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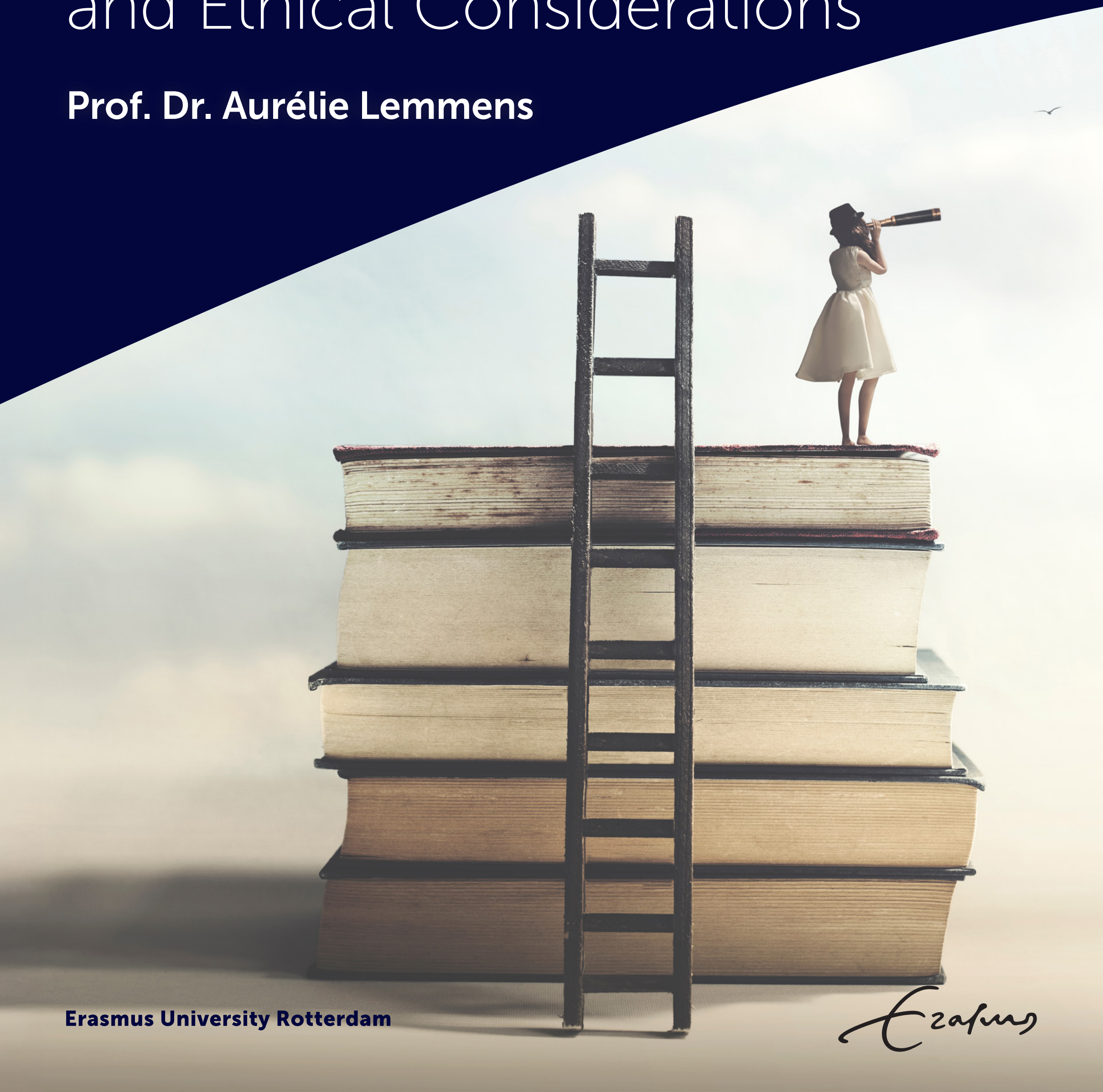
Who Gets the Offer?

Economic Objectives, Methodological Challenges and Ethical Considerations

Prof. Dr. Aurélie Lemmens



Erasmus University Rotterdam

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Prof. Dr. Aurélie Lemmens

Address delivered at the occasion of accepting the appointment as Professor of Customer Analytics at the Rotterdam School of Management, Erasmus University Rotterdam on Friday, September 19, 2025.

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Erasmus University Rotterdam

Inaugural Lecture on Friday September 19, 2025. Prof. Dr. Aurélie Lemmens

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Economic Objectives, Methodological Challenges and Ethical Considerations

Abstract

Since its inception, the field of marketing has recognized a simple but powerful truth: not all customers are created equal. One of its main goals has been to uncover, understand, and celebrate customer heterogeneity in meaningful ways. Early research focused on identifying segments of consumers who responded differently to products, prices, or promotions. Over time, segmentation evolved into personalization, powered by increasingly rich individual-level data and the rise of machine learning.

These methods have enabled firms to predict the future with remarkable accuracy—but prediction, as this lecture will argue, is not enough. Prediction models estimate what is likely to happen, yet marketing decisions, such as “Who Gets the Offer?”, require understanding what would happen under alternative actions. Effective decision-making demands counterfactual reasoning. The lecture will trace the field’s ongoing shift toward causal machine learning: methods that estimate how individuals respond to specific interventions.

However, even causal models may fall short if their objectives are misaligned with those of the organization. Standard algorithms often treat all customers equally, failing to distinguish between cases where the stakes are high or low. The lecture will present approaches to better align data, models, and business priorities—whether through profit-based loss functions or smarter experimentation strategies.

The final step in this evolution addresses a deeper challenge: ensuring that algorithmic decisions are not only effective, but also fair. As automated systems increasingly shape access to services, opportunities, and outcomes, concerns about bias and disparate impact are growing. Drawing on recent advances in fairness-aware causal decision-making, the lecture will outline how targeting systems can be made both efficient and equitable.

Together, these developments mark a progression—from prediction to intervention, from optimization to responsibility. The lecture will conclude with a vision for algorithmic systems that support better decisions—not only for firms, but for society.

Wie krijgt het aanbod?
Over winst, wetenschap en wat eerlijk is.

