

Skills4Retail
Building sustainable growth

AI4Retail

Designed by University of Bucharest for the Skills4Retail Initiative

Funded by the European Union. Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor the granting authority can be held responsible for them.

Co-funded by
the European Union

Module Introduction: Objective & Outcomes

Skills4Retail
Building sustainable growth

Module objective	Design, operate, and evaluate end-to-end AI-enhanced retail experiences-linking insight generation & customer profiling with omnichannel orchestration, journey mapping, and CX analytics - under explicit ethical guardrails to lift engagement and satisfaction.

01 AI role and foundations	02 Customer insights
Clarify AI's role in retail, data pipelines, and decisioning patterns that connect signals to actions.	Identify relevant data sources and use them responsibly to understand how customers shop today.
03 AI-driven profiles	**04 Omnichannel and personalization**
Select features, build and test profiles, and govern their use in personalization.	Coordinate web, app and store interactions. Explain targeting, testing and relevance controls. Apply AI to inventory, supply, staffing and store operations.
05 Journeys and CX analytics	**06 Prototyping and evaluation**
Identify friction, triggers and key moments. Translate journey data into metrics, predictions and concise scorecards.	Prototype experiences, run controlled tests and refine them within safeguards. Use case studies and benchmarks to build a repeatable playbook for decisions.

Co-funded by
the European Union

Skills4Retail
Building sustainable growth

Agenda

1. Introduction to AI in Retail
2. Understanding Consumer Behavior Through AI
3.AI-Powered Personalization
4. AI for Operational Efficiency in Retail
5. Omnichannel Strategies with AI
6. Customer Journey Mapping Enhanced by AI
7. AI in Customer Experience Analytics
8. AI Ethics and Challenges in Retail
9. Designing AI- Enhanced Retail Experiences
10. Case Studies and Practical Experiments in AI for Retail



Co-funded by
the European Union

1. Introduction to Artificial Intelligence in Retail

Skills4Retail
Building sustainable growth

1.1. The context of the emergence of AI in retail

1.2. What is AI and how does it work in retail?

1.3. Why is AI important in retail?

1.4. Areas of application of AI in retail

1.5 Case Studies

1.6. Application exercise

1.7. Conclusions

Co-funded by
the European Union

1.1 The context of the emergence of AI in retail (I)

Retail complexity	Computing capacity	Shopper expectations
Interactions among shoppers, products, channels and operations generate more varied data than teams can analyze manually.	Large datasets and greater computing power made AI feasible. Cloud services helped retailers deploy it at scale.	Mass customization raised expectations for individual service. AI helps anticipate behavior and make faster, more accurate decisions online and in stores.

Co-funded by
the European Union

1.1 The context of the emergence of AI in retail (II)

Daily decisions	AI supports rapid decisions in logistics, demand forecasting and customer service. Automating repetitive work at scale can ease staff shortages and reduce operating costs.
On-shelf availability	Shelf scans and predictive replenishment help teams restock before products run out.
Customer experience	Customer flow analysis guides layouts that improve product exposure and dwell time. Personalized service across channels can support profitability.

Co-funded by
the European Union

1.2 What AI is and how it works (I)

Machine learning	Forecast demand and segment customers.
Natural language processing	Interpret intent, analyze reviews and support customers.
Computer vision	Recognize products and support cashierless shopping.
Reinforcement learning	Adapt strategies and pricing as conditions change.

IoT devices and store sensors connect to systems that exchange data with ERP, e-commerce platforms and mobile apps.



Co-funded by the European Union

1.3 Why AI is important (I)

Volatile demand, global competition, rising costs and declining loyalty call for decisions that adapt to customers and changing market conditions.

Forecast demand	Tailor engagement	Adjust prices
Use ARIMA and LSTM models for short- and long-term forecasts.	Identify micro-segments and adapt the customer strategy to individual needs.	Respond to demand, competitors and inventory using contextual bandits, elasticity models or reinforcement learning.

Co-funded by the European Union

1.3 Why AI is important (II)

Routine work	Chatbots handle service requests and robots scan shelves.
Recommendations	Collaborative filtering, content-based models and hybrid neural recommenders improve relevance. A healthy-cooking book can lead to accessories, magazines or organic offers.
Operational resilience	During COVID-19 disruptions, early demand-spike warnings and alternative fulfillment routes helped retailers adapt and maintain service.

These examples introduce the retail application areas in the next section.

Co-funded by the European Union

1.4 Areas of application of AI in retail

Core retail functions

Retail function	How AI helps	Retail outcome
Digital marketing	Target customer segments	More relevant recommendations
Sales	Recommend related products or upgrades	Cross-selling and up-selling
Operations	Forecast demand and adjust inventory	Lower operating costs
Customer support	Answer queries with chatbots or voice bots	Faster responses, 24/7

Co-funded by the European Union

1.4 Areas of application of AI in retail

A closer look at retail operations

Retail function	How AI helps	Retail outcome
Merchandising	Analyze shelf images and shopper behavior	Improve displays and planograms
Security	Use facial recognition and detect fraud	Help prevent theft
Returns	Predict which items may come back	Plan for likely returns
Staffing	Forecast store traffic	Match shifts to demand
Store layout	Map how shoppers move	Increase dwell time and exposure to high-margin areas

Co-funded by the European Union

1.5 Case study: Amazon Go (Description & stack))

Enter	Choose products	Leave
The shopper scans the Amazon Go smartphone app at entry.	Cameras track and recognize items. Proximity and motion sensors detect movement and interactions.	Machine learning links items and actions to shoppers. Deep learning interprets video and behavior. The account is billed automatically (NASEM, 2021).

Co-funded by the European Union

1.5 Amazon Go (Results & analysis)

Checkout	Shoppers avoid checkout lines and waiting. The model requires no staff at payment points.
Shopper outcomes	The case reports higher retention and brand loyalty. The checkout-free visit changes customer expectations of service.
Store operations	Complex AI infrastructure processes large volumes of visual and behavioral data. In-store interaction patterns inform store design and operations.

Co-funded by
the European Union

1.5 Amazon Go (Challenges & adoption notes)

Adoption limits	Implementation and maintenance are costly. Facial recognition and behavioral tracking raise privacy concerns. Scaling beyond large, dense urban markets is difficult.
Smaller-scale uses	Affordable cameras and basic computer vision can monitor shelves, foot traffic and product engagement.
Investment choices	Start with measurable uses such as alerts for empty shelves or low-engagement zones. Match investment to local needs and data readiness before considering a full rebuild.

Co-funded by the European Union

1.5 Other retailer examples (global & regional)

Zalando	Predicts trends from social signals and real-time feedback.
Sephora	Uses computer vision and AR for virtual makeup try-on from selfies.
H&M	Uses machine learning to move stock between stores.
Carrefour	Smart shelves notify the ERP of stock shortages.
Decathlon	Multilingual AI chatbots give personalized advice.
eMAG (Romania)	ML supports recommendations and stock decisions, easybox logistics and real-time promotions.
Bringo (Carrefour ecosystem)	Assigns couriers by availability, proximity and ETA to reduce waits and improve efficiency.

Co-funded by the European Union

1.6 Application exercise (Scenario & questions)

A national online bookstore wants to personalize shopping and increase engagement. Give a concise, actionable answer to each question.

1 Data	2 Segments
What data would you collect?	How would you segment customers?
3 Algorithm	**4 Measures**
Which recommendation algorithm would you choose, and why?	How would you measure success?

Bonus: outline an NLP chatbot that answers natural-language questions in real time using stated interests, browsing history and purchases.

Co-funded by the European Union

1.6 Application exercise (Suggested answers)

1 Data	Purchase history, product-page time, clicks, ratings and cart abandonment.
2 Segmentation	Genre preference, purchase frequency, average order value and e-book versus print preference.
3 Algorithm	Use collaborative filtering or a hybrid model. A hybrid combines customer behavior with item attributes.
4 Measures	Conversion rate, average sales per visit, recommendation click-through rate and customer retention.

Bonus: specify what triggers the chatbot and how to evaluate it. Keep the plan feasible with the available data.

Co-funded by the European Union

1.7 Conclusions & next step

Prepare the organization	Start and learn	Next: consumer behavior
Define AI’s role in operations. Build the data maturity needed for decisions and prepare teams to redesign established processes.	Begin with a practical use, learn from results in the actual retail setting and scale thoughtfully. Lasting change is cultural as well as technological.	Chapter 2 turns customer data into insights for personalization and customer-centered strategy. This prepares the ground for journey mapping and omnichannel work.

Co-funded by
the European Union

2. Understanding consumer behavior through AI

Skills4Retail
Building sustainable growth

2.1. Introduction

2.2. Data sources and types of consumer insights

2.3. Building AI-driven profiles

2.4. How AI Models and Tools Drive Personalization

2.5 Case Studies and good practices

2.6. Obstacles, limits and future perspectives in behaviour analysis with AI

Co-funded by
the European Union

2.1 Why analyze behavior with AI

What shapes behavior	Motivation, culture, social context, marketing and brand history all influence a purchase. Understanding these influences supports personalization, loyalty and strategy.
What AI adds	Combine signals across touchpoints to see how each shopper acts in context. Validated predictive models help interpret behavior beyond demographics.
Why scale matters	Machine learning and natural language processing turn hours of manual analysis into real-time insights for millions of shoppers, speeding decisions across retail teams.

Co-funded by the European Union

2.1 From observation to interpretation & scale

Interpret	Predict	Act
What happened, and why? Read actions in their shopping context.	What is likely next? Models identify intent, risks and windows of opportunity.	What should the retailer do now? Leaders such as Amazon link these levels across the value chain to make timely, relevant decisions and measure business impact.

Co-funded by the European Union

2.2. Data sources and types of consumer insights

Select and organize	Collect relevant, diverse data ethically. Classify sources by origin and information type.
Prepare and validate	Address bias, duplicates, gaps and inconsistencies. Validate and refresh inputs: poor preparation can produce weak models and misleading trends.
Combine and interpret	Integrate sources into more robust profiles. AI interprets structured signals to guide decisions across the retail value chain.

Co-funded by the European Union

2.2. Data sources and types of consumer insights

Descriptive

What happened? Top searches and customer segments.

Diagnostic

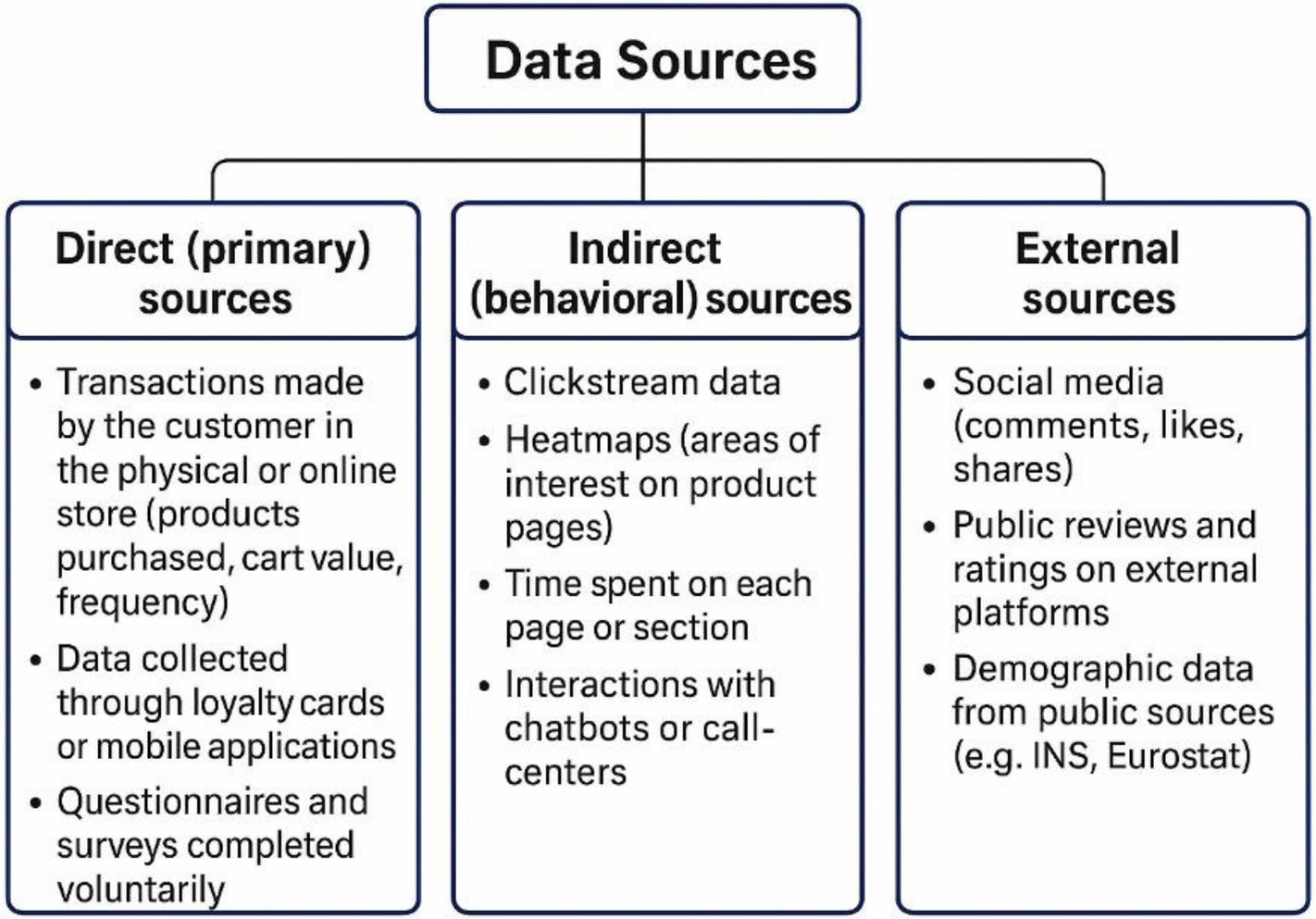
Why did mobile shoppers leave their carts? Check the interface and payment flow.

