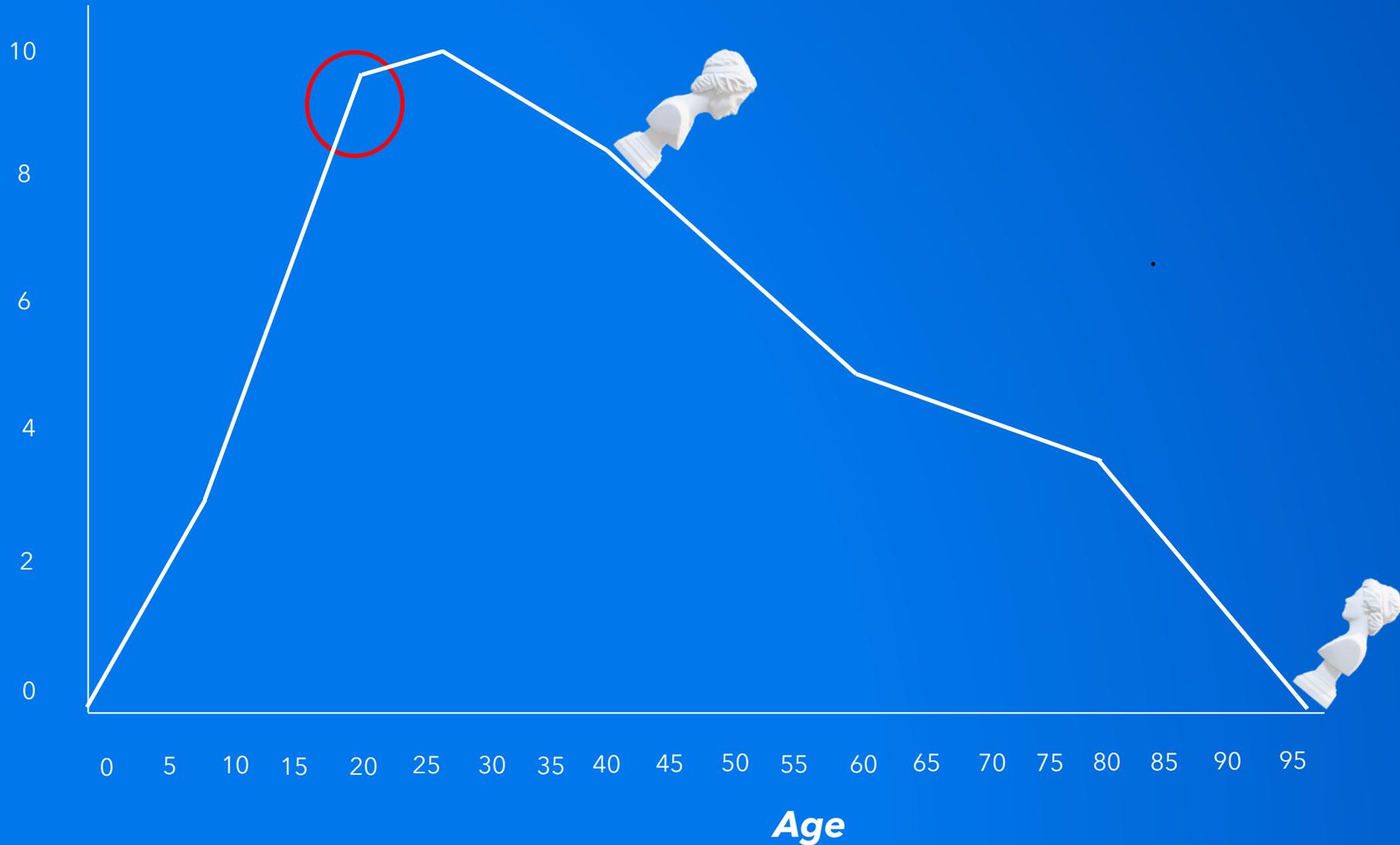


The time Cleo will spend with me during her lifetime

**Average
Hours
spent per
day**



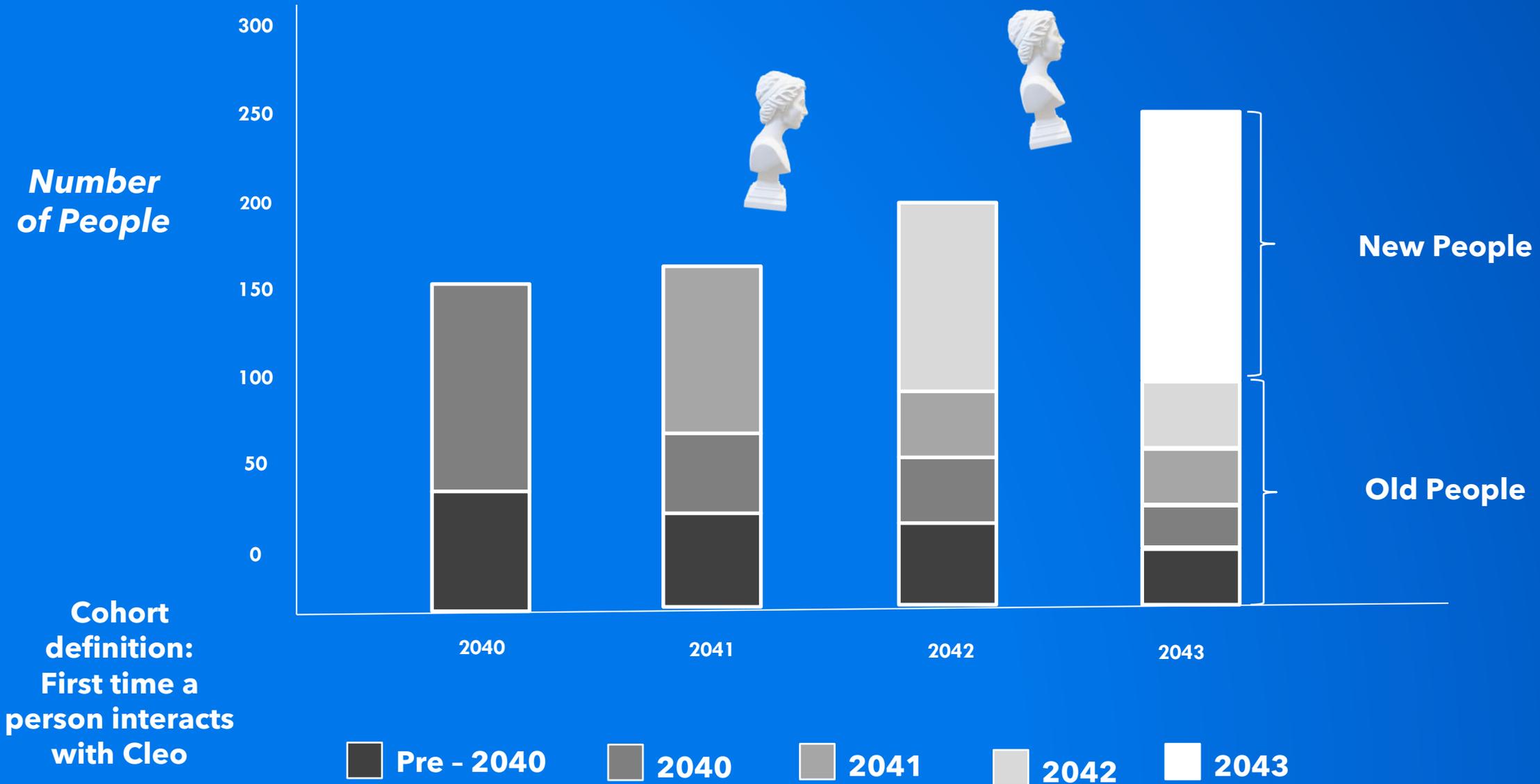
Pace of new people interaction over Cleo's lifetime