Samenvatting

Sinds het ontstaan van het marketingvakgebied is één eenvoudige, maar krachtige waarheid erkend: niet alle klanten zijn gelijk. Een belangrijk doel van marketing is dan ook altijd geweest om klantverschillen te ontdekken, te begrijpen en op een zinvolle manier te benutten. Waar vroege studies zich richtten op het identificeren van segmenten die verschillend reageerden op producten, prijzen of promoties, is segmentatie in de loop der tijd geëvolueerd naar personalisatie—mogelijk gemaakt door rijke data op individueel niveau en de opkomst van machine learning.

Deze methoden hebben bedrijven in staat gesteld om klantgedrag met opmerkelijke nauwkeurigheid te voorspellen. Maar zoals dit betoog zal laten zien: voorspellen alleen is niet genoeg. Voorspelmodellen geven antwoord op de vraag wat er waarschijnlijk zal gebeuren, terwijl marketingbeslissingen—zoals de vraag “Wie krijgt het aanbod?”—vragen om inzicht in wat er zou gebeuren onder verschillende beslissingen. Effectieve besluitvorming vereist dus tegenfeitelijk redeneren. Dit betoog schetst hoe het vakgebied steeds meer verschuift naar causale machine learning: methoden die inschatten wat het effect van een specifieke actie is op een individu.

Toch schieten ook causale modellen soms tekort als ze niet zijn afgestemd op de economische doelen van een organisatie. De meeste algoritmen behandelen alle klanten alsof ze even belangrijk zijn, en maken geen onderscheid tussen situaties met grote of kleine impact. In dit betoog worden benaderingen besproken om data, modellen en bedrijfsdoelen beter op elkaar af te stemmen—bijvoorbeeld via winstgebaseerde verliesfuncties of slimmere strategieën om te experimenteren.

De laatste stap in deze evolutie betreft een diepgaandere uitdaging: hoe zorgen we ervoor dat algoritmische beslissingen niet alleen effectief zijn, maar ook eerlijk? Nu geautomatiseerde systemen steeds vaker bepalen wie toegang krijgt tot informatie, diensten en kansen, groeit de bezorgdheid over bias en ongelijke uitkomsten. Op basis van recente inzichten in fairness-aware causal decision making laat dit betoog zien hoe targetingalgoritmes zowel efficiënt als rechtvaardig kunnen worden ingericht.

Samen markeren deze ontwikkelingen een fundamentele verschuiving—van voorspelling naar interventie, van optimalisatie naar verantwoordelijkheid. Het betoog sluit af met een toekomstvisie waarin algoritmische systemen niet alleen betere beslissingen mogelijk maken voor bedrijven, maar ook bijdragen aan een eerlijke(re) samenleving.

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1. Opening

Dear Rector Magnificus of the Erasmus University,
Dear Dean of the Rotterdam School of Management,
Dear family, friends, colleagues, and students,
Dear distinguished guests,

It is an honor and a privilege to accept the appointment of Professor of Customer Analytics at Erasmus University by means of this inaugural address, entitled "Who Gets the Offer? Economic Objectives, Methodological Challenges and Ethical Considerations."

Since its inception in the 1950s, the field of marketing has recognized a simple but powerful truth: *not all customers are created equal.* This was a striking departure from the dominant classical and neoclassical economic theories at the time that treated consumers as homogeneous agents with identical preferences and behaviors.

But marketers saw something different. They saw variation, or heterogeneity, in how people responded to products, pricing, and messaging. One of the first to formalize this view was Wendell Smith, among the early professors in our academic field. His landmark 1956 article in the *Journal of Marketing* laid the intellectual foundation for market segmentation.[1] Firms, he suggested, could "merchandise to a heterogeneous market." According to him, market segmentation was going to be "a force in the market that will not be denied." The real challenge, however, arises from "determining, preferably in advance, the level or degree of segmentation that can be exploited with profit."

Over time, segmentation evolved into personalization. With the rise of rich, individual-level data, which was not available at the time of Smith, and with the advent of direct digital channels via which firms could deliver personalized offers, emerged a new marketing era. Peter Fader calls it the age of *customer centricity*.[2]

But with these new opportunities, we face a challenge: how do we celebrate customer heterogeneity in a way that creates value for both firms and their customers?

At the heart of this challenge lies a deceptively simple question:

Who gets the offer?

1 Smith, W.R. (1956), "Product Differentiation and Market Segmentation as Alternative Marketing Strategies," Journal of Marketing, 21(July), 3-8.

2 Fader, P., & Toms, S. (2018). "The Customer Centricity Playbook: Implement a Winning Strategy Driven by Customer Lifetime Value." Wharton School Press.

A question that cuts across economic objectives, methodological challenges and ethical considerations, one that will guide us throughout this lecture.[3]

Today, I want to tell you a story: the story of how our field has evolved in answering that very question. I will do so by focusing on my own journey as a scientist—sharing the changes I witnessed and the key lessons I learned along the way. I will use examples from my own research to illustrate how our understanding has evolved, and how each step built on the last. This story is personal, subjective, and far from exhaustive. But perhaps that's the point. Because as you'll see, it's about learning to accept that the questions we ask are never fully answered—even when we think they are.

As scientists, our role is to offer the best possible answer based on the data, methods, and understanding available at the time. But just as important is the willingness to stay flexible: to revisit conclusions, challenge what we thought we knew, and adapt our models as new insights emerge.

Over the past 20 years, I've experienced several such moments when I realized that the very models I once relied on could be reimagined or redesigned to offer a better answer. Today, I want to share some of those moments with you. Perhaps they'll resonate with your own journey. And who knows—maybe they'll spark new questions of your own.

So, if you're ready—let me take you along for the ride.

3 Lemmens, A., Roos, J., Gabel, S., Ascarza, E., Bruno, H., Gordon, B., Israeli, A., McDonnell Feit, E., Mela, C., & Netzer, O. (2025), "Personalization and Targeting: How to Experiment, Learn & Optimize," International Journal of Research in Marketing, forthcoming.

2. A Front-Row Seat to the Prediction Revolution

When I began my academic career, marketing researchers were already deeply engaged in efforts to better understand how customers differ from one another. It was an exciting time.[4] For the first time, our field gained access to fine-grained data—scanner records from grocery stores or catalog-ordering histories—collected at the level of individual households. To make sense of this data, researchers turned to a class of models known as ***discrete choice models***. Two particularly successful approaches were hierarchical Bayes models and latent-class models.[5, 6]

These models were quite powerful. By pooling information across stores and households, they were able to identify households with the highest probability of making an order at a given point in time.[7] Some models could even track how behavior changed over time. In early work with Christophe Croux and Stefan Stremersch, we showed that you could even model whether an individual would switch from one segment to another as time goes by.[8]

Despite their early success, these models had limitations. Their predictions were sensitive to modeling assumptions, and as firms began collecting much richer data—especially from digital and online channels—they struggled to keep up with the scale and complexity.