Predictive

What will shoppers likely buy in the next seven days?

Prescriptive

Which promotion should the retailer trigger?



Co-funded by the European Union

2.2. The importance of websites: Signals & governance

Observe online activity	Track click paths, time on page, scroll depth, searches and interactions with visual elements.
Connect the journey	Combine web events with transactions to reveal intent and friction. Link sources to recognize the same shopper across touchpoints.
Govern the signals	Use clear notices and manage consent. A shared taxonomy and consistent event names reduce ambiguity and speed use. Refresh data and check quality continuously to keep recommendations timely and detect drift.

Co-funded by the European Union

2.3. Building AI-driven profiles (I): Concept

A living profile	Personalized decisions	Ongoing learning
Bring signals from different channels and devices into one view of a shopper’s journey. Update it as new information arrives.	Choose relevant content and timing for each shopper at scale. Better targeting reduces message fatigue.	Build profiles in repeatable stages. Test and refine decisions across customer segments.

Co-funded by the European Union

2.3. Building AI-driven profiles (II): Data & integration

1 Collect	2 Integrate	3 Use the profile
Gather behavioral and transaction data from CRM, point of sale, apps, web, email, call centers and loyalty programs.	Clean and combine fragmented records. Identity resolution links sessions and devices to one person.	A reliable profile across touchpoints gives teams a consistent basis for analysis and action.

Co-funded by the European Union

2.3. Building AI-driven profiles (III): Behavioral analysis

Discover groups

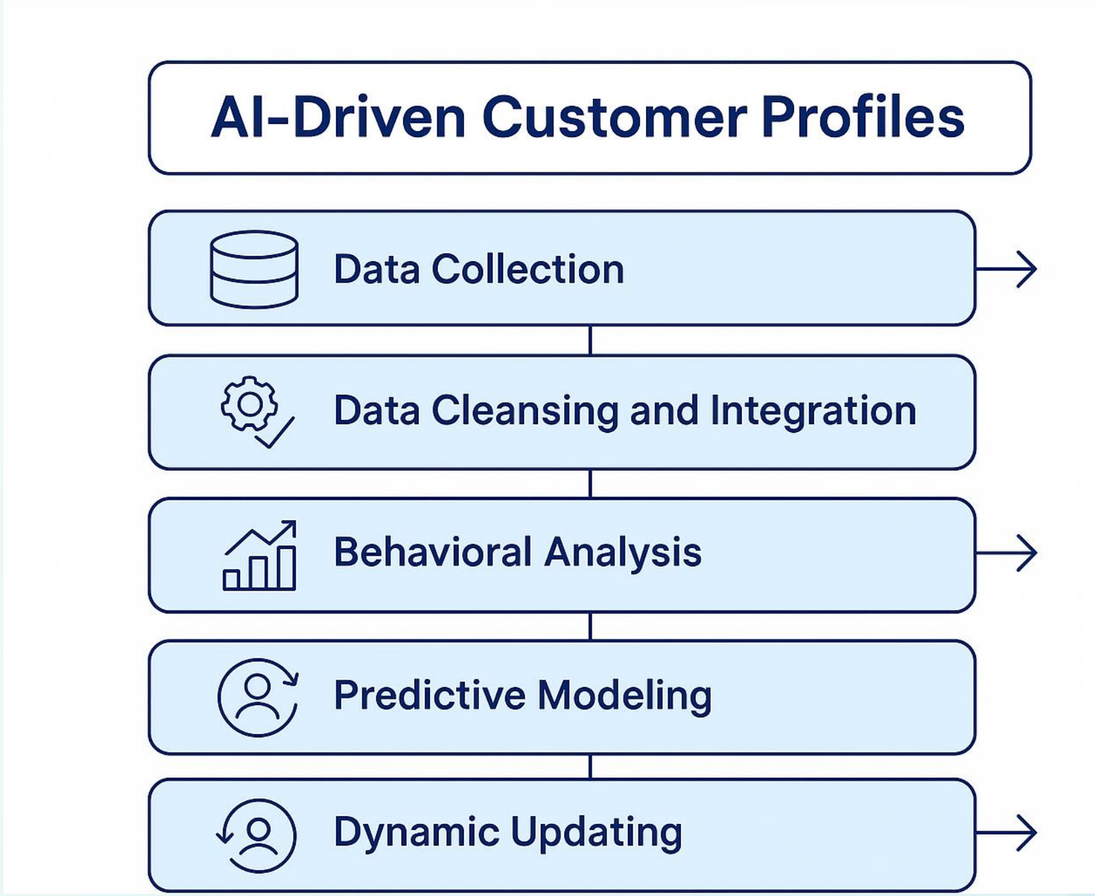
Unsupervised methods such as K-means and DBSCAN find patterns before teams assign labels or design campaigns.

Read the patterns

Compare product affinities, price ranges, shopping frequency and responses to content.

Refine the model

Use the groups to guide modeling and testing. Adapt as behavioral signals change.



Co-funded by the European Union

2.3. Building AI-driven profiles (IV): Predict & update

Predict future actions	Refresh the profile	Choose timing and content
Estimate the likelihood of a category purchase, a response to a promotion, inactivity within a given period or recommending the brand.	Update predictions and behavioral scores as new data arrive.	Align messages with current behavior. More relevant contact can reduce fatigue and improve conversion.

Co-funded by the European Union

2.4. How AI models and tools drive personalization

Skills4Retail
Building sustainable growth

I. Behavioral segmentation

1. Customer signals	Look beyond demographics: combine purchase recency, frequency and value (RFM) with channel and campaign responses.
2. Evolving segments	Clustering groups customers by behavior. Autoencoders can detect more complex patterns.
3. Personalized experiences	New signals update segments in real time and shape offers, journeys and recommendations.

Examples: loyal high-value customers, frequent visitors with no conversions, price-sensitive shoppers and occasional browsers.

Co-funded by
the European Union

2.4. How AI models and tools drive personalization

Skills4Retail
Building sustainable growth

II. Predictive scoring

Conversion probability	Prioritize investment where a purchase is more likely.
Abandonment probability	Identify customers who may leave and decide when to intervene.
Estimated customer lifetime value	Use expected long-term value to prioritize customers.

Examples: highlight premium products for high-value customers and offer targeted discounts to price-sensitive shoppers. Update scores in real time, document inputs and test impact with safeguards.

Co-funded by
the European Union

2.4. How AI models and tools drive personalization

Skills4Retail
Building sustainable growth

III. Tools for personalization

Customer data

CDPs such as Segment, Bloomreach and Tealium bring customer data together.

Customer behavior

GA4: automated insights and predictions. Hotjar and Microsoft Clarity: heatmaps and session tracking. NLP: topics and sentiment in reviews and conversations.

Analysis and reporting

Power BI, Tableau and Looker help teams explore and share findings.

Machine learning at scale

BigQuery and Snowflake: data warehouses for scalable ML.

Choose in-house tools or SaaS to match goals, maturity, budget and capacity to act. Modular platforms allow adoption in stages.

Co-funded by
the European Union

2.5. Case studies and good practices (overview)

Four cases	How to read each case	Transfer to retail
Netflix, Zara, Decathlon and IKEA show how digital and in-store signals guide decisions at scale.	Identify the signal, the tool that interprets it, the action taken and the outcome.	Use the reflection prompts to consider what fits another retail setting. Adapt the case to its context.

Co-funded by the European Union

2.5. Case study – Netflix: Personalized recommendations

Observe hesitation

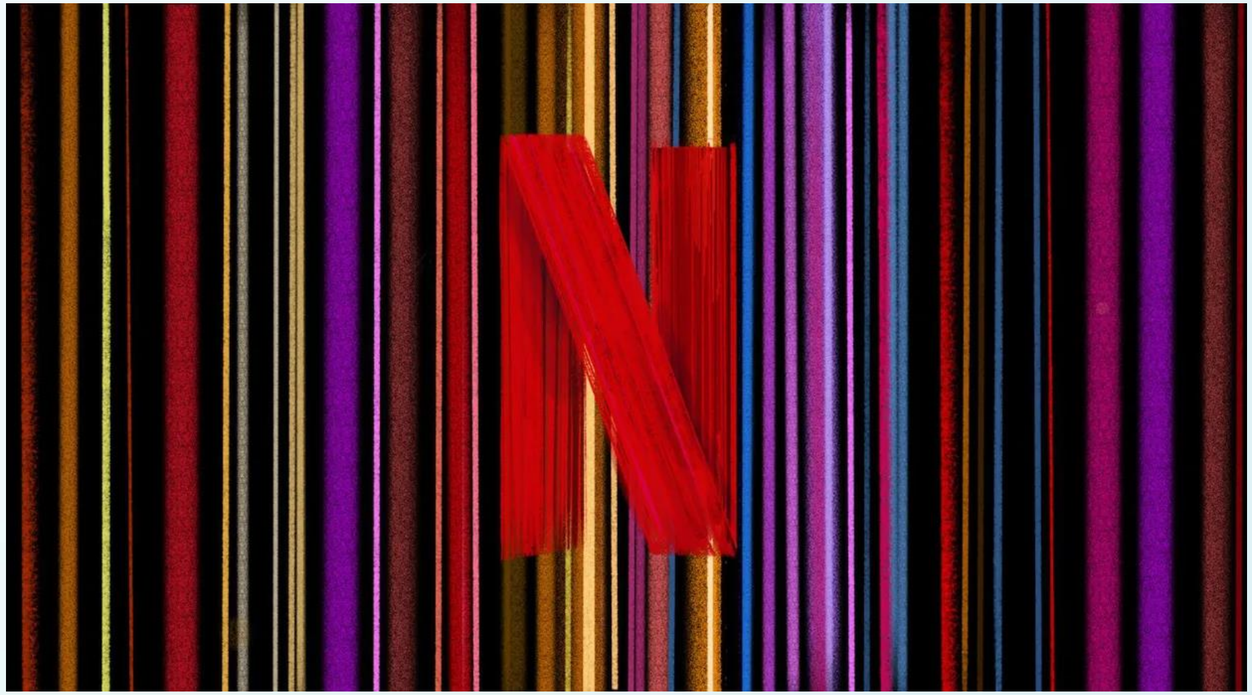
Netflix tracks preview hover time, partial plays, skips, scroll depth and navigation at scale.

Adapt recommendations

Real-time behavioral heatmaps inform personalization. Feedback loops continuously calibrate the models.

Retail reflection

Where do shoppers hesitate online? Use similar signals to improve product discovery and retention.



Co-funded by the European Union

2.5. Case study – Zara: In-store behavioral analysis

Observe the store

RFID and cameras reveal where shoppers touch, carry or try on items without buying, and where engagement drops.

Change the layout

Use movement patterns to adjust placement and local assortments. Coordinate staffing where relevant to improve conversion and satisfaction.

Retail reflection

Which layout change comes first? Compare performance before and after the change at each location.



Co-funded by the European Union

2.5. Case study – Decathlon: Real-time stock signals

Skills4Retail
Building sustainable growth

Read the shelf

The Tally robot scans RFID-tagged items outside opening hours to find misplaced products and shortages.

Act in the aisle

Ongoing stock visibility guides replenishment and improves on-shelf availability. Item and location data limit privacy risk without tracking people.

Retail reflection

What can continuous shelf data show about display effectiveness and replenishment?



Co-funded by the European Union

2.5. Case study – IKEA: Demand sensing & recommendations

Skills4Retail
Building sustainable growth

Forecast demand

IKEA uses 200+ inputs per product, including sales, seasonality, promotions, weather, holidays and store traffic.

Plan for peaks

Demand sensing anticipates payday and festival spikes. Forecasts need fewer corrections than the prior baseline.

Connect stock to recommendations

Better alignment reduces stockouts, overstock and logistics costs. Availability supports satisfaction, conversion and checkout completion.



Co-funded by the European Union

2.6. Obstacles and limits (I): Data, identity, privacy

Data quality	Incomplete, stale or biased data can mislead. Govern and validate inputs, then retrain with fresh, representative samples.
Identity	Fragmented identities across devices and channels call for customer identity resolution.
Privacy and ethics	Ordinary signals can reveal intimate preferences. Build transparency, consent and protection into workflows and support GDPR rights to access, portability and deletion.

Co-funded by the European Union

2.6. Obstacles and limits (II): Models & experience

Model transparency	Opaque models make decisions hard to audit or justify. Explain the logic and include human oversight to build trust.
Shopper experience	Excessive personalization can narrow discovery. Use ethical design and monitor risks as capabilities evolve.
Emerging directions	Generative simulations of behavior, streaming behavioral analytics, real-time emotion and intent signals, explainable AI, and AI with augmented reality for in-store suggestions.