Pace of new interactions (1-10 scale)

Age

Cleo's people interaction during her (potential) higher education



A person that Cleo interacts with during her lifetime



Invisible " coin" that either leans towards best friend or passing connection.

Elliot



Best Friend



Passing Connection

Molly



Best Friend



Passing Connection

AI Model



2026 2027 2028 2029 2030 2031 2032 2033 2034

General Generative Statistical Models for Predictive Customer Analytics



Peter Fader
Professor of Marketing
Wharton School of Business



Daniel McCarthy
Associate Professor of Marketing
Maryland University



Bruce Hardie
Professor of Marketing
London Business School



After the gym, I had a _____

Shower
90%

Meal
7%

Walk
3%

Probability:



I hadn't eaten all day, so after the gym I went for a _____



Shower
12%



Meal
83%



Walk
5%

Probability:

Will the customer purchase or not?



Yes
2022

No
2023

No
2024

?
2025

?
2026

?
2027

Will this customer have a
yes or no coin?



No
75%

Yes
35%

Probability:



Yes
2022

No
2023

No
2024

No 75% Yes 25%
2025

No 84% Yes 16%
2026

No 95% Yes 5%
2027



Yes
2022

No
2023

Yes
2024

No 77%
Yes 23%
2025

No 35%
Yes 65%
2026

No 54%
Yes 46%
2027

Sophisticated model mathematics but no black box

$$L(r, \alpha, s, \beta \mid x, tx, T) = \frac{\Gamma(r+x)\alpha^r\beta^s}{\Gamma(r)} \left\{ \frac{1}{(\alpha+T)^{r+x}(\beta+T)^s} + \left(\frac{s}{r+s+x} \right) A_0 \right\}$$

where for $\alpha \geq \beta$

$$A_0 = \frac{F_1(r+s+x, s+1; r+s+x+1; \frac{\alpha-\beta}{\alpha+tx})}{(\alpha+tx)^{r+s+x}} - \frac{F_1(r+s+x, s+1; r+s+x+1; \frac{\alpha-\beta}{\alpha+T})}{(\alpha+T)^{r+s+x}}$$

where for $\alpha \leq \beta$

$$A_0 = \frac{F_1(r+s+x, s+1; r+s+x+1; \frac{\beta-\alpha}{\beta+tx})}{(\beta+tx)^{r+s+x}} - \frac{F_1(r+s+x, s+1; r+s+x+1; \frac{\beta-\alpha}{\beta+T})}{(\beta+T)^{r+s+x}}$$



The data we need

Customer transaction data

Customer_ID	Purchase_date	Sales/Contribution margin
0001	22/10/01	£22
0001	22/11/01	£554
0002	22/10/01	£309
0003	22/11/01	£46
0004	22/10/01	£104



Test drive: Travel



- For illustrative purposes we focus on the **2022 customer cohort**
- A customer cohort is defined here based on the time-period when the customer made their **first purchase** ever
- There are **76 493** customers who made their first purchase in 2022
- Born during **Covid** so not the best one
- **But it gives us just enough years** to work with → even **more difficult** to predict due to potential behavioural irregularities!



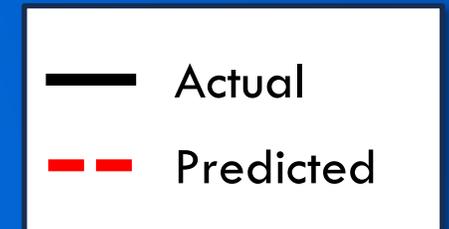
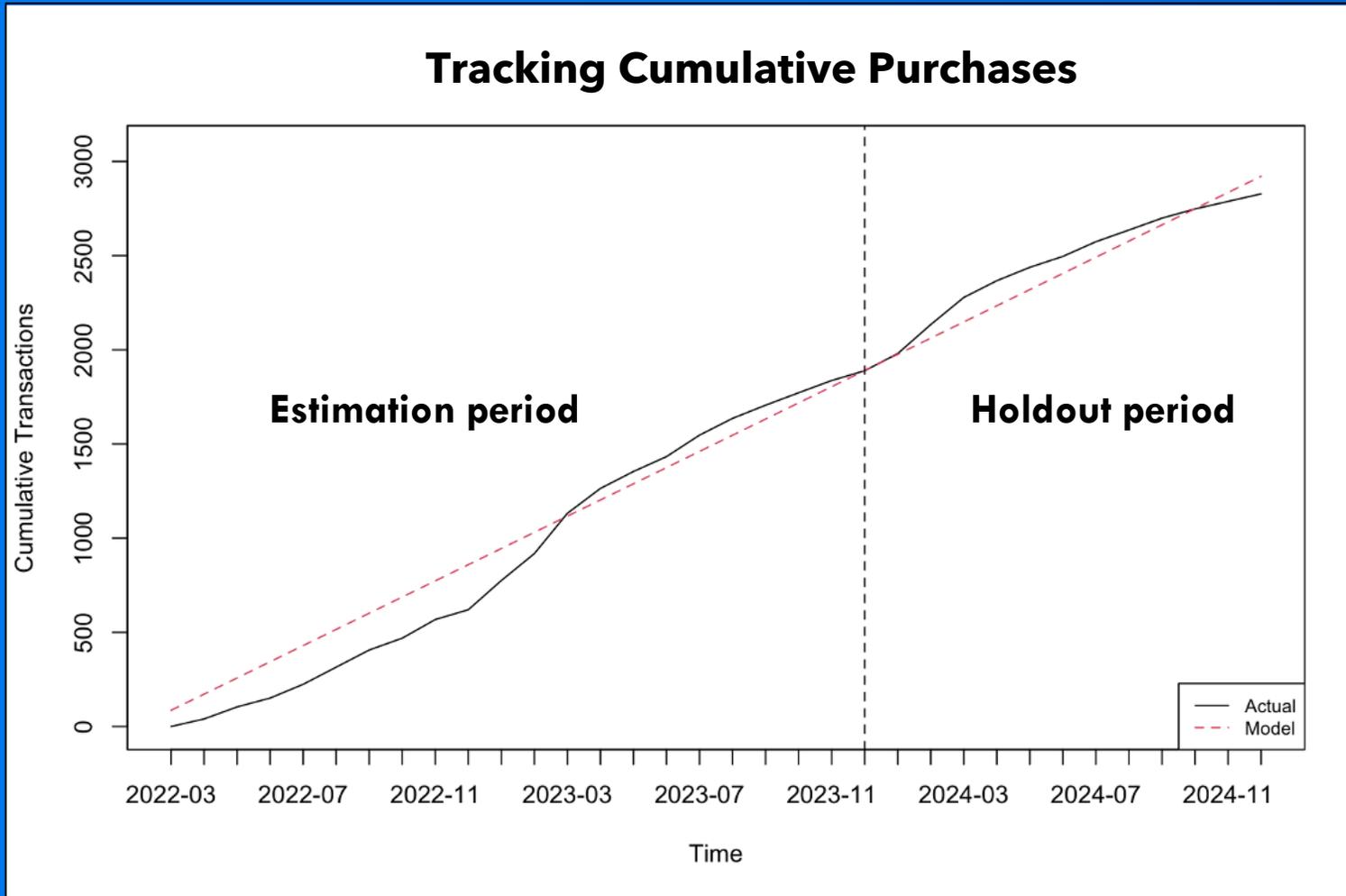
Purchase Behavior of the 2022 Customer Cohort