Fortunately, the ***machine learning revolution*** was just around the corner. In 2006, I published my first dissertation paper, entitled *"Bagging and Boosting Classification Trees to Predict Churn,"* in the *Journal of Marketing Research* and a sequel with fellow doctoral student Kristel Joossens a year later.[9, 10] To my knowledge, there were among the first papers in our field to apply machine learning techniques. At the time, I had no idea that, twenty years later, machine learning and AI would be on everyone's lips.

4 Bijmolt, T.H.A., Leeflang, P.S.H, Block, F., Eisenbeiss, M., Hardie, B.G.S., Lemmens, A. & Saffert, P. (2010), "Analytics for Customer Engagement," Journal of Service Research, 13(3), 341-356.

5 Rossi, P.E., & Allenby, G.M. (2003), "Bayesian Statistics and Marketing." Marketing Science 22(3):304-328.

6 Bijmolt, T.H.A., Paas, L.J., & Vermunt, J. (2004), "Country and consumer segmentation: Multi-level latent class analysis of financial product ownership," International Journal of Research in Marketing, 21(4), 323-340.

7 Wedel, M., & Kamakura, W. (2002), "Market Segmentation: Conceptual and Methodological Foundations," International Series in Quantitative Marketing (8), Springer Nature, page 331.

8 Lemmens, A., Croux, C., & Stremersch, S. (2012), "Dynamics in the international market segmentation of new product growth," International Journal of Research in Marketing, 29(1), 81-92.

9 Lemmens, A., & Croux, C. (2006). Bagging and boosting classification trees to predict churn. Journal of Marketing Research, 43(2), 276-286.

10 Croux, C., Joossens, K. & Lemmens, A. (2007), "Trimmed Bagging," Computational Statistics and Data Analysis, 52(1), 362-368.

I remain deeply grateful to the review team—and in particular to the late JMR editor Dick Wittink—for their willingness to take a risk on something so unfamiliar.

That risk paid off. The paper quickly gained traction, both within and outside the field of marketing, and it remains one of my most cited works. Machine learning proved to be a powerful tool, especially in its ability to work with large datasets—those with many customers and many variables—without relying on rigid modeling assumptions. Its flexibility allowed us to capture complex, nonlinear patterns in consumer behavior that traditional models had difficulty representing.

In my work with Christophe, we focused on predicting customer churn and used two tree-based ensemble methods to identify customers at risk of leaving: bagging and stochastic gradient boosting,[11, 12] the winning model of the Teradata Churn Modeling Tournament organized by Duke University under the supervision of Scott Neslin, Wagner Kamakura, Sunil Gupta, and others.[13]

Still, despite this early success, it took nearly two decades for the marketing field at large to fully embrace machine learning. A clear inflection point came around 2019–2020, when the top four marketing journals published more than thirty machine learning articles in just two years. Since then, the pace has only accelerated. Today, many companies use machine learning and AI to guide their decisions with unprecedented levels of predictive accuracy. And at Marketing Science conferences, it's now common to see every second presentation draw on machine learning in one form or another. We had entered a new era—what Ajay Agrawal and his colleagues called the era of *Prediction Machines*.[14]

11 Friedman, J.H. (2001), "Greedy Function Approximation: A Gradient Boosting Machine", The Annals of Statistics, 29, 1189-1232.

12 Friedman, J.H. (2002), "Stochastic Gradient Boosting", Computational Statistics and Data Analysis, 38, 367-378.

13 Cardell, S.N., Golovnya, M. & Steinberg, D. (2003), "Churn Modeling for Mobile Telecommunications: Winning the NCR Teradata Center for CRM at Duke University - Salford Systems," 2003 INFORMS Marketing Science Conference, Maryland.

14 Agrawal, A., Gans, J., & Goldfarb A. (2018), "Prediction Machines: The Simple Economics of Artificial Intelligence," Harvard Business Review Press.

3. When Prediction Isn't Enough

And yet—despite all this progress—a fundamental question remained: as powerful as prediction machines had become at forecasting the future, were they actually helping us make better decisions?

At first, this might seem counterintuitive. But take a step back, and it begins to make sense. Prediction machines are designed to fill in missing information. They take inputs—like customer history, browsing behavior, or demographics—and estimate what is likely to happen next, given the current state of the world.

Judea Pearl, always provocatively insightful, once wrote:[15]

> "Present-day learning machines [...] share the wisdom of the owl. [...] They operate almost entirely in an <u>association</u> mode. [...] Deep neural networks have added many more layers to the complexity of the fitted function, but raw data still drives the fitting process." (pp. 30–31)

But in customer-centric marketing, <u>association</u> is not enough. Firms do not just want to know what will happen—they want to know what they should do. "Who gets the offer" means that we need to figure out whom to target to reach a specific goal. And this goal needs to be defined a priori. For instance, firms can choose to increase their customers' lifetime value[16] or to maximize profits.

Take churn prediction. Prediction machines might accurately tell us which customers are likely to leave next week. But that doesn't answer the real question: *which customers can we actually retain?* Which ones should receive a retention gift in our upcoming proactive retention campaign? Predicting churn is not the same as preventing it. In fact, in an article I wrote with Sunil Gupta in 2020, we showed—using data from two firms, one in the US and one in Europe—that targeting the most likely churners can backfire—delivering little or even negative profit.[17] Put simply, knowing who will churn doesn't tell us whom to target. It may sound obvious now, but for years, both industry and we as marketing scholars focused on the wrong question.[18]

And let me make this clear, this blind spot wasn't limited to retention. Recommendation systems, for example, often suggest products with the highest predicted utility. But

15 Pearl, J. (2018), "The Book of Why: The New Science of Cause and Effect," Penguin, UK.

16 Glady, N., Lemmens, A., & Croux, C. (2015), "Unveiling the Relationship between the Transaction Timing, Spending and Dropout Behavior of Customers," International Journal of Research in Marketing, 32, 78–93.