Co-funded by the European Union

3. AI-Powered Personalization

Skills4Retail
Building sustainable growth

3.1. Introduction

3.2. What does AI personalization mean?

3.3. The role of AI in omnichannel strategy

3.4. Customer Journey Mapping and AI

3.5 Case Studies: AI Personalization in Action

3.6. Challenges and limits in AI personalization

Co-funded by
the European Union

AI-Powered Personalization - Introduction

Customer expectations	How AI responds	Retail strategy
Shoppers expect fast, relevant interactions. Using a first name in an email is no longer enough.	Real-time behavior and dynamic profiles inform recommendations and automated sequences for millions of customers.	Personalization can increase conversion and deepen relationships. The chapter covers designing and running a personalized omnichannel strategy.

Co-funded by the European Union

3.2. What does AI personalization mean? (I)

AI automatically adapts content, offers and recommendations to each shopper’s behavior, preferences and context.

1 Collect signals	Capture browsing and purchase activity, context, device information and subtle behavioral signals.
2 Update the profile	Use tracking and identity resolution to model the customer profile in real time.
3 Choose an action	Select the next best action, adapt a campaign or change the order of recommendations.
4 Deliver	Choose the most suitable channel: web, email, push notification or in-store screen.

Continuous adaptation: tactics evolve as each shopper’s behavior changes.

Personalization operates at two levels: segments (macro) and individuals (micro).

Co-funded by the European Union

3.2. What does AI personalization mean? (II)

Macro: customer segments

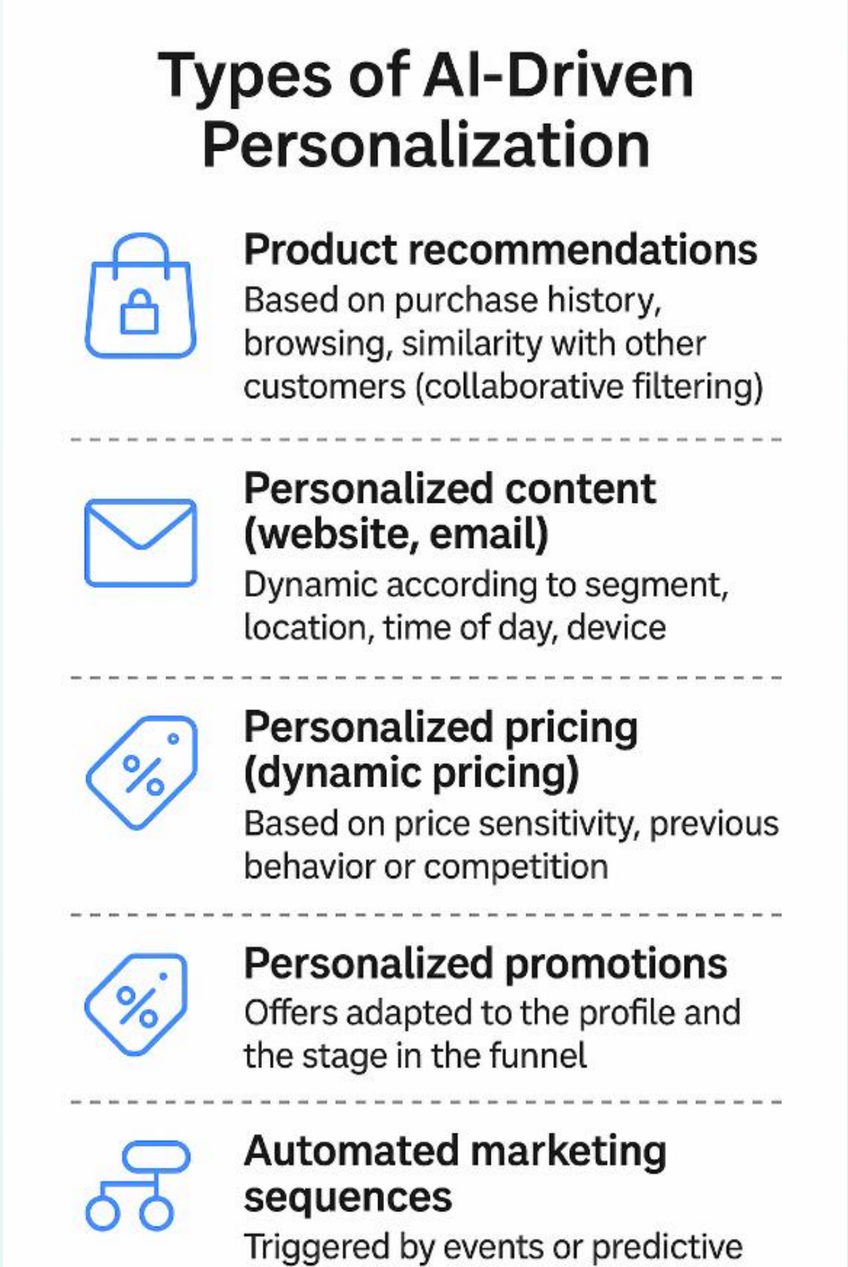
Group a large customer base into micro-segments to run targeted campaigns at scale.

Micro: individual sessions

Use real-time signals of intent to tailor content, assortment, page layout, channel and interface during each session.

How the two work together

Profiling, prediction and adaptive delivery support hundreds or thousands of real-time micro-campaigns. The goals are commercial efficiency and customer satisfaction.



Co-funded by the European Union

3.3. The role of AI in omnichannel strategy (I)

Recognize	Synchronize	Adapt
Identity resolution and customer data platforms connect each shopper’s activity across channels.	Update the profile after each interaction so recommendations and messages remain consistent at the next touchpoint.	Use location, time, device, season and stock to tailor offers. Prioritize channels for each customer to improve ROI.

Co-funded by the European Union

3.3. The role of AI in omnichannel strategy (II)

Mobile browsing

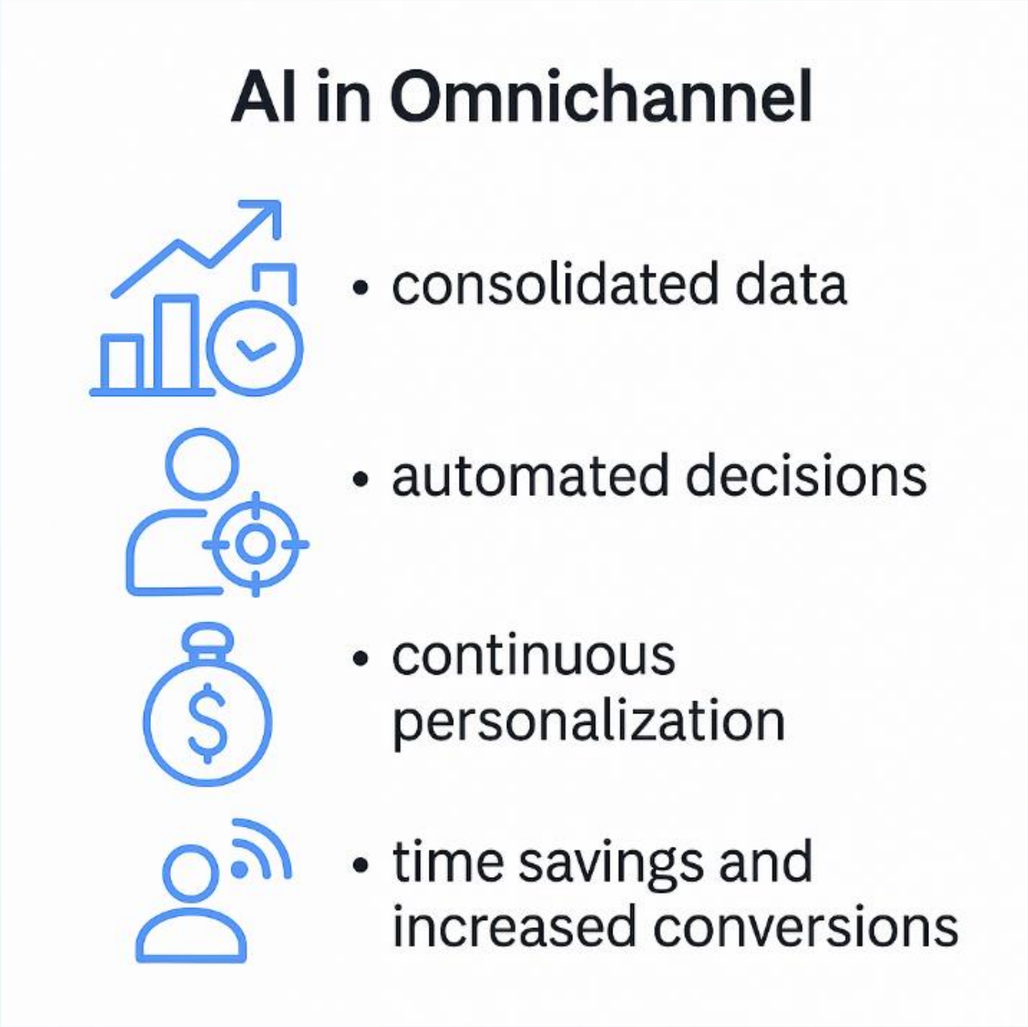
A shopper views a product on a phone and leaves without buying.

Next-day email

AI sends the same product with a limited-time discount tied to the nearest store.

Why it works

Behavior and location inform a timely offer that can increase conversion. See Chapter 5 for the wider omnichannel strategy.



Co-funded by the European Union

3.4. Customer Journey Mapping and AI (I)

Map actual paths	Locate friction	Adapt the journey
Trace the steps from awareness to loyalty or exit using observed customer behavior.	Identify pain points and key decisions. Estimate the risk of abandonment at each stage.	Create paths for individuals or segments and update them as interactions occur.

Co-funded by the European Union

3.4. Customer Journey Mapping and AI (II)

Connect the tools

Link CRM and marketing automation so journeys can change as shoppers act.

Adapt the response

Use past patterns to tailor reactivation flows. Adjust content, channel and offers automatically.

Data requirements

Clean data and frequent signals make timely, proactive interventions possible.

Technologies used:



Heatmaps and behavioral tracking



Machine learning for predicting the next step



NLP for textual feedback analysis



Behavioral scoring algorithms (e.g. lead scoring, churn risk)

Co-funded by the European Union

3.5. Case study
Amazon (Recommendation Engine)

Signals	Purchases, browsing, abandoned carts, reviews and the behavior of similar customers.
Personalization	Machine learning adapts pages, recommendation bars, emails and the app in real time.
Reported impact	The source attributes about 35% of revenue to the recommendation engine (IndustryARC, 2025).

Reflection	How could mid sized retailers leverage behaviour-based recommendation engines to drive a similar uplift without needing Amazon-level scale?

Co-funded by the European Union

3.5. Case study
Sephora (AR Virtual Artist)

Signals	A selfie supplies facial features and skin-tone information. Shade selections reveal preferences.
Personalization	Computer vision and AI power virtual makeup try-on and suggest products that suit the shopper's style.
Reported impact	Conversion increased 11% and product returns fell 30% (Anderson, 2025).

Reflection	What challenges might a retailer face when scaling AR-driven personalization (e.g., data quality, device compatibility), and how can they be addressed?

Co-funded by the European Union

3.5. Case study
Spotify (Hyper-Personalization)

Signals	Listening history, similar users, time of day and context such as a workout or commute.
Personalization	AI creates individual playlists and refreshes them daily as listening behavior changes.
Retail lesson	Context-sensitive curation supports engagement and retention and can inform product lists.

Reflection	Could a retail brand employ a similar approach to dynamically curate product lists or marketing content based on real-time user behaviour and context?

Co-funded by the European Union

3.5. Case study
H&M (Outfit Suggestions)

Signals	The app uses browsing, clicks, searches and purchases, alongside season, style and location.
Personalization	H&M recommends complete outfits and adapts push messages and newsletters to customer personas.
Retail lesson	Refresh suggestions as behavior changes to keep outfits relevant.

Reflection	How can a fast-fashion retailer ensure outfit recommendations remain both diverse and relevant as customer behaviour evolves across seasons?

Co-funded by
the European Union

3.5. Case study
Zalando (Trend Prediction)

Signals	Saved items and reviews express preferences. Behavioral signals and visual analysis of social media reveal emerging trends.
Personalization	Recommendations change as real-time trends and individual tastes evolve.
Retail lesson	Connect trend forecasting with what is relevant to each shopper.
Reflection	What operational challenges might arise when combining trend forecasting with individual recommendation engines in fast-moving categories like apparel?

Co-funded by
the European Union

3.5. Case study
Netflix (Behavioral Lessons)

Signals	Play duration, skipped titles and binge-watching patterns.
Personalization	Netflix changes title order, thumbnails and cross-genre suggestions. The case attributes a major share of engagement to personalization.
Retail lesson	Use behavioral signals to adapt product displays and messages.

Reflection	What insights from Netflix’s behavioural signal processing could be adapted to optimize product displays and personalized messaging in online retail environments?

Co-funded by
the European Union

3.5. Applied exercise

Choose a well-known brand and design an AI personalization campaign for one channel: website, app or email. Reference case: Decathlon (Retail Rocket, 2018).

Customer data	AI technology
What data is collected about customer behaviour?	What AI technology would you use for personalization?
Personalized content	**Measurement**
What types of content or offers would be personalized?	How would you measure the effectiveness of the campaign?

Reflection	How could you adapt this recommendation approach - using both similar and related product blocks - to improve conversions in categories with very wide product ranges (e.g. electronics, home appliances)?

Co-funded by the European Union

3.5. Applied prompts Replicating for eMAG

Use the Decathlon case to design a personalization campaign for one channel at eMAG.ro or a similar e-commerce platform.

Customer data	AI technology
What data about user behaviour could eMAG collect for this campaign?	What AI technologies could be used to drive personalization?
Personalized content	**Measurement**
What exactly would be personalized?	How would eMAG measure success?