2022	2023	2024	Customers	Customers %
Y	Y	Y	4244	6%
Y	Y	N	8073	11%
Y	N	Y	5704	7%
Y	N	N	58472	76%

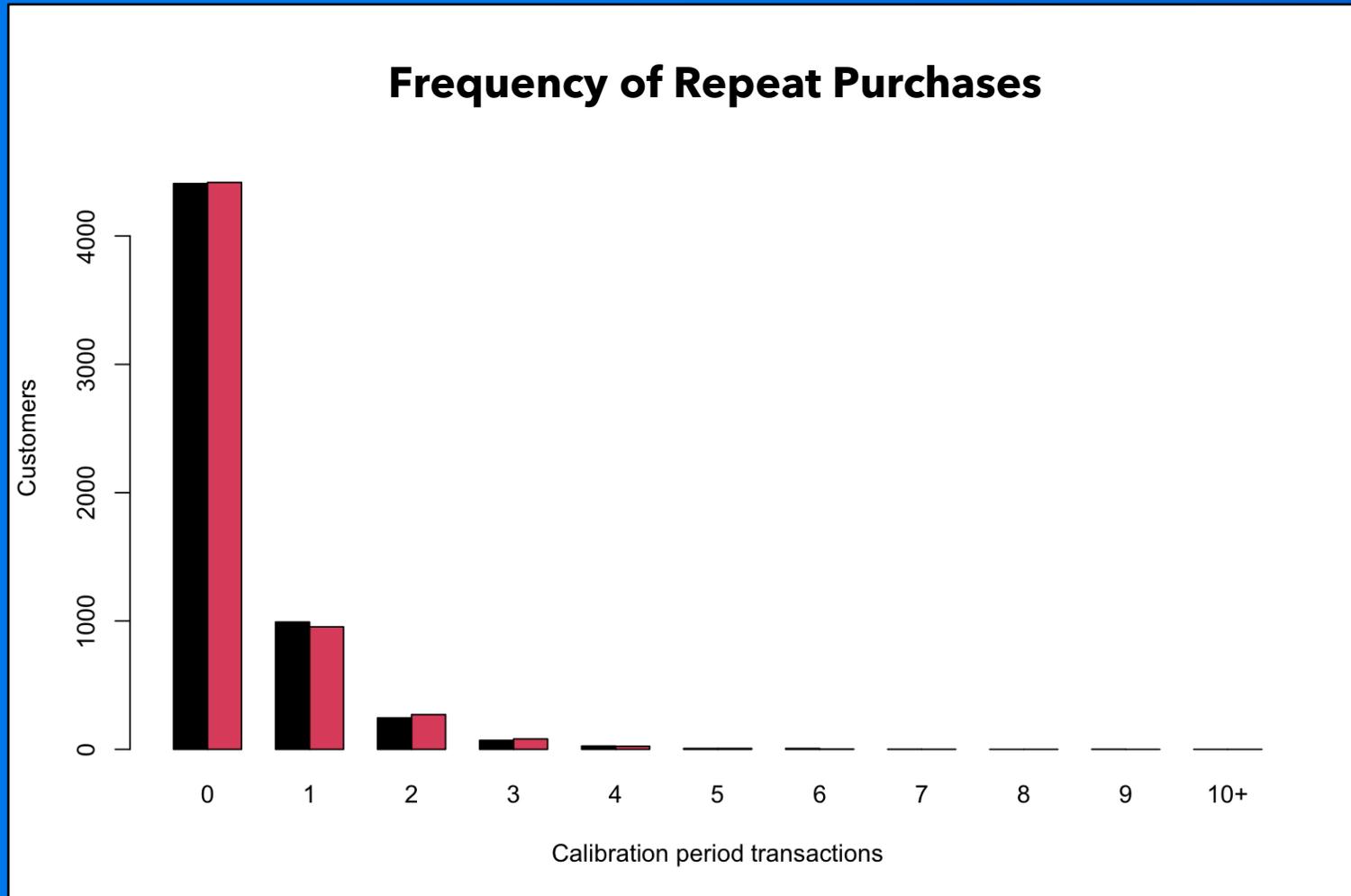
Y = Purchase

N = No Purchase

Model validation – How well can the model predict? (2022 cohort)



Model validation - How well can the model predict? (2022 cohort)