17 Lemmens, A., & Gupta, S. (2020), "Managing Churn to Maximize Profits," Marketing Science, 39(5), 956-973.

18 Ascarza, E. (2018). "Retention Futility: Targeting High-Risk Customers Might be Ineffective." Journal of Marketing Research, 55(1), 80-98.

these are typically items the customer was already likely to buy—rather than ones they might consider *because* of the recommendation.[19]

The deeper issue is this: when we make an offer or send a recommendation, we are not passively observing the world—we are actively intervening. To make good decisions, we need to understand how our actions *influence* outcomes. Correlation isn't enough. What we need is counterfactual reasoning: what would happen if we acted in a specific way and what would happen if we didn't?

This marked a shift from correlation to causation. From predicting what *is* to understanding what *could be* under different actions. That shift put us squarely in the domain of causal inference, and marked the beginning of the next revolution: the ***causal machine learning revolution.***

19 Bodapati, A. V. (2008). "Recommendation Systems with Purchase Data." Journal of Marketing Research, 45(1), 77-93.

4. The Causal Machine Learning Revolution

Judea Pearl calls it "the new science." At its core, the new science consists of understanding that most of the questions we care about—as marketers, as scientists, as decision-makers—are causal ones.

> *What price should a manufacturer set to maximize profits?*
> *Should retailers invest in private labels? Should they push their omnichannel strategy?*
> *Can emotions in advertising improve ad liking and brand perception?*
> *Which movie artwork should a streaming platform show to boost engagement?*
> *Can personalized recommendations promote healthier eating or exercise habits?*
> *How can we help consumers make more sustainable choices?*

Each of these is ultimately a question about cause and effect, and over the past decade, it has become clear that answering such questions causally can dramatically improve decision-making. It is what we call causal decision-making.[20]

Let me return to the retention example. Suppose we are considering six customers: A, B, C, D, E, and F (Figure 1). The key causal question is: *If we send a retention gift to one of these customers, are they more likely to stay than if we hadn't?*

In the language of Judea Pearl, what we want to estimate for each customer is:

$$\text{Retention} \mid \text{do(target)} - \text{Retention} \mid \text{do(not target)}$$

This expression captures the difference in a customer's behavior across two hypothetical worlds—one where we intervene, and one where we don't. It is the causal effect of our action on this customer.

For simplicity, I'll refer to this effect as the "lift" throughout the rest of this lecture even though, as academics, we might prefer the term Conditional Average Treatment Effect (or CATE). This lift is the key quantity that we must estimate to guide targeting decisions in a proactive retention campaign. And the same principle applies to every other example I mentioned earlier.

What is fascinating is that once we find a way to estimate this lift, we're just one step away from the decision-making stage. The logic is straightforward: we rank customers from highest to lowest lift and target the most persuadable ones (those on the right-hand side of Figure 1).

20 Fernández-Loría, C., & Provost, F. (2025). "Observational vs. Experimental Data When Making Automated Decisions Using Machine Learning." Journal on Data Science, Forthcoming.

The customers on the right are the most *persuadable*—they're more likely to stay if we send the offer. All others are best left alone. Some won't respond, and others might even react negatively. Practitioners sometimes call them "sleeping dogs."[21]

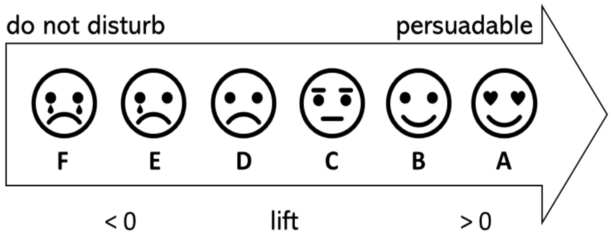

Figure 1: Lift of A, B, C, D, E, and F to the retention gift

Despite the simplicity of this framework, it's important to recognize that predicting lift is much harder than predicting churn. That is because we never get to observe both hypothetical worlds for the same customer—one where we intervene, and one where we don't. Luckily, science has come up with a brilliant solution to this problem. It combines the strengths of two fields that once spoke very different languages: machine learning and causal inference. The result is what we now call *causal machine learning.*

This causal machine learning revolution likely emerged in parallel at Stanford and MIT. At Stanford, Stefan Wager and Susan Athey introduced causal forests.[22] At MIT, Victor Chernozhukov and colleagues developed generic/double machine learning.[23, 24] These methods allow decision makers to estimate lift, ideally using experimental data, or, when experiments aren't feasible, using observational data. The output is a ranking like the one in Figure 1.

In a forthcoming article in *IJRM*, my RSM colleagues Jason Roos, Sebastian Gabel, and I teamed up with brilliant scholars in our field, Eva Ascarza, Hernán Bruno, Brett Gordon, Ayelet Israeli, Elea Mcdonnell Feit, Carl Mela, Oded Netzer, to lay out on paper the key steps for effective causal decision making.[25] We call it: *test and learn.*

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21 Ascarza, E., Neslin, S., Netzer, O., Anderson, Z., Fader, P., Gupta, S., Hardie, B., Lemmens, A., Libai, B., Neal, D., Provost, F., & Schrift, R. (2018), "In Pursuit of Enhanced Customer Retention Management: Review, Key Issues, and Future Directions," Customer Needs and Solutions, 5(12), 65-81.

22 Wager, S. & Athey, S. (2018), "Estimation and inference of heterogeneous treatment effects using random forests." Journal of the American Statistical Association 113(523), 1228-1242.

23 Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018), "Double/debiased machine learning for treatment and structural parameters," The Econometrics Journal, 21(1), C1–C68.

24 Chernozhukov, V., Demirer, M., Duflo, E., & Fernandez-Val, I. (2025), Generic Machine Learning Inference on Heterogenous Treatment Effects in Randomized Experiments, Econometrica, Forthcoming.

25 Lemmens, A., Roos, J., Gabel, S., Ascarza, E., Bruno, H., Gordon, B., Israeli, A., McDonnell Feit, E., Mela, C., & Netzer, O. (2025), "Personalization and Targeting: How to Experiment, Learn & Optimize," International Journal of Research in Marketing, forthcoming.

5. Test and Learn

The idea behind test and learn is to use experiments to estimate individuals' lift, and then use that lift to guide decisions (Figure 2). Tech firms, such as Booking.com and Netflix, call these experiments A/B tests. For instance, suppose a firm wants to find out which customers are most responsive to a retention campaign. They could randomly assign half the customers to receive a retention gift, and the other half to receive nothing. Once the experiment is complete, the firm can predict the lift for all customers who weren't part of the test. These predictions tell them who should get the offer.