Reflection	How would you adapt your personalization logic if eMAG sold high-margin electronics versus low-margin groceries? Should the personalization strategy vary by product category?

Co-funded by the European Union

3.6. Challenges and limits in AI personalization

Data and continuity

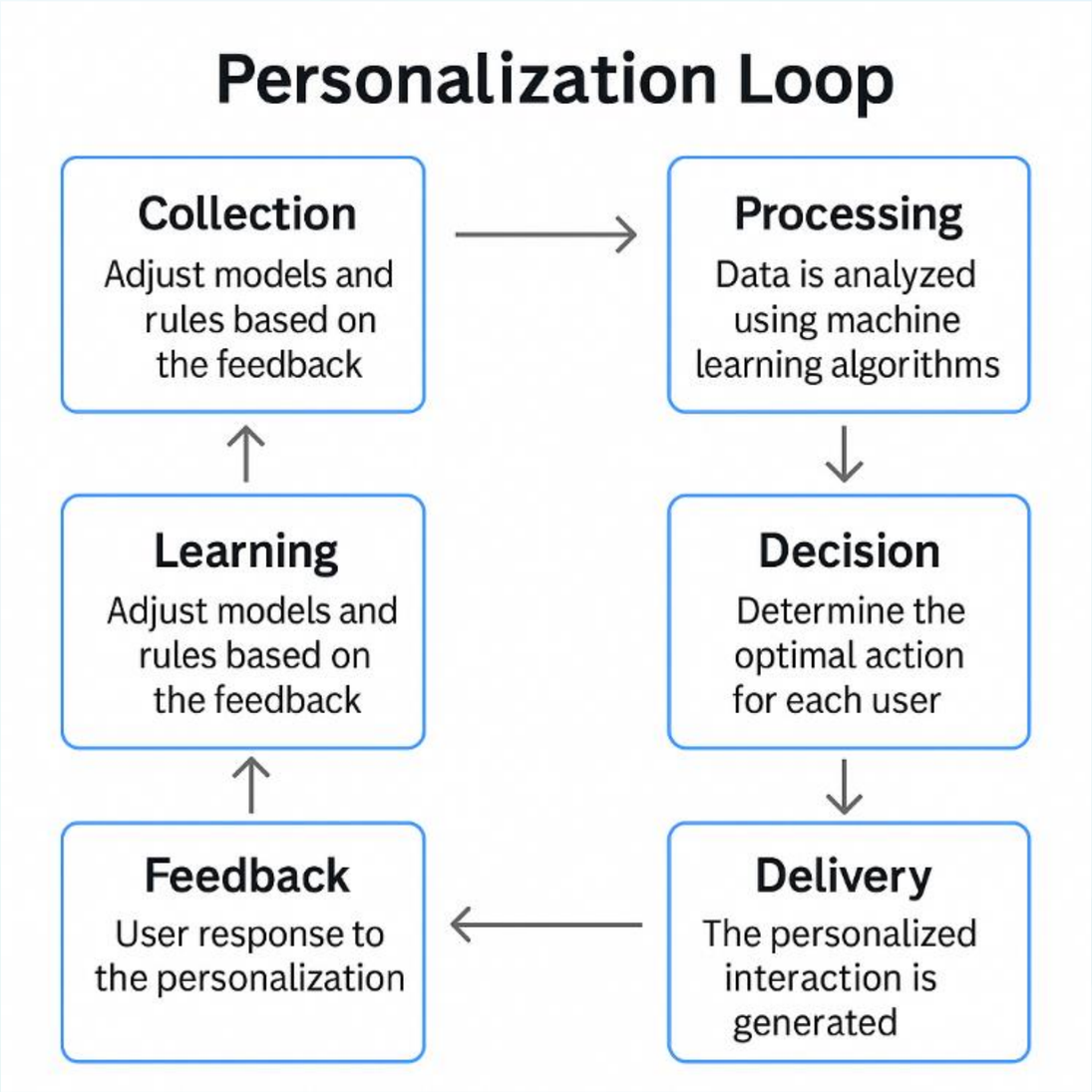
Fragmented data and weak profile unification can create inconsistent experiences across channels.

Trust and fairness

Invasive uses, consent concerns and excessive messages can erode trust or cause fatigue. Historical bias can produce unfair outcomes.

Cost and explainability

Infrastructure and scaling costs challenge smaller retailers. Models can be opaque, and real-time explainability remains limited as XAI develops.



Co-funded by the European Union

4. AI for Operational Efficiency in Retail

Skills4Retail
Building sustainable growth

4.1. Introduction

4.2. Supply chain optimization

4.3. Inventory management and price dynamics

4.4. Workforce planning and resource allocation

4.5 Repetitive Process Automation (RPA)

4.6. Predictive maintenance and asset management

4.7. Applied exercise

4.8. Conclusions

Co-funded by
the European Union

AI FOR OPERATIONAL EFFICIENCY IN RETAIL INTRODUCTION

Forecast demand	Automate routine work	Manage the risks
Detailed forecasts guide logistics, staffing and maintenance. Predictive models help prevent stockouts and waste.	RPA handles repetitive tasks governed by clear rules. Teams can respond faster, improve accuracy and lower costs.	Poor data quality, disconnected systems and weak governance can undermine those gains.

The chapter compares operating strategies, performance measures, benefits and implementation challenges.

Co-funded by the European Union

4.2. Supply chain optimization

Planning replenishment across the supply network

01 Demand signals	02 Scenario planning	03 Replenishment
Combine sales, trends, shopper behavior and external factors.	Forecast demand and test disruptions to strengthen contingency plans.	Plan upstream logistics and replenish proactively across the network.

Performance measures

Availability	Planning	Fulfillment
Stockout rate and on-shelf availability	Forecast accuracy and inventory turnover	Lead time and cost per order

Expected benefits	Less overstock, better service levels and lower costs.
Implementation risks	Integration failures and fragmented data pipelines.

Co-funded by the European Union

4.2. Supply chain optimization (II):

Case study – Walmart, forecasting and replenishment at scale

01 Forecast demand

Use real-time signals to anticipate shortages.

02 Generate orders

Automatically create replenishment orders for each store.

03 Detect anomalies

Flag unusual logistics events to increase throughput and reduce manual work.

Reported outcomes

≈15–20%

fewer stockouts

≈10%

lower operating costs

Higher on-shelf availability and customer satisfaction.
Faster reordering and fewer logistics errors.

Reflection

What organizational capabilities and data infrastructure would a smaller retailer need to replicate Walmart's forecasting and proactive replenishment at scale?

Co-funded by the European Union

4.3. Inventory management and price dynamics (I): Concepts & KPIs

Read local demand	Static rules miss local and seasonal changes. Use live signals to coordinate stock, pricing and promotions for each SKU.
Adjust by item	Respond to demand surges and competitor moves with intraday prices. Flag slow sellers for bundles or targeted markdowns.
Measure results	Track on-shelf availability (OSA), price levels, sell-through and margin after price adjustments.

More precise stock decisions and responsive prices can reduce shortages and overstock while protecting margins.

Co-funded by the European Union

4.3. Inventory management and price dynamics (II): Case study - REMA 1000

Process	AI uses real-time data to set intraday prices. Electronic shelf labels (ESLs) display changes immediately across the store, improving price compliance and transparency.
Operational decision	Flag perishables for timely promotions. Faster adjustments help maintain competitiveness and margins while reducing waste.
Reported results	Up to 80% less manual pricing effort. Shelf pricing errors fell significantly, perishable food waste declined and promotions were updated faster.

Reflection	What would be the necessary steps and technologies for a mid-sized retailer to adopt electronic shelf labeling and dynamic pricing in a scalable way - without compromising pricing integrity or customer trust?

Co-funded by the European Union

4.4. Workforce planning and resource allocation (I): Concepts & KPIs

Demand signals	Combine sales, weather, events, footfall and absenteeism to estimate staffing needs.
Scheduling decisions	Apply business rules and allocate staff by hour, zone or department. Rebalance in real time during peaks and quiet periods.
Performance measures	Track labor cost as a percentage of sales, schedule coverage accuracy, absenteeism and employee satisfaction.

The aim is lower labor cost with consistent service quality.

Co-funded by the European Union

4.4. Workforce planning and resource allocation (II): Case study - VTI (Japanese supermarket chain)

Process	The supermarket uses VTI to forecast demand and plan shifts for each department. An integrated workforce management platform adjusts staffing in real time.
Operational decision	Move coverage to footfall peaks and offer fair, flexible schedules to support engagement.
Reported results	Labor costs fell 15% and employee productivity rose 20%. Staff satisfaction improved and overtime declined.

Reflection	In workforce optimization, what trade-offs might exist between cost reduction and employee satisfaction - and how can AI help maintain a balance between them?

Co-funded by the European Union

4.5. Repetitive Process Automation (RPA) (I): Concepts & KPIs

Workflows	Invoices, purchase orders and inventory reconciliation generate substantial administrative and transactional work.
Automation	RPA verifies records, matches documents and enters data. An end-to-end audit trail supports faster, more accurate processing.
Performance measures	Track cycle time, error rate, exceptions handled and cost to assess efficiency and quality.

Redesign the workflow as part of introducing automation.

Co-funded by the European Union

4.5. Repetitive Process Automation (RPA) (II): Case study - Major U.S. retailer (UiPath Document Understanding)

Process	UiPath Document Understanding uses OCR and machine learning to scan invoices and extract fields for invoice and order processing.
Operational decision	Validate fields against purchase orders, route exceptions for review and populate the ERP to speed up payment. Align change management with compliance.
Reported results	Up to 95% less time spent on invoices. Processing fell from hours to minutes per invoice, accuracy exceeded 99% and manual errors declined.
Reflection	What change management steps and data governance practices should a medium-sized retailer adopt when transitioning core financial workflows to RPA to ensure compliance and continuity?

Co-funded by the European Union

4.6. Predictive maintenance and asset management (I): Concepts & KPIs

Monitor assets	IoT sensors, wireless telemetry and cloud analytics track refrigeration, HVAC, lighting and safety equipment.
Detect and intervene	Models learn normal behavior and flag early anomalies. Predictive dashboards guide real-time interventions and repairs before peak periods.
Performance measures	Track mean time between failures (MTBF), mean time to repair (MTTR), downtime percentage, asset utilization and failure prediction accuracy.

The module cites a 20–40% reduction in downtime, lower costs and fewer emergencies.

Co-funded by the European Union

4.6. Predictive maintenance and asset management (II): Case study - National grocery chain

Process	Sensors continuously stream temperature, vibration and power readings from refrigeration units. Models detect deviations that can signal an approaching failure.
Operational decision	Early alerts let teams schedule repairs, stabilize operations and limit service interruptions.
Reported results	Unplanned downtime fell by about 40%. Savings exceeded US$1.4 million, emergency calls declined and more faults were fixed on the first visit.

Reflection	How should a mid-sized retailer prioritize sensor deployment and model training for predictive maintenance to balance cost effectiveness and early failure detection?

Co-funded by the European Union

4.7. Applied exercise (I): Task - Design an AI intervention

1 Select a process	2 Match data and model	3 Assess the proposal
Choose inventory, pricing, staffing, maintenance or logistics. Define one measurable process that a retailer could realistically improve.	Identify internal and external data, structured or unstructured. Choose regression, classification, reinforcement learning, anomaly detection or clustering.	State the expected gains in cost, efficiency or accuracy. Identify one plausible risk or limitation.

Co-funded by the European Union

4.7. Applied exercise (II): Example - Workforce planning

Objective and inputs	Schedule cashiers and floor staff per shift in large urban stores. Use hourly footfall, POS data, promotions, weather and absenteeism.
Model and benefits	Use regression with seasonality and decision trees for scenarios. Expected gains include less overtime, better service levels and higher satisfaction.
Risk and response	Unexpected demand spikes may leave shifts understaffed. Validate in pilots and adjust thresholds.

Co-funded by the European Union

4.7. Applied exercise (III): Example - Predictive maintenance

Objective and inputs	Predict compressor failures in food retail cold chains. Combine temperature, vibration and power readings with maintenance logs and equipment load.
Model and benefits	Combine anomaly detection and supervised classification. Aim to reduce product loss, downtime and costs.
Risk and response	Balance false alarms against missed failures. Tune sensitivity and define when alerts should be escalated.

Co-funded by the European Union

4.7. Applied exercise (IV): Example - Dynamic pricing

Objective and inputs	Adjust daily prices for fast-selling seasonal items as demand and competition change. Use sales history, stock, scraped competitor prices, calendar and conversion rate.
Model and benefits	Use reinforcement learning such as Q-learning or DDPG. Aim for better margins, faster stock movement and quicker responses.
Risk and response	Frequent or unexplained price changes may upset customers. Set pricing guardrails and make changes transparent.

Co-funded by the European Union

4.8. Conclusion

Where AI helps	How gains combine	What makes it work
Supply chains, inventory and pricing, staffing, process automation and maintenance each offer different operational gains.	Connected systems reinforce one another. Together they can lower costs, improve availability and speed up operations.	Invest according to local needs, assign accountability and support each change with reliable data, sound process design and governance.