Test drive: Online retail



Purchase Behavior of the (Feb) 2022 Customer Cohort

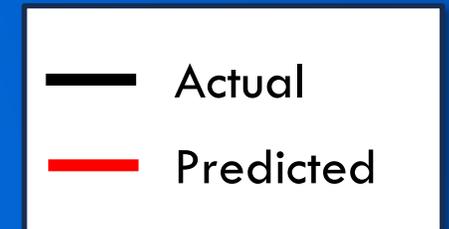
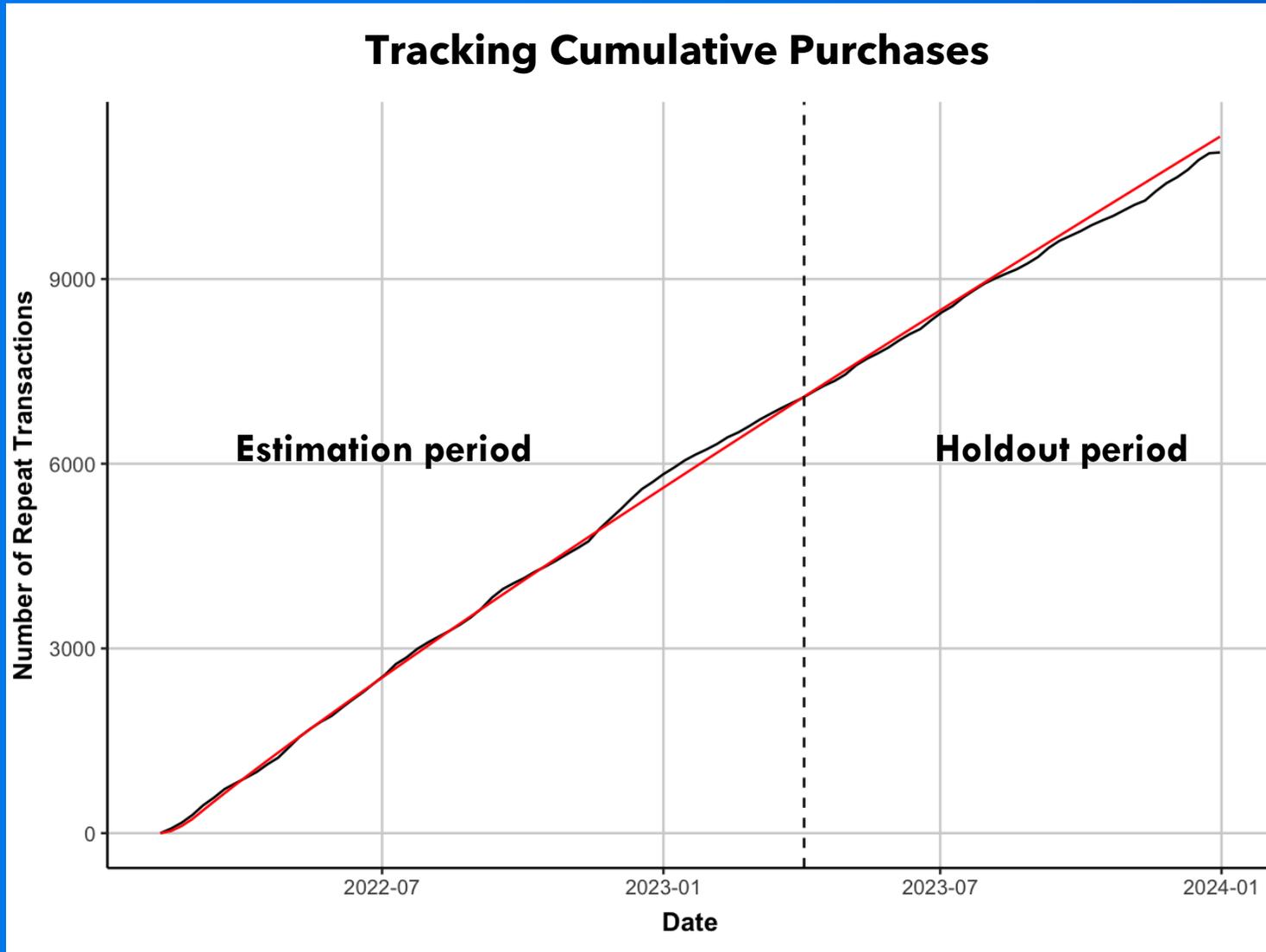


2022 (H1)	2022 (H2)	2023 (H1)	2023 (H2)	Customers	Customers %
Y	Y	Y	Y	567	8%
Y	Y	Y	N	353	5%
Y	Y	N	Y	355	5%
Y	Y	N	N	709	9%
Y	N	Y	Y	226	3%
Y	N	Y	N	493	7%
Y	N	N	Y	522	7%
Y	N	N	N	4255	57%

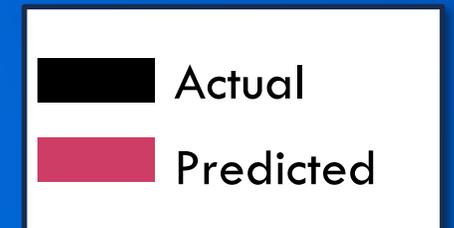
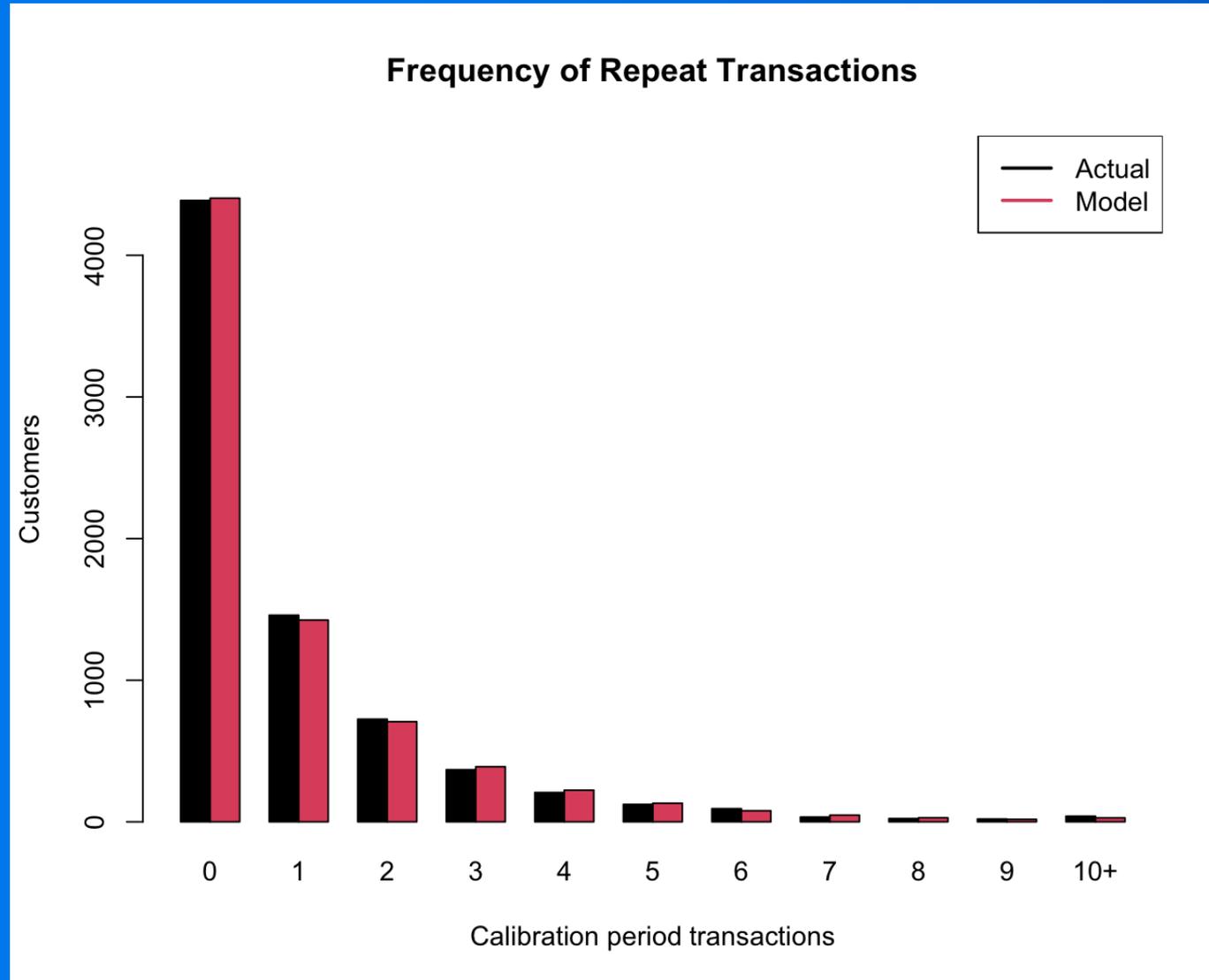
Y = Purchase