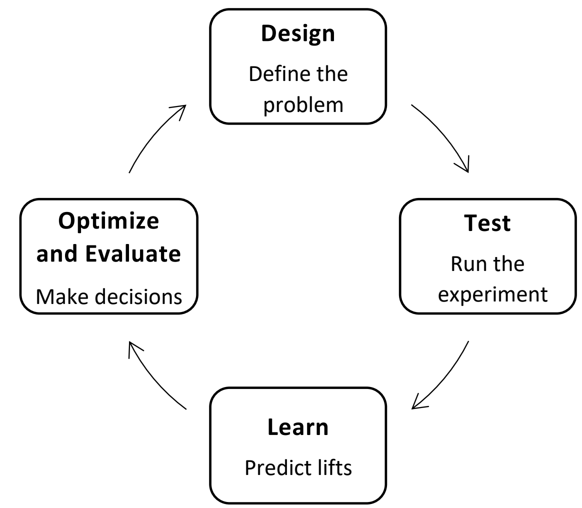

Figure 2. Test and learn framework (Lemmens et al. 2025)

Over the past decade, I have had the privilege of applying the test and learn framework with several external partners, some of them are here in the room today, and I would like to take the opportunity to sincerely thank them. These collaborations were not only enriching, but also a lot of fun. In fact, I would argue that the causal revolution has not only changed how we approach problems scientifically speaking. It has also encouraged us to seek more collaborations with practitioners. So, to the doctoral students in the room: engage with practitioners, build relationships. You will learn more, tackle meaningful problems, and perhaps discover greater purpose in your work.

Sharon Wei, currently doctoral student in our department, does not need convincing. She is already collaborating with Greenchoice, a Dutch energy provider located in Rotterdam. Together, we have run a series of A/B tests to improve the firm's retention program. The project is ongoing, but we are already discovering important differences in how energy consumers respond—some are more sensitive to price incentives, while others are more motivated by transparent communication about the environmental impact of their consumption. Using causal machine learning and off-policy evaluation, we are now testing how these insights can be scaled.

Test and learn can also be valuable in the nonprofit sector. In my view, a beautiful example comes from a paper I co-authored with Emilie Esterzon and Bram van den Bergh, in collaboration with a Belgian charity.[26] The charity wanted to raise more donations but didn't know how. Bram knew! He proposed a simple but powerful idea: what if donors could choose which specific project their donation would support? For instance, some donors could opt to fund wells, others education, or medical aid. We called it giving donors a sense of *agency*. With the charity and the amazing coordination skills of Emilie, we ran a large experiment with over 40,000 donors to answer this causal question. The results were striking: donations rose by 42%.

But what truly stood out was what we learned when we started exploring how different donors reacted. Surprisingly, the response to agency was *not* unanimously positive —only 20% of donors showed a positive lift, but the rest did not. This insight allowed us to propose a donor-centric approach: offer agency only to the segment most likely to respond positively. This had major practical value for the charity. Not only did it increase donations, but it also reduced operational complexity by limiting the number of donors whose preferences needed to be honored in resource allocation.

To me, this is a perfect illustration of what it means to celebrate customer heterogeneity.

26 Esterzon, E., Lemmens, A., & Van den Bergh, B. (2023). "Enhancing Donor Agency to Improve Charitable Giving: Strategies and Heterogeneity." Journal of Marketing, 87(4), 636-655.

6. Aligning Data and Model with Business Objectives

Despite these rewarding experiences, one question kept nagging at me: Is it enough to frame a business problem as a causal question to ensure that algorithmic decisions actually achieve the decision maker's objectives? Or were we still missing a crucial ingredient?

I found the missing piece during a research visit to Harvard Business School, where Sunil Gupta and I explored how to run customer retention campaigns more effectively. Together, we took a step back and began to rethink what truly drives the profitability of such campaigns. And here's what we discovered.

Remember our six customers: A, B, C, D, E, and F. Earlier, we saw that A, B, and C had higher lift than D, E, and F, and so they looked like promising candidates for our retention campaign. But there is more to learn from that figure. Some customers, like C and D, show lift values very close to zero. Others, like A and F, have much more extreme responses—either strongly positive or strongly negative.

Why does that matter? Because the profitability of a campaign hinges on those extreme cases. Customers like A and F are the ones that can really move the needle. And that means that getting A right (by sending a gift) or F right (by holding back) has a much bigger impact than making a mistake on C or D. In other words, we really want our model's predictions to tell us to target A and to not target F. Otherwise, we risk leaving a lot of money on the table. Put simply, *not all prediction errors are created equal.*

But here is the problem: most off-the-shelf algorithms do not know that. They treat all customers as equally important. They try to get every prediction right, weighting every error the same. This means that their objective is *not* aligned with the business goal. That would not be an issue if our models made no prediction errors. But in practice, predictions are rarely perfect. Even the most advanced causal models make mistakes. Therefore, we must align our models more closely with the company's true objective.

To address this, I proposed two alternative approaches. One focuses on the model, the other on the data.

Profit-based Loss Function

One solution, which I developed with Sunil Gupta in our 2020 Marketing Science article, was to tweak the model.[27] In particular, we focused on the *loss function* of the model. Think of the loss function as the model's heart: it tells the algorithm what to care about. Typical loss functions treat all customers as equally important. So we

27 Lemmens, A., & Gupta, S. (2020), "Managing Churn to Maximize Profits," Marketing Science, 39(5), 956-973.

replaced that with what we called a profit-based loss function. This new function told the model to focus on the customers where the stakes were highest—like A and F. The results were amazing. The campaign earned significantly more than the classic approach.

Smart Experiments

Rather than adjusting the model, another route is to rethink the data we feed into it. After all, if a company plans to run an A/B test, it is worth considering which customers to include in the experiment. Experiments can be expensive, especially if they involve a lot of customers. Firms are understandably resistant to send out gifts at random without knowing whether they will have an impact.

Together with my former doctoral student Zoltan Puha (now at Uber) and Maurits Kaptein (Eindhoven University), we asked: can we be smarter about whom we include in the experiment?[28] We developed an approach called *batch-mode active learning* which identifies the customers from whom we can learn the most, and the fastest, thereby increasing the chances that the experiment will support the firm's objective. What we found is that firms could cut experiment costs by 34% on average simply by selecting the right customers to learn from.