Co-funded by the European Union

5. Omnichannel Strategies with Artificial Intelligence

Skills4Retail
Building sustainable growth

5.1. Introduction

5.2. Key elements of an AI-driven omnichannel strategy

5.3. The role of AI in cross-channel coherence

5.4. Case Studies: Omnichannel AI in Action

5.5 Applied Exercise – Designing an AI-Powered Omnichannel Flow

5.6. Conclusion

Co-funded by
the European Union

Omnichannel Strategies with Artificial Intelligence - Introduction

Customer identity	Recognize shoppers across devices and sessions so an online interaction can inform an in-store visit.
Context and intent	Interpret intent in light of time, place and device. Coordinate messages and offers in real time across touchpoints.
Strategy design	Connect identity, context, channel synchronization, the customer journey and inventory. AI makes shared decisions possible at speed and scale.

Customers expect a smooth, personal and consistent experience. The research cited in the module links this approach to better CX, loyalty and consistency.

Co-funded by the European Union

5.2. Key elements of an AI-driven omnichannel strategy (I)

01 Unified identity	Identity resolution & unified view (centralized, dynamic profile) Unifies purchases, preferences, browsing, reactions, subtle signals Every decision starts from an up-to-date customer picture
02 Customer context	Contextual personalization (time, location, device, season, weather) In-app vs. email can differ, yet remain consistent Context reduces friction and increases engagement
03 Channel synchronization	Syncing between channels (cart → email/push/store alert) Turns disparate steps into a fluid path; boosts conversion Requires tight coordination across martech + ops.

Co-funded by the European Union

5.2. Key elements of an AI-driven omnichannel strategy (II)

04 Adaptive journeys	Optimizing the customer journey with real-time signals Re-rank pages, recommend similar items, adapt messaging Dynamic, adaptive, personalized micro-journeys
05 Inventory and offers	Intelligent inventory & offer management Balance stock across locations; align promos to context Prevent channel discrepancies for a coherent experience
All five pillars together	The five pillars operate interdependently AI continuously connects, prioritizes, adapts Needs precise data infrastructure and governance.

Co-funded by the European Union

5.2. Key elements of an AI-driven omnichannel strategy (III): Data & governance prerequisites

Identity and data	Precise identity resolution across touchpoints Consistent data quality & taxonomy across sources Real-time pipelines for cross-channel sync
Consent and frequency	Consent & privacy governance, plus frequency control
Coordination and measurement	Alignment across marketing, IT, and store ops Coherent metrics: conversion, returns, CX signals
Role of AI	Treat AI as orchestrator across people/process/tech These prerequisites make §5.2 pillars actually work

Co-funded by the European Union

5.2. Key elements of an AI-driven omnichannel strategy (IV): Orchestration guardrails

Before automation	Avoid automation-first without foundations Fix fragmentation in profiles, messaging, inventory
Pilot and refine	Pilot → monitor → iterate before broad rollout
Staff and channel handoffs	Keep staff tools simple for clienteling moments Plan for latency and online/offline handoffs
Transparency and empathy	Be transparent on triggers and decision logic Anchor decisions in customer empathy & context Sets up §5.3 orchestration and §5.4 case execution

Co-funded by the European Union

5.3. The role of AI in cross-channel coherence (I)

Connect the journey

Link fragmented actions to the same shopper across daily touchpoints, including visits when the shopper is signed out.

Choose the channel

Use audience preferences to select the channel most likely to deliver a return on investment.

Learn from responses

Clicks, purchases and ignored messages inform real-time changes in tone, frequency and content.

Consistent contact that respects preferences and avoids intrusion can give retailers a competitive advantage.

Co-funded by the European Union

5.3. The role of AI in cross-channel coherence (II)

AI coordinates the message, channel, timing and format across a journey.

Product view	Push notification	Personalized email
A shopper views an item.	The product view triggers a relevant follow-up.	A later email continues the interaction. Channel choice adapts as preferences become clearer.

A global fashion retailer also tracks the path from an ad to a store purchase. AI enables this coordination at scale. Chapter 7 examines CX outcomes.

Co-funded by the European Union

5.4. Case study - Sephora: Unified digital & in-store

Connected touchpoints	Sephora’s clienteling app links mobile browsing to store visits. Consultants can see purchases, browsing history and saved preferences in one profile.
Personalized service	Consultants use the digital journey to tailor advice. Computer vision and AI can suggest makeup using a face scan and skin tone.
Reported outcomes	Higher in-store conversion among shoppers who had browsed online, alongside increased satisfaction and loyalty.
Reflection	What technological and organizational prerequisites must be in place for retail staff to deliver real-time personalization based on digital profiles without disrupting the in-store experience?

Co-funded by the European Union

5.4. Case study - Nike: Loyalty & app integration

Connected touchpoints	Nike App, Run Club, Training Club, SNKRS and NikePlus connect community, workouts and shopping. The apps also provide data for personalization.
Personalized service	Store staff can see saved items and preferences. Behavior, location or membership tier can trigger alerts. Early access to product drops rewards loyalty with exclusivity.
Reported outcomes	Member engagement rose, and limited product launches had higher conversion.

Reflection	How can retailers balance personalization and exclusivity with fairness and accessibility in loyalty-driven omnichannel strategies?

Co-funded by the European Union

5.4. Case study - Zalando: Cross-platform personalization

Connected touchpoints	A shared engine links web, app and email. Phone-to-web identity matching, observed behavior and stated preferences keep curated suggestions consistent and reduce friction.
Personalized service	Visual search, dynamic styling and query intent shape recommendations. An AI assistant answers outfit questions in natural language.
Reported outcomes	Better fit and context supported higher conversion and fewer returns. The case reports reductions of up to 90% in content production time and costs.

Reflection	Considering these examples, what core capabilities - such as data integration, identity resolution, or cross-channel synchronization - would you prioritize when designing an AI omnichannel system for a mid-sized retail brand?

Co-funded by the European Union

5.5. Applied exercise
Design an AI omnichannel flow (I)

A retailer wants to improve conversion and retention online and in stores. Digital marketing and IT will map the journey together to identify where AI can help most.

1 Map the journey	2 Link data to action	3 Connect the steps
Identify three key customer touchpoints.	For each touchpoint, specify what data are collected and what action AI should trigger.	Explain how the three touchpoints form one consistent customer experience.

Co-funded by the European Union

5.5. Applied exercise - Extended example (II)

Touchpoint	Signals	AI action
Product view	Category, time, visits, source	Email related products, reviews and nearby stock availability.
In-app cart	Items, activity patterns, history	Use the prediction to select a time-limited offer or a shipping incentive.
In-store loyalty scan	Purchase history, interests, loyalty tier	At the point of sale, suggest a complementary item and give staff an upselling script.

Reflection	How would you ensure data consistency and real-time synchronization between all touchpoints in your proposed scenario, considering the latency or fragmentation issues across platforms?

Co-funded by the European Union

5.6. Conclusion (I)

Recognize patterns	Coordinate action	Operate efficiently
Each touchpoint feeds a shared system that learns from interactions and anticipates individual needs.	Time communications and synchronize offers with stock. Apply what the system learns continuously and at scale.	Retailers can respond to individual shoppers while maintaining operational efficiency and gaining a competitive advantage.

This shift requires cultural change and investment in digital systems and analytics.

Co-funded by the European Union

5.6. Conclusion (II): From promise to practice

Prepare the foundations	Connect decisions	Track the benefits
Clarify the customer need. Resolve gaps in data, messages and inventory before scaling automation, which can amplify existing problems.	Combine dispersed data to personalize at scale and keep channels synchronized throughout the journey.	Integrated adoption can support sales growth and customer loyalty. Keep the shopper's perspective central as the program expands.

Chapter 6 applies these principles to AI-supported customer journey mapping.

Co-funded by the European Union

6. Customer Journey Mapping Enhanced by AI

Skills4Retail
Building sustainable growth

6.1. Introduction

6.2. The Role of AI in Modern Journey Mapping

6.3. Practical Applications in Retail

6.4. AI Journey Mapping Tools and Platforms

6.5 Case Studies

6.6. Applied Exercise – AI for Journey Mapping in Retail

6.7. Conclusions

Co-funded by
the European Union

Customer Journey Mapping Enhanced by AI - Introduction

Traditional maps	Manual maps are slow to update and depend on assumptions. A fixed path misses changes in how shoppers behave.
Connected evidence	Web and app activity, store sensors and service logs reveal actual paths, intent and friction in real time.
Retail decisions	Use the map to design, personalize and improve interactions. Timely responses also support better operations and customer-focused innovation.

Co-funded by the European Union

6.2. The Role of AI in Modern Journey Mapping (I)

Observe the path

Machine learning detects small steps toward purchase, hesitation and repeated loops across a journey.

Find turning points

Identify where a step succeeds or fails. Compare paths by segment and context.

Refresh the map

New behavioral data continuously updates the map, including routes that depart from the assumed ideal path.

Co-funded by the European Union

6.2. The Role of AI in Modern Journey Mapping (II)

Interpret feedback	Anticipate needs	Adapt the experience
NLP draws meaning from reviews, chats and feedback. Clustering groups shoppers by what they do.	Predict the risk of cart abandonment or the likelihood that a shopper will need help.	Adjust content and the next step in real time. Learn from responses to improve engagement.

Journey analysis can guide a timely intervention as well as explain past behavior.

Co-funded by the European Union

6.3. Practical Applications in Retail (I)

Funnel analysis	Identify where shoppers leave and why. Use the findings to improve the interface, message or timing.
Session personalization	Use current intent to reorder items and adjust layouts and promotions.
Online-to-store handoff	Let shoppers browse online and complete the purchase in store. Coordinate offers and stock across touchpoints.

Intervene at the point of friction to reduce abandonment.

Co-funded by the European Union

6.3. Practical Applications in Retail (II)

Route service requests	Match the issue to a channel or agent. Use recent events to set priority and guide the conversation.
Plan store operations	Use journey flows to anticipate peaks and allocate staff and fulfillment resources early.
Evaluate outcomes	Look for higher satisfaction, less friction and better yield. Integrating these capabilities into CX systems enables greater automation.

Retail examples in this section include IKEA, Target and ASOS.

Co-funded by the European Union

6.4. AI Journey Mapping Tools and Platforms (I)

Demand is growing for tools that interpret customer journeys as events happen.

Adobe Journey Optimizer	Triggers journey steps as events happen.
Salesforce Customer 360 + Einstein	Combines customer data into a unified view with predictive insights.
SAS Customer Intelligence	Uses models to guide decisions in real time.

Retail-focused suites	**Speed and scale**
Insider, Emarsys and Algonomy	Templates for segmentation, churn and lifecycle flows help teams see value sooner and launch journeys at scale.

Co-funded by the European Union

6.4. AI Journey Mapping Tools and Platforms (II)

Enterprises can also build a custom, cloud-native platform.

01 Data and models

Stream events.

Use scalable storage and manage models in production.

02 Journey design

Marketers design adaptive journeys in visual editors.

Combine A/B testing and business rules with AI decisions.

03 Execution

Connect CRM, CDP, CMS, ERP and fulfillment systems.

Carry out decisions where the customer interaction or operational action takes place.

Connecting these layers keeps the customer journey consistent from end to end.

Co-funded by the European Union

6.5. Case Studies
Lowe’s (Overview & Methods)

Observe store zones	Test layouts	Adjust each store
Computer vision tracks shopper movement and dwell time. Spatial analysis and 3D digital twins show how people use each zone.	Simulate changes to improve product exposure and traffic flow. Compare store behavior with online interest, including seasonal browsing.	Use those patterns to align staffing, placement and promotions. Apply the approach across stores while retaining local detail.

Co-funded by
the European Union

6.5. Case Studies
Lowe’s (Impact & Reflection)

Reported outcomes	Staffing and layout changes improved store conversion. Peak-period stockouts fell, and smoother journeys improved satisfaction metrics.
Store-level evaluation	Calibrate sensors, validate models and track measurable journey KPIs. Use the findings to refine layouts by store type.
Reflection	How could a mid-sized retailer implement store-level journey monitoring and layout testing without requiring large-scale 3D modeling infrastructure?

Co-funded by
the European Union

6.5. Case Studies
Tesco (Overview & Methods)

Connect interactions

Clubcard maps activity across channels. Profiles refresh in real time, and segments change with each interaction.

Predict the response

Use purchase history and current context to predict the next purchase and the likelihood of responding to an offer.

Personalize in store

Align offers with digital intent so insights from the loyalty program inform the next in-store interaction.

Co-funded by the European Union

6.5. Case Studies
Tesco (Impact & Reflection)

Reported outcomes	In-store promotions matched to intent converted better. Fewer coupons went unused, improving loyalty ROI. Basket value and cross-channel engagement rose.
Customer control	Make consent and choices clear. Guard against over-targeting and fatigue to preserve trust as personalization scales.
Reflection	What steps are essential for ensuring data privacy and customer control while leveraging loyalty-based behavioural insights in journey mapping?

Co-funded by
the European Union

6.5. AI Deployment Matrix - Lowe’s vs. Tesco

Element	Lowe’s	Tesco
Overview	In-store AI for optimizing shopper journeys via sensor-based data	Loyalty-driven personalization across both digital and in-store touchpoints
Journey Application	Foot traffic analysis, heatmapping, and layout simulation for product placement	Real-time segmentation and dynamic promotions based on past purchases and behaviour
Impact Metrics	Conversion rates, product discoverability, customer satisfaction	Coupon redemption, basket value, cross-channel engagement
Reflection Focus	Reliance on physical infrastructure and calibration; scalability across stores	Risk of data fatigue, over-targeting, and privacy perception issues

Co-funded by the European Union

6.6. Applied Exercise - Scenario & Tasks

Scenario: a retailer with an online shop and physical stores wants to map interactions and reduce friction across the journey.