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Model validation – How well can the model predict? (2022 cohort)



Model validation - How well can the model predict? (2022 cohort)



Email



2026 2027 2028 2029 2030 2031 2032 2033 2034

**Who should we nudge
with emails to drive
value?**



Four repeat purchase readiness tiers

High readiness = **Partners**

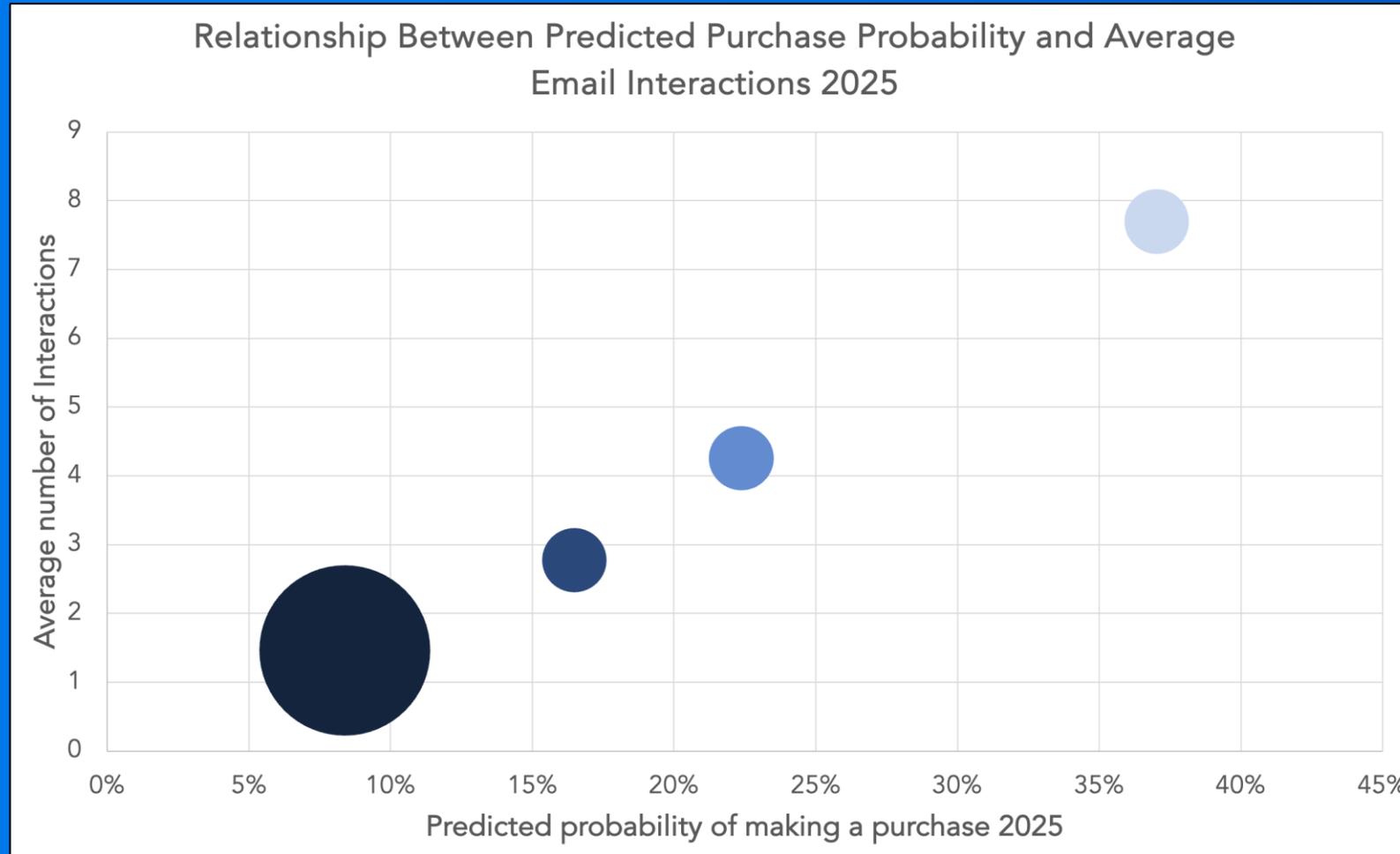
Medium-High readiness = **Friends**

Medium readiness = **Acquaintances**

Low readiness = **Strangers**



Travel: Relationship between email engagement and purchase probability in 2025 (2022 cohort)