The Takeaway

So, what is the takeaway? Do not rely blindly on off-the-shelf algorithms—even causal ones. Always ask whether they are truly optimized for the outcome that matters. We cannot afford to treat algorithms as black boxes. As researchers, we need to roll up our sleeves. In some cases, it is almost like performing open-heart surgery: we examine the model's heart—its loss function—and, if needed, we repair it or replace it with a new hearth that better serves our objective.

28 Puha, Z., Kaptein, M., & Lemmens, A. (2020), "Batch Mode Active Learning for Individual Treatment Effect Estimation," 2020 IEEE International Conference on Data Mining Workshop Proceedings, Sorrento, Italy, 2020, 859-866.

7. Designing Decisions that Work—and Work Fairly

These papers changed everything for me. Suddenly, we had the tools to solve real-life problems with unprecedented effectiveness. But the power of these tools also forced me to confront a new reality.

As algorithms become more precise in identifying which customers should receive an offer, they also become more precise in deciding who should not. And as we give our models permission to prioritize customers based on monetary considerations, we risk overlooking other ones—social, ethical and human.

For every person selected, someone else is left out. That might make perfect sense from a purely economic viewpoint, but it raises ethical questions we can no longer ignore: *Have we built systems that quietly reinforce existing inequalities?* Is it, for instance, possible that the customers we deprioritized in our profit loss function were the ones already marginalized?

A Worrying Emergence of Algorithmic Scandals

Unfortunately, this is a question we must now ask in all seriousness. Over the past decade, we have seen a growing number of algorithm-driven decisions that harmed individuals from protected groups—people defined by characteristics such as gender, ethnicity, age, income, or religion. These incidents, often labeled as cases of algorithmic bias, have raised public concern and so they are closely monitored by the OECD (Figure 3).[29] In fact, a recent KPMG study found that in 2023, for the first time, more Dutch citizens believed algorithms were bad for society (26%) than good (22%).[30]

I could easily spend the next hour recounting cases of algorithmic bias around the world—but we do not have that kind of time, and frankly, it might be too unsettling. Still, some examples hit close to home. Here in the Netherlands, the "Toeslagenaffaire" shook the nation. SyRi, a risk-scoring system developed by the Ministry of Social Affairs, repeatedly flagged people from poorer areas as more suspicious than those from wealthier one.[31]

29 Retrieved from https://oecd.ai/en/incidents

30 Retrieved from https://kpmg.com/nl/nl/home/topics/digital-transformation/artificial-intelligence/algoritme-vertrouwensmonitor.html

31 Burack, J. (2020), Addressing Algorithmic Discrimination in the European Union. Retrieved from http://pathforeurope.eu/addressing-algorithmic-discrimination-in-the-european-union/

In marketing, too, the risks are real. Personalized pricing is increasingly popular but it is also raising serious concerns.[32] A 2024 report by Consumer Watchdog revealed a troubling pattern: across services like high-speed internet and ride sharing, the best deals went disproportionately to wealthier—and often whiter—consumers, while those with the fewest alternatives consistently paid more.[33, 34] And this issue is not limited to everyday goods. In the U.S., Harvard researchers found that Asian high school students were nearly twice as likely to be charged higher prices for online SAT prep—right when they were trying to access educational opportunity.[35] Advertising faces similar issues. Online, female job seekers are much less likely than men to see ads for high-paying jobs, further reinforcing existing gender pay gaps.[36]

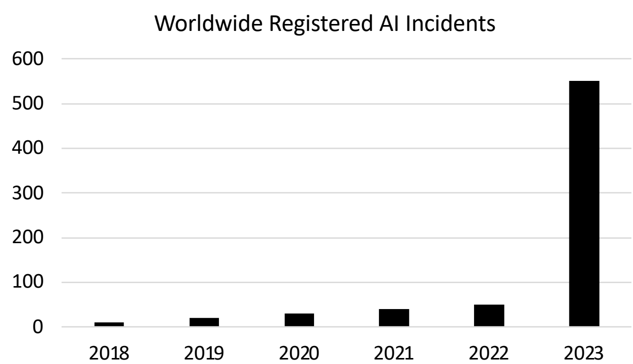

Figure 3: OECD AI incidents monitor (AIM)

These cases of algorithmic bias are often not intentional, but governments are starting to take serious action. Many countries have now created agencies to oversee algorithmic decision-making—such as the Department for the Coordination of Algorithmic Oversight (DCA) here in the Netherlands—and are actively reaching out to academics for help. Earlier this year, the Dutch Ministry of Education organized a roundtable with experts from various academic fields, which I had the opportunity to attend. We discussed the allegations of discrimination against DUO and explored ways to address them.

32 Ivanova, I. (2025), Delta moves toward eliminating set prices in favor of AI that determines how much you personally will pay for a ticket. Retrieved from https://fortune.com/2025/07/16/delta-moves-toward-eliminating-set-prices-in-favor-of-ai-that-determines-how-much-you-personally-will-pay-for-a-ticket/

33 Yin, L., & Sankin, A. (2022), How We Uncovered Disparities in Internet Deals. Retrieved from https://themarkup.org/show-your-work/2022/10/19/how-we-uncovered-disparities-in-internet-deals

34 Kloczko, J. (2024), Surveillance Price Gouging. Retrieved from https://consumerwatchdog.org/wp-content/uploads/2024/12/Surveillance-Price-Gouging.pdf

35 Vafa, K., Haigh, C., Leung, A., & Yonack, N. (2015), "Price Discrimination in The Princeton Review's Online SAT Tutoring Service." Journal of Technology Sciences, September.

36 Gibbs, S. (2015), Women less likely to be shown ads for high-paid jobs on Google, study shows. Retrieved from https://www.theguardian.com/technology/2015/jul/08/women-less-likely-ads-high-paid-jobs-google-study

It is in this pressing context that I received a major grant from the Dutch Research Council (NWO) to explore a central question: How can we design targeting systems that are not only effective, but also fair?[37]

What is fair?

To answer the question of fair targeting, we first need to agree on what fairness means—and that is no easy task.

One widely shared view is that people should not be treated differently based on characteristics they cannot *control*. Take my own children, Victor and Norah. Imagine that when they turn 18 and start thinking about what to study, my son receives ads from Erasmus University promoting a degree in econometrics, but my daughter receives none. Would I find that discriminatory? Absolutely. Kids do not choose to be born a boy or a girl.