Choose three moments	Select touchpoints where shopper paths diverge or a change could have a large impact.
Identify data and models	For each point, specify the signals: clickstream, GPS, history or sentiment. Choose a method such as classification, anomaly detection, NLP or sequence modeling.
Define the response	State what the model should trigger at each touchpoint to improve the experience.

Co-funded by the European Union

6.6. Applied Exercise - Cross-Channel Integration

Connect identities	Explain how the touchpoints form one journey. Link sessions and devices through identity resolution.
Coordinate actions	Use live inference for timely responses. Synchronize offers and stock across channels and set latency budgets for in-the-moment decisions.
Evaluate the whole journey	Make consent and privacy constraints explicit. Measure uplift using journey-level KPIs.

Co-funded by the European Union

6.6. Applied Exercise - Extended Example

Touchpoint	Signals	Model and action
First mobile visit	Clickstream, source and device	Cluster the visitor into a behavioral profile and adapt the homepage to inferred interests.
Abandoned app cart	Items, time and frequency	Predict dropout probability. Send a timely push message, such as free delivery when intent was strong.
In-store loyalty scan	Full history and visit context	Use a next-best-action model on sequence data. At checkout, recommend a bundle based on recent app activity.

Reflection 1	How can AI balance between personalization and over-targeting in a cross-channel context?
Reflection 2	What safeguards are needed to ensure ethical handling of behavioural and biometric data in journey tracking?

Co-funded by the European Union

6.7. Conclusion

Understand and act	Build the foundations	Keep learning
Use real behavior to keep the journey map accurate and adapt in real time. Connect experience design to measurable outcomes.	Invest in data quality, explainability and governance. Align teams, build skills and redesign the processes that act on the map.	Use results to refine journeys continuously. This capability matters as competition and customer expectations rise.

Co-funded by the European Union

7. Customer Experience Analytics with AI

Skills4Retail
Building sustainable growth

7.1. Introduction

7.2. Core Metrics and CX KPIs in Retail

7.3. AI Techniques in Customer Experience Analytics

7.4. Personalization and Predictive Insights

7.5 CX Optimization through AI Feedback Loops

7.6. AI in Action: CX Case Studies and Reflections

7.7. Applied Exercise - AI-Driven CX Optimization in Response to NPS Decline

7.8. Conclusions

Co-funded by
the European Union

Customer Experience Analytics with AI - Introduction

Customer experience	Patterns at scale	Retail decisions
Every interaction, online or in a store, shapes how customers see a brand. That perception differentiates retailers.	Traditional analytics struggle with the volume and complexity of these interactions. AI identifies patterns and predicts behavior.	Teams can move from reporting what happened to deciding how to respond in real time.

Use these insights to adapt engagement as customer behavior changes.

Co-funded by the European Union

7.2. Core Metrics and CX KPIs in Retail (I): Experience

CSAT	NPS	CES
How satisfied was the customer after a particular interaction or experience?	How likely is the customer to recommend the brand?	How easy or difficult was it to complete a task?

Experience is one of three KPI groups, alongside operations and relationship value. Compare expectations with the experience delivered before assessing AI improvements.

Co-funded by the European Union

7.2. Core Metrics and CX KPIs in Retail (II): Operations & Value

Support operations	First-contact resolution (FCR) measures issues resolved at the first contact. Average resolution time captures how long support takes.
Channel performance	Compare conversion rates across channels to assess effectiveness.
Relationship value	Track churn, customer lifetime value (CLV) and purchase frequency to understand the long-term relationship.

AI combines data sources to reveal what drives each KPI. Link each measure to a decision the team can act on.

Co-funded by the European Union

7.3. AI Techniques in Customer Experience Analytics (I)

Language processing	Machine learning
Identify topics and sentiment across languages.	Estimate churn risk, propensity to act and conversion probability.
Computer vision	**Voice analytics**
Detect footfall, engagement and signals of sentiment.	Analyze tone, pitch and intent in service calls.
Anomaly detection	**Recommendation engines**
Flag unexpected KPI shifts early.	Personalize the customer journey.

Choose the technique according to the customer experience objective.

Co-funded by the European Union

7.3. AI Techniques in Customer Experience Analytics (II)

1 Combine signals	2 Detect friction	3 Respond
Bring behavioral, demographic and contextual data into a shared CX architecture.	Look for small frustrations and early disengagement. Use observed patterns to identify likely drivers.	Offer proactive help tailored to customer intent and expectations.

Use the results to refine the response in the next optimization cycle.

Co-funded by the European Union

7.4. Personalization and Predictive Insights (I)

Content and offers	Adapt banners and offers in real time using browsing behavior, customer history, context and device.
Recommendations	Use collaborative filtering, graph models or deep learning to predict relevant products.
Pricing	Adjust prices in context using demand, inventory and loyalty signals.
Service outreach	Offer help when visits to help pages or failed searches signal a need.

Personalization evolves as shopper behavior and context change.

Co-funded by the European Union

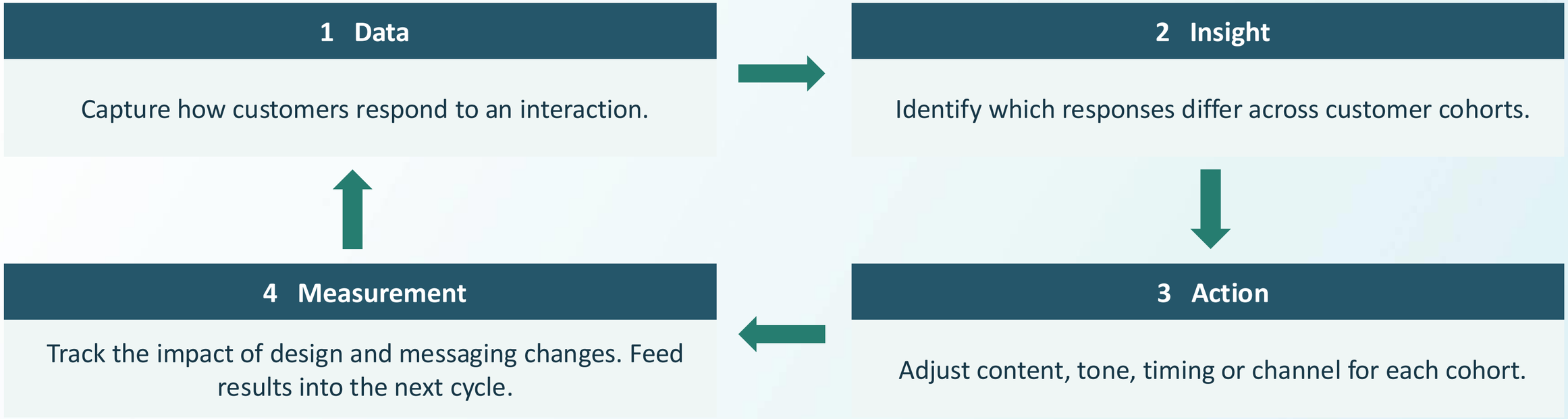
7.4. Personalization and Predictive Insights (II)

Across channels	A unified profile lets behavior in one channel inform the next interaction. Continuity supports trust and satisfaction.
Within a scenario	Look beyond the next action to identify barriers and motivations. Adapt messages and design to objections seen before.

The module cites Amazon, Netflix and Nike as examples of personalization at scale.

Co-funded by the European Union

7.5. CX Optimization through AI Feedback Loops (I)



Rapid feedback	Micro-feedback cycles can operate in milliseconds, helping teams improve CX as interactions unfold.
Reactivation example	Use reinforcement learning to test sequences and learn which ones best re-engage dormant customers.

7.5. CX Optimization through AI Feedback Loops (II)

How feedback reaches the team that can act

01 Detect

Generate an alert when a CX metric crosses its threshold.

02 Route

Send the alert to the relevant team with context and a recommended action.

03 Respond

Marketing, product and operations teams can act on issues such as sizing or navigation.

Managing CX over time

AI can take on more of the day-to-day management of customer experience. As personalization scales, keep safeguards in place and align automated decisions with ethical and business goals.

Co-funded by the European Union

7.6. AI in Action
Case Study - Starbucks: Deep Brew

Goal and signals	Deep Brew combines app behavior, transactions and context to deepen engagement and encourage repeat purchases.
Applications	Personalize offers and journeys in real time. Use demand signals to plan staffing and inventory.
Reported results	Engagement linked to repeat purchases rose 300%. Peak-demand prediction and operational efficiency improved.
Reflection	How can retailers balance predictive personalization with avoiding intrusive or overly automated customer experiences?

Co-funded by the European Union

7.6. AI in Action
Case Study - L’Oréal: Virtual Try-On

Shopper need	Reduce hesitation in online beauty purchases by letting shoppers explore products without visiting a store.
Application	Modiface combines augmented reality and AI for virtual try-on. It suggests shades based on skin tone, facial features and preferences.
Reported results	More than one billion virtual try-ons across brands. Sessions lasted longer, return visits increased and product pages saw a significant conversion lift.
Reflection	What data privacy considerations emerge when deploying computer vision–based personalization tools in beauty or fashion?

Co-funded by the European Union

7.6. AI in Action
Case Study - Zappos: Sentiment-Aware Support

Service challenge	Scale digital support while preserving a customer-first approach.
Application	Analyze sentiment across support channels, cluster topics and give agents real-time insights for proactive service.
Reported results	First-contact resolution rose 18% and average handling time fell 25%. Adaptive self-service reduced support volume.
Reflection	In what ways can sentiment-aware support systems maintain empathy while reducing agent workload?

Co-funded by the European Union

7.6. AI in Action - Comparative Summary
AI Use Cases Across Customer Experience Touchpoints

Brand	Main CX Focus	Key Metric	Critical Insight
Starbucks	App-based personalization and loyalty	+300% repeat engagement	Risk of over-targeting; need for opt-out transparency
L'Oréal	Conversational AI for diagnostics	+25% match accuracy; site engagement	Ethical issues around biometric use; bias in skin tone recognition
Zappos	Sentiment-aware post-sale support	+18% FCR; –25% handling time	Misinterpretation risk; importance of human-AI balance

Co-funded by the European Union

7.7. Applied Exercise
Diagnose NPS Decline (Data)

Regional NPS has fallen over the past two weeks. Investigate the decline as part of the real-time CX feedback loop.

Locate the decline	Break down NPS by location and channel. Compare purchases and returns by region.
Inspect digital journeys	Use clickstream data and heatmaps on the localized site.
Listen to customers	Analyze sentiment in social posts and reviews with NLP. Examine support tickets, chats and resolution logs.

Co-funded by
the European Union

7.7. Applied Exercise
Detect Root Causes (Models)

Text feedback	Use NLP and topic modeling to group issues raised in open-text comments.
Unexpected shifts	Apply anomaly detection to changes in returns and sessions.
Possible drivers	Use SHAP or decision trees to identify factors correlated with the decline.
Local friction	Cluster observations by geography to locate problems specific to a region.

Base conclusions on patterns rather than assumptions. Present findings in structured dashboards and prioritize issues by KPI impact.

Co-funded by
the European Union

7.7. Applied Exercise
Act & Close the Loop

1 Act	2 Coordinate	3 Measure
Update chatbots and FAQs for top complaints. Trigger re-engagement incentives and adapt delivery estimates and returns messages by market.	Alert CX, UX and operations teams with context and recommended actions. Link signals to journey maps and branch flows across channels.	Track NPS change and sentiment shifts. Look for fewer returns and complaints, more campaign opens and higher conversion.

Feed results back into the system and retrain models continuously.

7.8. Conclusion

Respond earlier	Interpret behavior in real time, act on the drivers behind lagging indicators and adapt the experience.
Support teams	Automate repetitive analysis to reduce workload and make room for tailored, empathetic service.
Protect trust	Be transparent about data use. Balance measurement and automation against the risk of manipulation.

Retailers that align AI decisions with customer experience goals can build a competitive advantage.

Co-funded by the European Union

8. AI Ethics and Challenges in Retail

Skills4Retail
Building sustainable growth

8.1. Introduction

8.2. Algorithmic Bias and Fairness

8.3. Data Privacy and Consent

8.4. Transparency and Explainability

8.5 Surveillance and Autonomy

8.6. Labor and Automation

8.7. Ethical AI Governance in Retail

8.8. Case Studies and Ethical Dilemmas in AI for Retail

Co-funded by
the European Union

AI Ethics and Challenges in Retail - Introduction

How does AI affect shoppers and workers?	
Risks to examine	Bias, privacy and consent, transparency, surveillance and working conditions.
What is at stake	Weak governance can harm people, expose retailers to legal risk and damage their reputation.
Design decisions	Evaluate accuracy and real-world impacts. Identify risks early and build controls into systems and processes.

Accountability, inclusion and human dignity guide the balance between business value and protection for people. These choices shape trust and long-term customer relationships.

Co-funded by the European Union

8.2. Algorithmic Bias and Fairness (I)

How bias reaches the shop floor

Historical patterns	Retail decisions	Consequences
Models can reproduce or amplify past inequities. Language, proxy variables and interaction signals can conceal bias.	Bias can shape what shoppers see, the prices they receive and the service they get.	Exclusionary pricing, unfair service or excessive policing can harm shoppers and the retailer’s reputation.

Set fairness requirements at the start. Detect bias systematically and document assumptions and data lineage so teams can trace its causes.

8.2. Algorithmic Bias and Fairness (II)

Fairness checks before and after launch	
Audit the data	Check representation across groups and use robust sampling. Restrict sensitive inferences to uses that are clearly justified and disclosed.
Test and monitor	Set measurable fairness goals, test before deployment and monitor results continuously in production.
Review outcomes	Give users a way to question decisions and request review. Address inequitable results even when a feature is innovative.