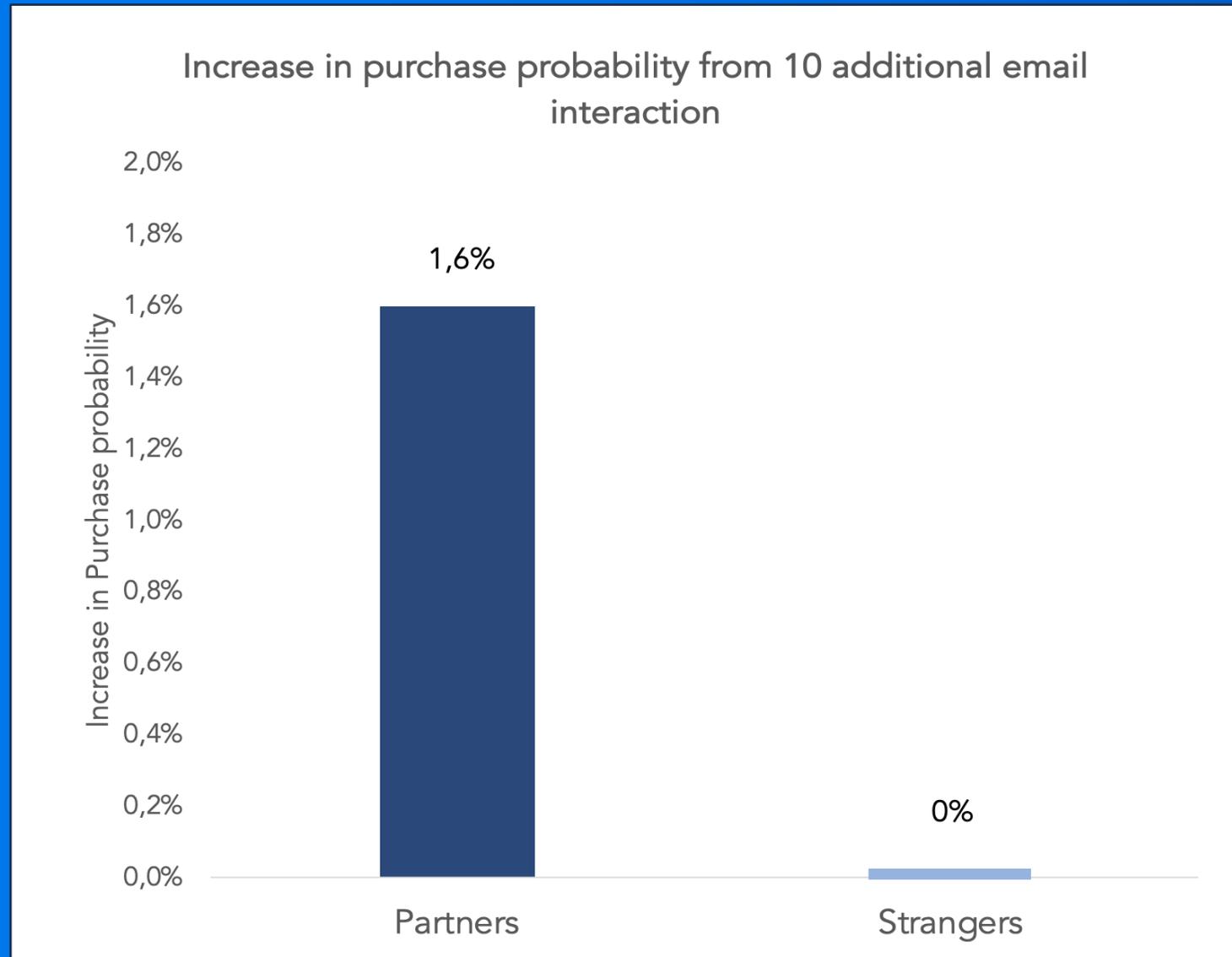
Strangers

Acquaintances

Friends

Partners

Difference in the effect of email engagement on purchase probability between Partners and Strangers



Partners respond

Increasing email engagement by 10 interactions lifts purchase probability by **1.6 points among Partners**

At cohort scale, that's **around 120 extra purchases.**

Using a typical UK travel order value of about **£1,700**, that's **roughly £200k in incremental revenue** - or **about 3-4% more value from that 2022 cohort alone.**

Scaled across all cohorts that is some **real value gain**



Most customers don't respond to better email.

The right customers can respond massively - and that's where the value often is.