Now imagine a different situation. This time, the ad is for an extracurricular singing class. Norah is passionate about singing and has already performed in several musicals. Victor, on the other hand, has never shown an interest in singing. If the platform uses this information to show more singing lesson ads to Norah and fewer to Victor, is that unfair? This feels less clear.

So why does equal treatment feel crucial in the first case but less so in the second? It comes down to what people stand to gain—or lose—from seeing the ad. In the university example, we assume both a boy and a girl would benefit equally from the opportunity. Nothing tells us that Norah would be less interested in econometrics than Victor. In fact, she has always loved math at school. If one sees the ad and the other does not, the difference is not about interest—it is about access. That feels unfair.

But in the singing class example, the advertiser correctly inferred that Victor had no interest in singing, so showing him the ad would not make any difference.

In both cases, we are really asking whether our decisions create disparate impacts—unequal effects on different groups, even if the algorithm was not designed to discriminate.

These examples point to an important insight: fairness is not always about treating everyone the same. It can be about providing people equal benefits, based on what we believe the action will actually do for them.

Building Systems That Are Not Just Efficient, But Also Fair

Together with doctoral student Zhuoyu Shi,[38] we recently translated these ideas into a causal decision-making framework. We defined a targeting decision as fair when two

37 Lemmens, A. (2023), Debiasing Algorithms: A Fair Machine Learning Approach Protecting Against Discriminatory Outcomes, NWO Talent Programme Vici SSH 2023, grant number VI.C.231.028.

38 Shi, Z., & Lemmens, A. (2025), Fair Active Learning for Targeted Marketing Campaigns, Working Paper.

people with the same expected lift have the same chance of being selected, no matter their gender, age, or background. Based on this definition, we then designed a new active learning algorithm to maximize fairness right from the data acquisition stage.

And, with the generous collaboration of my colleague Romain Cadario, we are also investigating in parallel when consumers themselves perceive algorithmic decisions as fair or unfair. This perception matters, too—because trust in the system depends not only on what we do, but on how people experience it.

What is deeply satisfying in this new journey is the realization that the tools we developed to maximize profit can now be adapted to serve fairness. The core principle remains: focus on the people for whom the decision matters most. But now, we broaden what "matters" means. It includes not only financial impact, but also ethical responsibility. For example, instead of weighting high-profit customers more heavily, we can give more weight to protected groups—either during experimentation or in the modeling process. In doing so, we balance commercial goals with societal values.

Science is cumulative. Each insight builds on the last. And by walking this path—step by step—we can move from better profits to better outcomes. For companies and for society. That, I believe, is a future worth building.

8. Closing words: A Future Worth Building

The last thing I want is for you to go home today thinking that algorithmic decision-making is inherently bad, or that we should return to a world where decisions are made without data. After everything I have said, it would be easy to feel skeptical. And yet, I believe there is real reason for hope. Not because the risks of algorithmic bias aren't real, but because I would strongly argue biased algorithms are, in many ways, easier to fix than biased people.[39]

Discrimination—whether by humans or machines—is harmful. But that is where the comparison ends. Human biases are often invisible, deeply rooted, and hard to change. Algorithms, by contrast, can be audited, tested, and improved. We can feed them data, track the patterns, and run the numbers. We can find out where they go wrong.

And once bias is found, the difference becomes even clearer. Changing human minds is slow and uncertain. Diversity training, for example, often shows little lasting effect. People may not even be aware of their own biases.[40, 41] But algorithms do not hold on to beliefs. They can be adjusted. They can be re-designed. If my lecture has shown anything, I hope it is this: algorithms can be shaped based on the objective of the ones who design them. If built responsibly, they offer a level of transparency, traceability, and adaptability that human judgment cannot match.

To achieve that, we must recognize that every experiment we run, every model we estimate, and every policy we implement encodes a set of values: Who matters? Who is worth retaining? Who is seen? As marketers, data scientists, and researchers, we now hold extraordinary power to predict and influence behavior. And with that power comes responsibility. We must design the right systems. That means building robust infrastructure for responsible experimentation. It means developing review and auditing tools for decisions that affect people's lives. It means establishing governance and regulation. Just as financial markets require firms to retain and report detailed records while protecting sensitive information, we must ensure that the data used to train, test, and audit algorithms are carefully stored and available for oversight. And for us as scientists, it also means embracing the principles of open science: transparency in data, methods, and findings in order to enable replication, scrutiny, and shared progress.

Above all, we must hold ourselves to a dual mandate: to be effective and to be fair. That is the promise of decision machines—not merely to optimize outcomes, but to help

39 https://www.nytimes.com/2019/12/06/business/algorithm-bias-fix.html

40 Chang, E.H., Milkman, K.L., Gromet, D.M., Rebele, R.W., Massey, C., Duckworth, A.L. & Grant, A.M. (2019), "The mixed effects of online diversity training," Proceedings of the National Academy of Science, 116 (16), 7778-7783.

41 Celiktutan, B., Cadario, R., & Morewedge, C. K. (2024). People see more of their biases in algorithms. Proceedings of the National Academy of Sciences, 121(16).

build a future where opportunity is guided not by accident or bias, but by evidence, insight, and care.

Because in the end, "who gets the offer" is not just a business question. It is not just a technical question. It is also a filtering decision:

Someone is in.

Someone is out.

9. Words of Thanks

Let me end by saying thank you.

First of all, I would like to thank my former PhD advisor, Christophe Croux—because I would never even have considered an academic career without him. A little over two decades ago, I was studying in my hometown, Brussels, for a degree called Business Engineer—a five-year program that probably does not exist anywhere else. It combined math, physics, chemistry, economics, finance, marketing, accounting, statistics, econometrics, programming, and Dutch and English classes. The director of the program had the original idea that students could learn their Dutch while studying econometrics. So, Christophe, professor at KU Leuven, was invited to teach us econometrics in Dutch—which, admittedly, was a challenge, as I heard for the first time about p-waarde and uitschitters. Looking back, this course had a lifelong impact. I learned the foundations of quantitative research—and, even more importantly, I met Christophe. In the final year of the program, when it was time to write my thesis, I found a Belgian DIY company willing to share all their transaction data (on floppy disks!) so I could analyze their customers' behavior. Naturally, I asked Christophe to be my thesis coach. The thesis was called "Data Mining for Customer Relationship Management." By the time I finished, Christophe suggested I consider a PhD at KU Leuven under his supervision. To be honest, I had no idea what a PhD was, but his description made it sound appealing—so I said yes. I could not have wished for a better advisor. I remember him coming to my desk almost every single day to ask how my research was progressing. I also remember sitting with him in his office while he showed me how to program in S-Plus—now better known as R—at a time when everyone else was still using SAS or SPSS. Christophe was also open-minded. When I told him I wanted to study marketing, despite being part of the Operations Research and Statistics department, he introduced me to Marnik Dekimpe, who became my second advisor. Marnik helped me write a proper marketing paper and introduced me to the marketing community, so I owe him a lot as well. Looking back, I feel extremely privileged to have had such an amazing pair of advisors.