Connect fairness reviews to transparency (§8.4) and governance (§8.7). Revisit the goals as evidence accumulates.

Co-funded by the European Union

8.3. Data Privacy and Consent (I)

Privacy choices across retail channels	
Collect for a purpose	Establish a lawful basis, define the purpose and collect only the personal data needed. Give clear notices and meaningful consent choices.
Manage the data	Set retention and deletion rules. Prevent reuse for unrelated purposes. Meet vendor obligations and cross-border transfer requirements.
Honor individual rights	Support requests for access, portability and erasure. Carry privacy choices through to downstream model behavior.

Co-funded by the European Union

8.3. Data Privacy and Consent (II)

Privacy controls in day-to-day operations	
Secure data flows	Protect pipelines and prevent linked records from re-identifying people. Treat inferences about special-category data with extra caution.
Enforce preferences	Record privacy choices and apply them consistently across tools. Tell people when automated decisions are used.
Reassess risk	Carry out data protection impact assessments for high-risk processing. Update them after changes and flag possible surveillance impacts (§8.5).

Keep these checks active throughout the life of the system.

Co-funded by the European Union

8.4. Transparency and Explainability (I)

What happens after an automated decision?

1 Disclose	2 Explain	3 Offer review
Tell customers and employees when AI makes a decision and what its limits are.	Summarize the main factors in plain language where feasible. Give frontline staff a usable explanation to share with customers.	Show how to challenge an outcome and seek a remedy. Route high-impact cases to a human reviewer by design.

Co-funded by the European Union

8.4. Transparency and Explainability (II)

Keeping explanations useful and accurate	
Set thresholds	Define when an explanation is mandatory. Use plain language so customers and staff know what they can do next.
Check accuracy	Monitor model drift and update explanations to reflect current behavior. Protect intellectual property while providing meaningful transparency.
Keep a record	Log when an explanation was given and whether the outcome changed. Link these records to accountability and performance indicators.

Co-funded by the European Union

8.5. Surveillance and Autonomy

Monitoring in stores, on websites and across devices	
Recognize the risks	Even lawful monitoring can feel intrusive or coercive. Watch for monitoring without consent, new uses beyond the original purpose and covert profiling.
Protect choice	Let customers act without undue pressure. Keep sensitive behavioral profiling off by default unless approved.
Check who bears the burden	Assess whether surveillance disproportionately affects particular groups. Document decision rules and keep audit logs for regulators.

Weigh the practical benefit of monitoring against its effect on customer autonomy when designing the system.

Co-funded by the European Union

8.6. Labor and Automation (I)

Automation changes roles at the checkout and in the back office. Who benefits, and who bears the transition costs?

Risks to workers	Goals for workers	Transition support
Work can intensify. Continuous monitoring can reduce employee autonomy.	Define outcomes for workers alongside cost savings. Use AI to support people in their roles wherever feasible rather than replacing them.	Offer digital literacy training and counseling. Tailor support to vulnerable groups and check whether outcomes are equitable.

How to track outcomes	Employee Net Promoter Score (eNPS), injury and strain rates, and retention after reskilling.

Co-funded by the European Union

8.6. Labor and Automation (II)

Fair scheduling	Monitoring and autonomy
Publish how shifts, overtime and shift swaps are assigned so staff can see how scheduling decisions are made.	Explain which data feed performance dashboards. Rule out covert monitoring and set limits on productivity prompts.
Job quality	**Employee voice and recourse**
Protect breaks and prevent work from intensifying. Build in opportunities for progression, training and better ergonomics.	Announce changes and offer a way to challenge them before rollout. Give staff channels for feedback on schedules and metrics, with clear response deadlines.

Early signs of harm	Track eNPS, staff attrition, and health and safety indicators.

Co-funded by the European Union

8.7. Ethical AI Governance in Retail (I)

Set the rules	Define permitted uses, risk tiers and decision rights. Set safeguards in advance instead of relying on guesses about intent.
Assign oversight	Bring operations, legal and data teams together on an ethics committee. Maintain policies on acceptable use, fairness, transparency and accountability.
Enable challenges	Give customers and employees a way to contest decisions. Offer internal and external channels for reporting ethical concerns.
Review and report	Audit AI systems and assess risks regularly. Publish the actions taken.

Co-funded by the European Union

8.7. Ethical AI Governance in Retail (II)

Assess risks	Conduct DPIAs and security reviews. Prepare incident and breach playbooks. Check vendors and data transfers through due diligence and audit rights.
Document and monitor	Use model cards, audit logs and version histories. Train teams, schedule audits and publish corrective actions.
Review and redress	Require human review for high-risk or high-impact decisions. Define deadlines for appeals and remedies.
Standards and law	Align with the OECD AI Principles and ISO/IEC 42001. Comply with applicable laws.

Section 8.7 covers fair scheduling, algorithmic oversight and appeals. Section 8.8 applies these ideas to ethical dilemmas.

Co-funded by the European Union

8.8. Case Studies and Ethical Dilemmas in AI for Retail (Overview)

Cases	Rite Aid and Southern Co-op / Facewatch: live facial recognition. Target: inference of sensitive traits. Applied dilemma: dynamic pricing and fairness.
How to read each case	Trace the data used, how the decision was made, who was affected and what could reduce harm. Compare regulatory responses and organizational lessons.
Reflection	Use the existing questions to test how your own governance program would respond.

Governance measures in sections 8.7–8.8 include fair scheduling commitments, paid training time and escalation routes.

Co-funded by the European Union

8.8. Case Study 1
Rite Aid: Facial Recognition for Loss Prevention

Practice	From 2012 to 2020, Rite Aid used facial recognition for loss prevention. A watchlist match at entry alerted store staff.
Ethical dilemma	People lacked notice. False matches caused harm that disproportionately affected women and people of color.
Reported outcome	The FTC settlement included a five-year facial recognition ban and algorithmic risk assessments with CEO certification.
Reflection	How would you redesign this program (governance, testing, notices, appeal routes) to reduce harm while pursuing loss-prevention goals?

Such high-risk surveillance practices should not be deployed without demonstrable accuracy, fairness, and publicly available governance frameworks.

Co-funded by the European Union

8.8. Case Study 2
Target: Predictive Inference of Pregnancy

Practice	Target used ordinary transaction data to infer stages of pregnancy and trigger marketing.
Ethical dilemma	Shoppers could not see how the model inferred a sensitive trait. Targeted marketing risked revealing a pregnancy unintentionally.
Reported outcome	The practice drew scrutiny in 2012. The case reports no enforcement action that year.
Reflection	What minimum transparency and control safeguards should be required when models infer sensitive attributes from non-sensitive data?

Inferring sensitive traits without explicit consent should be deemed an unethical practice in retail personalization.

Co-funded by the European Union

8.8. Case Study 3
Southern Co-op (UK) & Facewatch: Live Facial Recognition

Practice	Southern Co-op used Facewatch to scan people entering stores and alert staff to watchlist matches. Civil society groups and the regulator scrutinized the system.
Ethical dilemma	Was scanning necessary and proportionate? What recourse did someone have after being flagged?
Reported outcome	The ICO recognized a legitimate purpose subject to conditions: DPIAs, signage and notice, a data protection officer, and safeguards for vulnerable people.
Reflection	If you permit LFR in limited scenarios, what are your minimum conditions (use-case scope, signage, accuracy testing, watchlist governance, appeal SLAs) to keep it lawful, fair, and trusted?

Live facial recognition in retail must remain an exceptional, narrowly justified measure rather than a default security tool.

Co-funded by the European Union

8.8. Case Studies and Ethical Dilemmas in AI for Retail (Comparative Summary)

AI Application	Ethical Dilemma	Corrective / Preventive Measures
Rite Aid – Facial Recognition for Loss Prevention	Accuracy failures, disparate impact on minorities, lack of transparency	Independent audits, public notices, accuracy benchmarks, clear appeal routes
Target – Predictive Inference of Pregnancy	Inference of sensitive traits, unintended disclosure	Explicit consent for sensitive inferences, blended targeting, transparency statements
Southern Co-op & Facewatch – Live Facial Recognition	Proportionality, erroneous watchlists, fairness concerns	Narrow scope to serious/repeat offenders, DPO oversight, accuracy testing, signage

Co-funded by the European Union

8.8. Applied Ethical Dilemma “Dynamic Pricing & Fairness”

Your online store launches real-time dynamic pricing. Post-launch analysis shows systematic price differences correlated with low-income postcodes.

1 Test the pattern	What data and tests would you run to confirm a discriminatory pattern?
2 Choose safeguards	What fairness controls and transparency would you implement (price-band caps, explanations, audits)?
3 Measure impact	How would you measure impact (complaints, conversion by segment, elasticity, authority engagement)?

Co-funded by the European Union

9. Designing AI-Enhanced Retail Experience

Skills4Retail
Building sustainable growth

9.1. Introduction

9.2. Human-Centered AI Design Principles

9.3. Frameworks for Designing AI Retail Experiences

9.4. Evaluating AI-Driven Retail Experiences

9.5 Real-World Examples of AI-Enhanced Experiences

9.6. Applied Exercise - AI-Enabled First-Time Visitor Flow

9.7. Conclusions

Co-funded by the European Union

Designing AI-Enhanced Retail Experience - Introduction

Experience quality guides decisions about where to use AI.

Shopper outcomes	Design practice	Measurable impact
Start with human needs before introducing automation. Focus on trust, satisfaction and shoppers' ability to make their own choices.	Connect strategy with practical design decisions. Combine service design, data and experimentation.	Build the understanding and skills to put ideas into practice. Link each experience goal to a measurable outcome.

Co-funded by the European Union

9.2. Human-Centered AI Design Principles (I)

Three principles for AI-assisted shopping	
Purposeful personalization	Start with what the shopper needs in context. Use intent or calendar cues selectively and avoid repeatedly showing similar items.
Transparency and recourse	Make AI involvement and its limits clear. Give shoppers a way to challenge outcomes. Use explanations that customers and staff can understand.
Choice and control	Set safeguards before launch, make participation opt-in and preserve the shopper's autonomy at every interaction.

Co-funded by the European Union

9.2. Human-Centered AI Design Principles (II)

Design choices across digital and in-store journeys	
Context	Adapt the depth of information and the interaction to the device, channel, time and shopper's goal. A mobile visit calls for a different design from a desktop visit.
Continuity	Remove friction quietly so shoppers can continue what they are doing, both online and in the store.
Inclusion	Account for cultural differences and accessibility needs. Check that tools and content do not reinforce stereotypes.

Retail examples: Sephora, Nordstrom and Zalando. See Chapter 3 for personalization and Chapter 5 for omnichannel strategy.

Co-funded by the European Union

9.3. Frameworks for Designing AI Retail Experiences (I)

Service design, data science and experimentation extend familiar design methods to account for AI.

01 Read the signals	02 Identify the moment	03 Define success
Go beyond personas. Use observed behavior and the journey insights from Chapters 6–7 to brief the design team.	Pinpoint a moment such as hesitation. Specify exactly when and where assistance would help the shopper.	Connect the proposed assistance to the business outcome it should support and the safeguards it must respect.

Co-funded by the European Union

9.3. Frameworks for Designing AI Retail Experiences (II)

Develop and test the intervention at the chosen moment in the journey.

01 Explore options	02 Prototype the flow	03 Test and refine
Consider a prompt, an assistant or a change in ranking. Map how recommendation, language and vision models would work together.	Mark AI triggers on the journey map. Show what the shopper sees alongside the logic that determines the response.	Run online A/B tests continuously as the system evolves. Use a consistent set of tools and governance practices.

See Chapter 6 for experimentation and journey orchestration.

Co-funded by the European Union

9.4. Evaluating AI-Driven Retail Experiences (I)

Conversion and revenue show only part of the customer experience.

Engagement	Conversion	Customer sentiment
Do longer sessions help shoppers progress?	**How much lift comes from the AI feature?**	**How do shoppers respond to the feature?**
Assess the quality of time spent. Identify where AI helps shoppers move toward their goal and where it creates detours.	Compare conversion with a holdout group to estimate the incremental effect.	Use micro-surveys, CSAT, NPS and NLP. Check how tone and clarity correlate with feature adoption.

Guardrail metrics	Enforce limits on latency, errors and returns.

Co-funded by the European Union

9.4. Evaluating AI-Driven Retail Experiences (II)

		Review cycle
Trust and autonomy	Track opt-ins, opt-outs and feature disablement. An opt-out after initial consent can signal pressure.	**Before launch**
Accessibility and fairness	Test across diverse cohorts. Escalate disparities for correction, even when overall results look acceptable.	Complete the pre-launch checklist.
Sustainability	Assess model and runtime costs and whether the system can scale.	**After launch**
		Hold scheduled reviews.
		At each review
		Use a shared workspace to measure results, learn and adapt.

When a guardrail is triggered, change how the AI behaves (NIST, 2023).

Co-funded by the European Union

9.5. Real-World Examples of AI-Enhanced Experiences - Amazon Go

Checkout-free shopping	Entry authentication, cameras and shelf sensors link items to shoppers. AI works in the background and supports accurate receipt adjustments.
Trust and recourse	Check accuracy and safety. Give shoppers a way to challenge charges. Review video retention, watchlists and appeals (Ch. 8).
Evaluation	Assess checkout queues and waiting time eliminated, visit duration and receipt adjustment rates. Compare conversion and basket size at comparable traffic levels.
Reflection	What minimum transparency and contestability mechanisms preserve trust when the core interaction (checkout) is automated?