**What if online retail email
campaigns were more profit-
centred?**

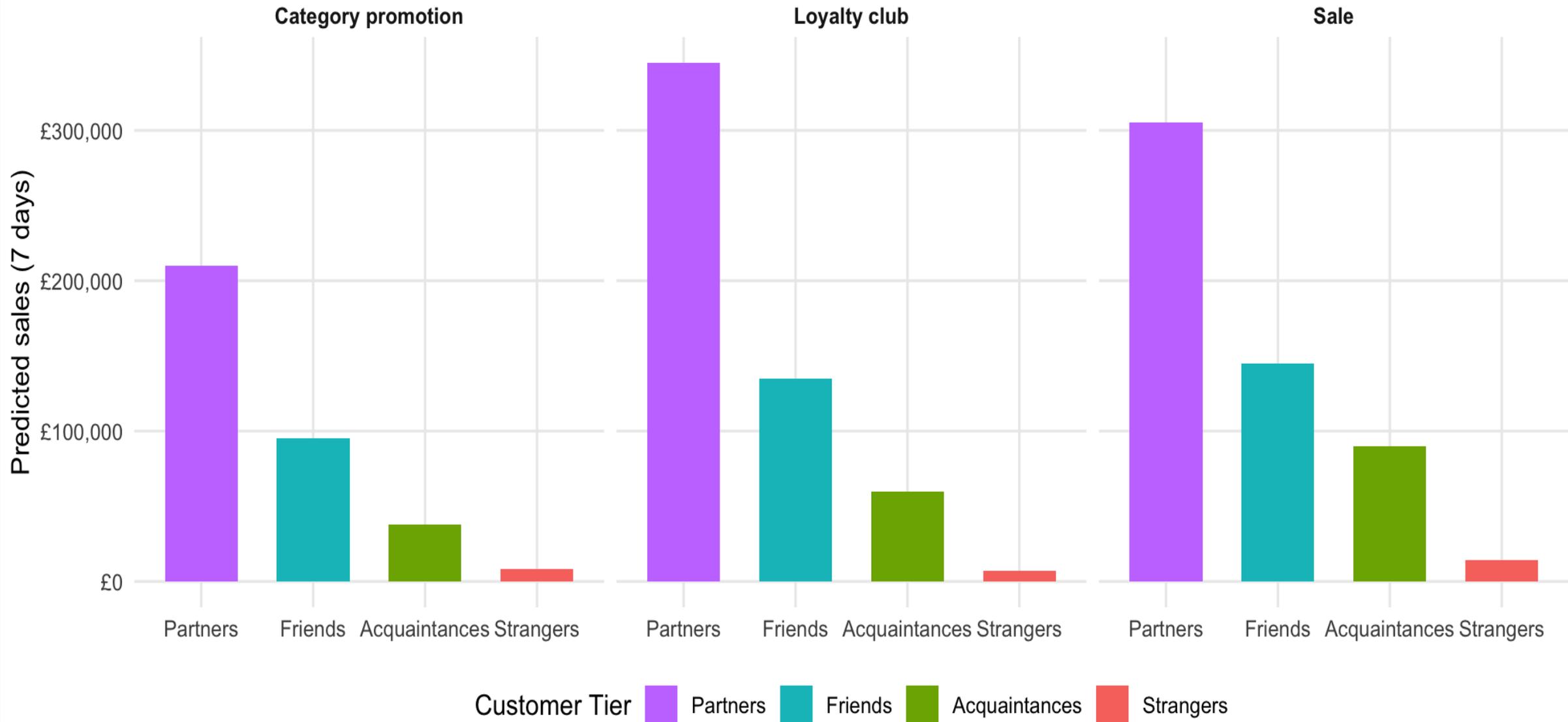


Three common email campaign types

- Category promotion
- Loyalty club
- Sale



predicted sales over 7 days by campaign and relationship tier

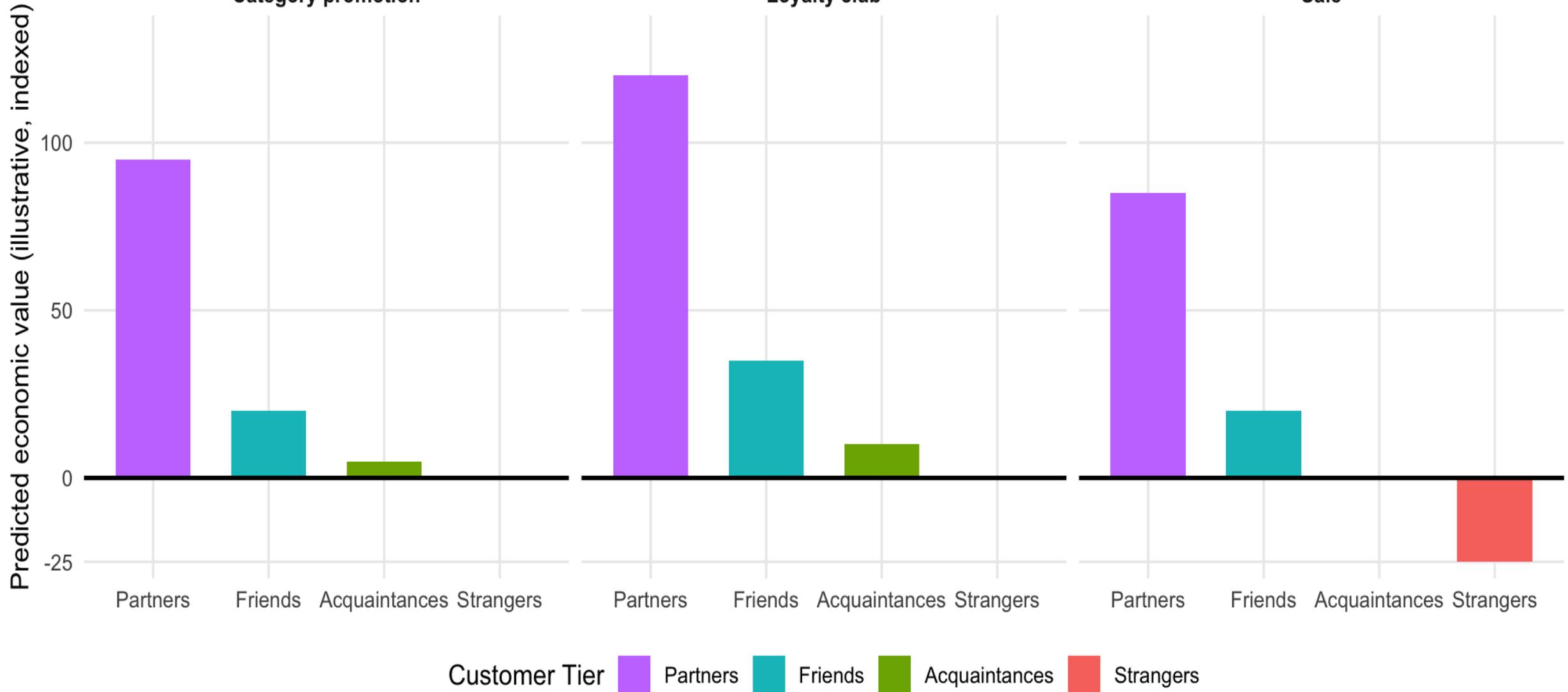


Illustrative predicted economic value by campaign and relationship tier (indexed)

Category promotion

Loyalty club

Sale



**What this could look like to
users of your CRM or CDP**



Customer name: Laura Greenwood



Customer value

Individual-level predicted CLV: 3 years

Value tier (derived): Partner, Friend, Acquaintance, Stranger

Demand

Purchase likelihood 3 / 6 / 12 months: 0-100 %

Purchase readiness score: 0-100

Purchase readiness state: Cold/Warm/Hot

Channel

Email interaction score: 0-100

Email interaction state: Cold/**Warm**/Hot

Email interaction state transition probability:

- Warm ➡ Hot 0-100 %
- Warm ➡ Cold 0-100 %

Customer



Decision



Future



2026 2027 2028 2029 2030 2031 2032 2033 2034

Decision-Driven Analytics

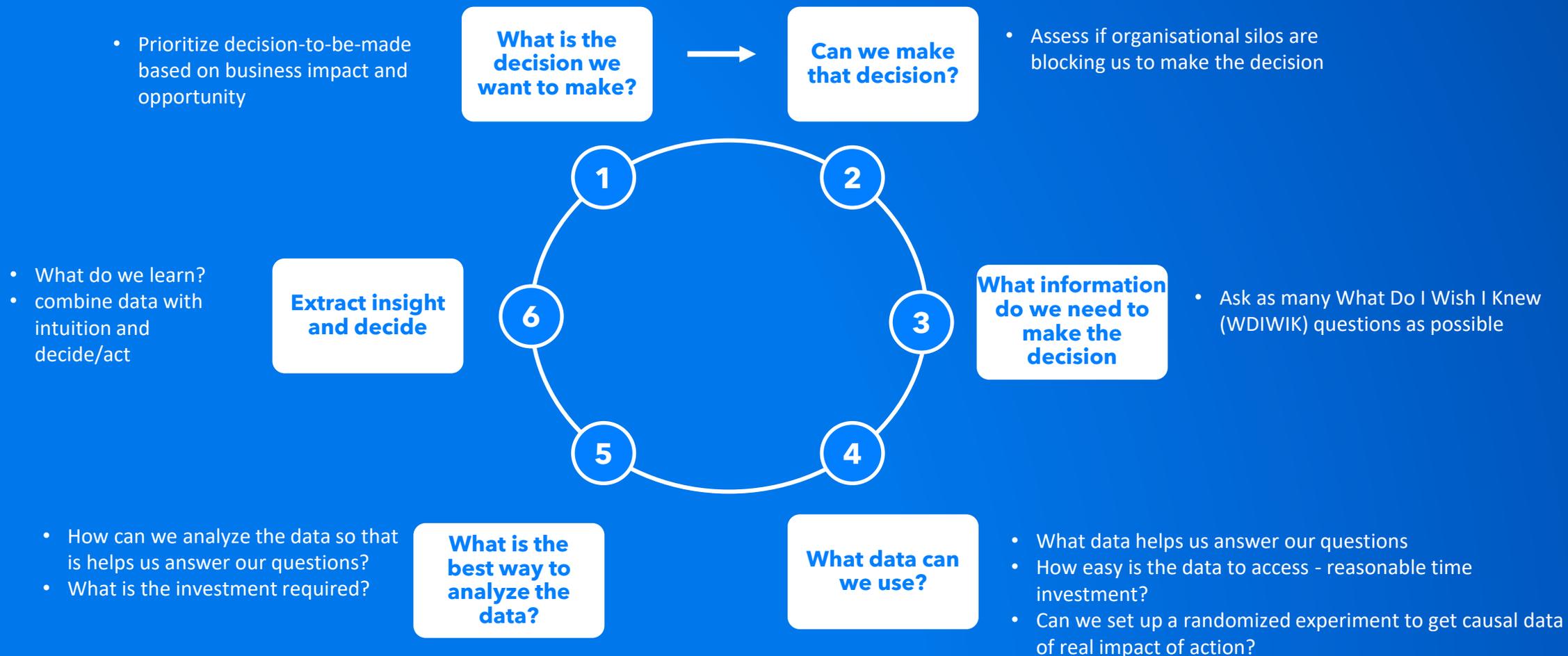


“The Diver”

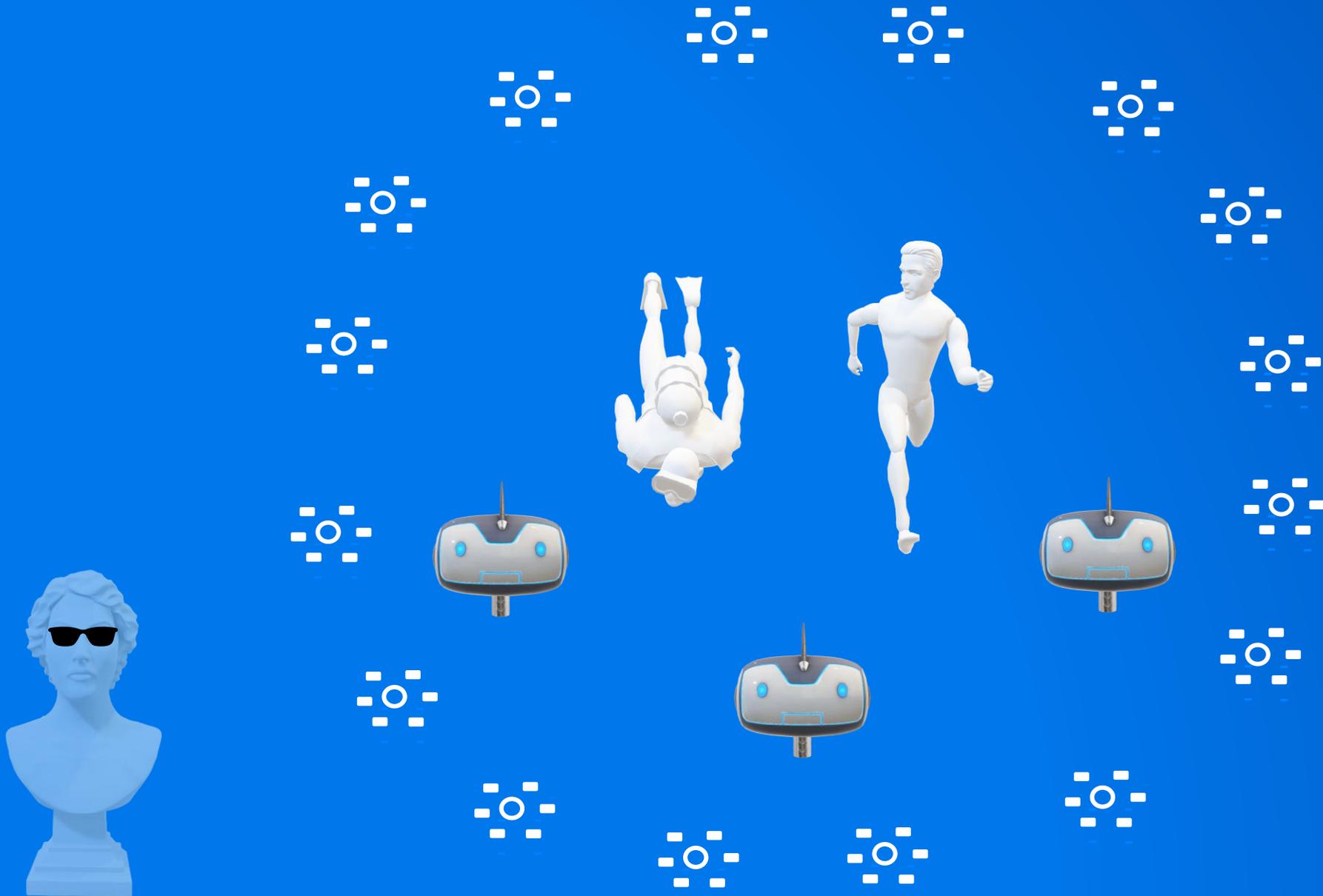
“The Runner”



The Decision-Driven Analytics Cycle



Decision-Drive Potential with Productive AI Agent Collaboration



Garbage in garbage out!

Human + AI Agent need robust future gazing customer signals to base their automated actions on!