I would also like to thank my former colleagues at the Erasmus School of Economics and at Tilburg. You gave me the chance to grow in stimulating academic environments. Along the way, I met many inspiring scholars and made lasting friendships—many of whom have now followed their own paths around the world. I'm grateful we met and hope we stay in touch.

During this journey, I also had the chance of spending time at Harvard Business School, where I worked with Sunil Gupta. Sunil, thank you for that opportunity and for the many insightful conversations about research and our role as academics. You are the one who encouraged me to reach out to companies and governments. I took note of how you did it—what kind of mindset and attitude it requires. This has made my path as a marketing scholar much more fulfilling than I had ever imagined. I also want to thank the colleagues from Tuck, who hosted me several times during my stays in the

US—Kusum Ailawadi, Scott Neslin, Praveen Kopalle, Peter Golder, Kevin and Punam Keller. I really enjoyed the time I spent with you in Hanover. I also would like to take the opportunity to thank the NWO and the European Union for funding a large part of my research agenda and visits over the years. I am grateful for the trust and the support.

And now, to my dear RSM colleagues. What can I say? You are amazing. I still remember how happy I was back in 2019 when I met with Ale and he shared the good news—that I could join the department. From the very beginning, I felt at home at RSM. And perhaps even more importantly, I felt that I could be myself. There is something special about our department, and if I had to give it a name, I would call it *intellectual curiosity*. But by that, I do not mean an abstract ideal. I mean something very real, something you feel in the day-to-day. It's the way we allow each other to work in our own style, without forcing a single mold. It's the way each of you is genuinely interested in what your colleagues are doing—just think of our infamous lunch clubs. And it's the trust we place in one another: the shared sense that everyone is doing their best, and that this trust will carry us further than control ever could. In many ways, I dare to hope that our department's spirit came through in my lecture today—when I tried to argue that diversity is not a problem to be solved, but a strength to be embraced.

The next series of thank you go to all my co-authors, many of whom I mentioned earlier, Bram, Kristel, Maurits, Nicolas, Rik, Sarah, Stefan, Sunil, and Willem. In particular, thanks for former and current PhD students, Constant Pieters, Zoltan Puha, Emilie Esterzon, Zhuoyu Shi, Sharon Wei and Joric Donnet. Having the opportunity to make you discover what doing academic research is and try to convey you some of the things I learned myself over the years give me a lot of joy. My sincere wish is that I have passed on some of my passion for this work, and that you wake up each morning happy to do what you do.

Next, I want to thank all the company partners I have had the chance to collaborate with over the years. I hope this lecture has shown just how much your involvement has meant to me and how much it has enriched my work. In particular, thank you to the team at Rockfeather—Jonathan, Alexander, Boy, Magdalena, Rodrigo, and many others. To the team at Greenchoice, and especially Michiel and Jelte—I always look forward to our Wednesday afternoon meetings. A warm thank-you as well to the Dutch Ministry of Education, and especially the team at DUO. Lukas and Jorrit, the conversations we have had so far have been motivating, and I look forward to continuing them. Thanks also to Amélie from Clifford Chance, Ruud from KPN, Nadia from Booking.com, and Christine from Veepee. Finally, a heartfelt thank-you to the many company partners who gave their time to support our MSc students: Christophe from Agilitic, Jade from ANWB, Didi from Greenchoice, Marie from Fourandhalf, Tycho and Eleni from Dapper and of course, my best friend Elena from Liebre Style. And thank you to all the students I've had the chance to teach—in our MSc, MBA, and EMBA programs at RSM, and earlier at ESE and Tilburg. A special thanks to those who made it here today.

Lastly, I would like to thank my family. First, my parents—who surely never expected their daughter to become a professor, let alone in the Netherlands, married to a Feyenoord supporter. As a child, I dreamed of performing on the stages of Paris—Phèdre, Andromaque, Silvia, Juliette. But my parents advised me to pursue a "serious" education first to make sure I could be independent financially before trying an artistic career. I never started the artistic career, but I did follow the serious education, which brought me here. And, luckily, I still get to be on stage today and in front of my students—though the script is a little different now. Papa & Maman: Thank you for being here today, even though I know it isn't simple. I know the past years have not been easy, but you made it. Thank you also to my little brothers and my sister of heart—Benjamin, Ludovic, and Angélique. I am sorry we do not see each other more often but I'm so proud of who you have become and the families you have built. I love you all very much and I hope we get to spend many more summers together.

I also want to thank Robert's family: Linda, Jerry, Demi and Daan. In particular, Jan and Hannie—for making me feel at home in Rotterdam. In many ways, you have become my adoptive Dutch family here, and I am so grateful for your warmth and support, and for all the Tuesdays you spend with Victor and Norah.

And my last words go to Robert, Victor, and Norah. It is not always easy to be part of a family with two busy professors, two different cultural backgrounds, and four strong personalities—but how lucky we are. Robert, meeting you at the Marketing Science Conference in Vancouver changed our life in ways we never anticipated. Neither of us was looking for this—but as they say, the best things in life come unplanned. So, thank you for saying "yes, oui, ja" to the journey. And what a journey it has been—two beautiful, healthy, and incredibly smart children, building our own house just steps from campus... what more could we hope for? Victor and Norah, I am so proud of you. Becoming a professor means a lot to me, but more than anything, I am even prouder to be your mum. Something tells me beautiful things lie ahead of you, and I cannot wait to witness them. Do what you love—whether that's being a professor, a police officer, or a comedian. Wherever life takes you, I'll be right there with you.

Ik heb gezegd.

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