Co-funded by the European Union

9.5. Real-World Examples of AI-Enhanced Experiences - Zara (Trend Intelligence)

Trend detection	Combine creator and social signals with in-store sales velocity to spot micro-trends, bring products to the floor faster and replenish to local demand.
Responsible use	Check where content comes from, address bias in visual analysis and compare outcomes across cohorts (Ch. 8).
Evaluation	Track time to the sales floor, lift in attach rates and cross-selling, and local sell-through. Monitor returns and satisfaction with fit as guardrails.
Reflection	How should teams balance trend responsiveness with safeguards against stereotype reinforcement or manipulative nudging?

Co-funded by the European Union

9.5. Case Snapshot - IKEA (Omnichannel Personalization)

Connected journey	IKEA’s Upptäcka program connects channels and refines personalization using several sources of signals, extending the analytics perspective in Ch. 2.
Channel handoffs	Evaluate how customers move from web to app to store. Use the findings to improve the in-store journey.
Privacy and choice	Explain handoffs, obtain consent and collect only what continuity requires. Offer an equivalent experience without tracking where appropriate.
Reflection	What consent, handoff transparency, and data-minimization rules are required when moving a shopper’s online configurations into in-store kiosks - and how would you provide a privacy-respecting, non-tracked equivalent?

Co-funded by the European Union

9.5. Case Snapshot - Lululemon (Human-in-the-Loop Clienteling)

Assisted service	Machine learning gives store associates customer context for more personal service.
Associate discretion	Associates decide how to use suggestions. Disclosures and preference controls help prevent pressure and stereotyping.
Evaluation	Track signs of trust alongside sales outcomes. Measure how trust changes over time as assisted service expands.
Reflection	Where should the boundary sit between AI suggestion and associate discretion, and what disclosures and preference controls are needed to avoid pressure or stereotyping - while measuring the trust impact over time?

Co-funded by the European Union

9.6. Applied Exercise - First-Time Visitor Flow (Scenario)

A mid-sized fashion brand is redesigning its online journey to reduce returns and increase product-page engagement.

Sizing uncertainty	Sparse product Q&A	Weak follow-up
Offer an opt-in visual fit assistant that asks for minimal information.	Use retrieval-augmented Q&A to answer questions from product information and community content.	Use a short post-purchase chat to check satisfaction and invite a review.

Design task	Outline the simplest visitor flow before building variants.

9.6. Applied Exercise - First-Time Visitor Flow (Design)

First-time visitor journey

1 Onboarding	2 Discovery	3 After purchase
Offer an optional quick fit check. Explain why it helps and let visitors edit or delete their inputs.	When visitors hesitate, offer relevant guidance and community fit notes. Make it easy to reach a person.	After 48–72 hours, ask about fit and fabric in a short chat. Invite a brief review if the experience was positive.

Visitor control	Keep controls visible across devices and sessions.

Co-funded by the European Union

9.6. Applied Exercise - First-Time Visitor Flow (Evaluation & Guardrails)

Fit and return visits	Track the size-related return rate and repeat visits.
Product-page engagement	Measure product-page depth, Q&A views and assisted clicks.
Comparison	Break down the results by device and cohort.
Guardrails	Apply the disclosure, opt-out, data minimization and equity checks in sections 9.2 and 9.4 (see Ch. 8).

Co-funded by the European Union

9.6. Applied Exercise — First-Time Visitor Flow (Reflection)

Guidance and pressure	Fallback and choice	Decisions and learning
Where is the boundary between guidance and pressure?	What human fallback is offered if AI guidance misfires?	Which measurements decide iteration vs. rollback?
How is that boundary communicated to first-time visitors?	How are opt-out choices propagated across channels?	How will findings feed back into design and ops?

9.7. Conclusion

AI can deepen customer relationships when retail teams design around shoppers' needs.

1 Understand	2 Design and evaluate	3 Apply and learn
Combine human-centered design principles (§9.2) with real-time customer data (Ch. 7).	Use the design frameworks (§9.3) and assess outcomes through balanced evaluation (§9.4).	Use patterns from the cases (§9.5) to build responsible journeys (§9.6). Keep safeguards explicit and improve the design as evidence comes in.

Design goal	Make retail experiences more personal, thoughtful and human.

Co-funded by the European Union

10. Case Studies and Practical Experiments in AI for Retail

Skills4Retail
Building sustainable growth

10.1. Introduction - From Playbook to Practice

10.2. Tools, Platforms, and Datasets for Hands-On Work

10.3. Mega Case Study

10.4. Applied Scenario –
AI-Enabled First-Time Visitor Flow

10.5. Execution & Enablement Toolkit

10.6. Conclusion

Co-funded by
the European Union

10.1. Introduction – From Playbook to Practice

Build a playbook teams can use from day one: the smallest set of tools, roles and safeguards needed to move from a pilot to lasting value.

01 Prepare the data	02 Apply the playbook	03 Govern the pilot
Start with data readiness and customer profiling (Ch. 1–2). Match tools and datasets to each capability to simplify setup.	Use Carrefour to examine enterprise operations (§10.3). Then focus on a first-time visitor choosing a size with confidence (§10.4).	Build in disclosure, a “why this?” explanation and opt-out. Plan for multivariate testing (MVT) and rollback.

Earlier tactics come together in one operating routine. Measurement and governance guide tool choices and rollout.

Co-funded by the European Union

10.1. Introduction – Scope & Non-Goals

Scope: integrate capabilities from earlier chapters. Brand selection and a repeat of the architecture are outside the scope.

Ch. 3 and 5 Personalization across channels	**Ch. 6–7 Measurement**
Connect personalization decisions with omnichannel delivery.	Combine journey maps and CX scorecards to measure the same experience.
Ch. 8 Ethics	**Ch. 9 Design and evaluation**
Apply fairness, consent and explainability principles. Provide a route to appeal.	Prototype, instrument and test the experience. Evaluate its overall impact.

Sensitive journeys	Require “AI-assisted” labels, “why this?” explanations and opt-out.
Scaling decisions	Assign roles and decision rights, document rollback plans and use evidence to decide when to scale.

Co-funded by the European Union

10.2. Tools, Platforms, and Datasets – Capability Map (I)

Data and storage	Ingestion and transformation
Warehouses: BigQuery, Snowflake, Redshift. Object storage: GCS, S3, ADLS. Development: PostgreSQL.	Airbyte or Fivetran for ingestion, dbt for versioning and tests, Airflow or Dagster for orchestration.
Analytics and BI	**Product and CX analytics**
Looker, Tableau and Power BI for reporting. Metabase or Superset for lightweight exploration.	Amplitude or Mixpanel for funnels, cohorts and event taxonomy. Export GA4 data to BigQuery for web journeys at scale. Redact session replays by default.

Use this map to reproduce the enterprise case (§10.3) and visitor scenario (§10.4) quickly. For end-to-end suites, see §6.4.

Co-funded by the European Union

10.2. Tools, Platforms, and Datasets – Capability Map (II)

Experimentation and feature flags	Model operations and serving
Optimizely, VWO, Statsig. LaunchDarkly provides kill switches.	MLflow, Weights & Biases, Docker/K8s, Vertex, SageMaker, Azure ML.
Feature store	**Search, ranking and recommendations**
Feast keeps online and offline features consistent.	Vector search (ES/OpenSearch kNN), learning to rank, implicit matrix factorization, LightFM and deep sequence models.
NLP and language models	**Conversational AI**
spaCy, Hugging Face Transformers. Use LangChain or LlamaIndex for RAG.	Rasa for intents, dialogue flows and end-to-end tests.
Design and prototyping	**Monitoring and reliability**
Figma for prototypes and disclosures such as “AI-generated” and “why this?”.	Prometheus/Grafana, Sentry/ELK and Great Expectations for data quality checks.

Co-funded by the European Union

10.2. Tools, Platforms, and Datasets – Privacy & Datasets

Privacy and consent	Use a consent management platform, a data catalog with lineage, and DPIA templates (Ch. 8).

§10.3 Carrefour enterprise case	§10.4 First-time visitor
Data warehouse with dbt/Airflow, MLflow/W&B, Looker, Feast, Optimizely, ranking and vector search.	Amplitude/GA4 for hesitation signals. Combine feature flags, Rasa and MLflow.

Public lab datasets without personally identifiable information	
Forecasts and repeat baskets	M5 Forecasting (Walmart), Instacart MBA
Recommendations and journeys	Retailrocket, OTTO, H&M
Language analysis	Amazon Reviews, Yelp
Funnels and attribution	GA Sample (BigQuery)
Fit and product imagery	ModCloth/RtR for fit signals, Fashion Product Images for visual attributes

Co-funded by the European Union

10.3. Enterprise Case – Carrefour: Data & Architecture

Cloud infrastructure

Carrefour moved SAP to Google Cloud, uses GCVE and Apigee, and centers analytics on BigQuery.

Search and discovery

Empathy.co integrates with GCP. Shoppers can see why results appear, while editors retain control over ranking.

Shared foundation

One platform supports real-time e-commerce and in-store uses, as well as personalization across the group.

Deployment

Reusing the platform was intended to shorten time to market. Carrefour announced generative AI shopping features on the existing stack.

The architecture supports Carrefour’s digital acceleration and its data governance and ethics commitments (URD).

Co-funded by the European Union

10.3. Enterprise Case – Carrefour: AI Applications

Personalization	Search and discovery
A unified data layer on Google Cloud powers personalization and product recommendations.	Empathy.co combines transparent search with editorial control over ranking.
Retail media	**Generative AI**
Carrefour Links offers advertisers first-party data packages. Unlimitail expanded retail media in 2023 across the EU, Brazil and Argentina.	Carrefour uses OpenAI technology to speed up content and campaign creation.

These publicly announced initiatives connect data and AI to shopper tools, with a focus on measuring transactions.

Co-funded by the European Union

10.3. Enterprise Case – Governance & Evaluation

Governance: corporate materials cover GDPR, privacy and business ethics. Personalization and retail media require consent and transparency.

GCVE: reported operating costs fell by about 40% and energy use by about 45%.

Service reliability	Track SLA uptime, p95/p99 latency for search and recommendation APIs, MTTD/MTTR, peak burst capacity, rollbacks and failed deployments.
Unit costs	Measure cost per 1,000 inferences or searches, and energy per 1,000 inferences.
Shopper outcomes	Track adoption, “why this?” views and engagement quality. Measure incremental lift against controls and attach/cross-sell by cohort. Set return-rate guardrails.
Longer-term effects	Track retention. When a randomized trial is infeasible, use geo-sequential difference-in-differences (DiD).

Co-funded by the European Union

10.3. Enterprise Case – Reflection Questions

1 Consent across channels	How should consent and preference flows be designed so that retail-media activation (Links/Unlimitail) remains both effective and respectful across channels? (see Ch.8)
2 Search transparency	What is the minimum transparency a shopper needs in search & recommendation (“why this result/offer?”) to maintain trust without overwhelming the interface? (see Ch.9)
3 Campaign safeguards	If genAI accelerates campaign creation, how are bias checks and brand-safety reviews embedded in the workflow before large-scale activation?

Co-funded by the European Union

10.4. Applied Scenario – First-Time Visitor: Frictions & Foundations

First-time visitors face size uncertainty, brief product-page visits and weak follow-up. The goals are sizing confidence, on-page engagement and learning after purchase.

Product and behavior data

Combine sizes and materials, return reasons, clickstream, reviews and Q&A. Check local stock before suggesting “try two sizes.”

Optional shopper inputs

Ask for height, weight or usual brand size only with consent.

Data reliability

Set contracts and SLAs for each flow. Trace raw data through curation to the feature store. Check for missing sizes and outliers.

Review text

Use NLP to summarize how the fit feels. Filter profanity and personally identifiable information before display.

Co-funded by the European Union

10.4. Applied Scenario – AI Toolkit & Orchestration

During the visit: fit	During the visit: hesitation
An opt-in visual assistant estimates fit probabilistically without biometric identification.	Size toggles, dwell time and backtracking trigger help. An optional next-best-action score selects an explanation, human handoff or deferral.
At the point of choice	**After purchase**
Retrieval-augmented Q&A uses review and FAQ excerpts to explain “why this size.”	A micro-chat asks about fit, fabric and the overall experience, then invites a review.

Sync visit and follow-up touchpoints (Ch. 5–6). Use CX scorecards (Ch. 7) and safeguards throughout (Ch. 8). Include AI labels, “why this?” copy and a multivariate testing cadence (Ch. 9).

Co-funded by the European Union

10.4. Applied Scenario – Guardrails & Measurement

Shopper control

At every sensitive point, label AI assistance and offer an easy opt-out. Show “why this?” for size suggestions, help and prompts.

Release controls

Set latency and error limits before exposure. Use feature flags for controlled rollouts and document how to roll back.

Success measures

Target fewer size-related returns and more add-to-bag actions in hesitant sessions. Track review completion after micro-chat and engagement with Q&A and the fit tool.

Fairness and accessibility

Monitor results by device, cohort and region. Check accessibility and fairness within these groups.

Follow retention and repeat purchases over time to check for long-term erosion.

Co-funded by the European Union

10.4. Applied Scenario – Reflection Questions

1 Inventory and sustainability	Ch.3 vs. Ch.4. When personalization recommends “try two sizes,” what inventory and sustainability thresholds should gate the option - and how should these thresholds adapt during peak season?
2 Review data and fit	Ch.2 & Ch.8. Which NLP signals from reviews are acceptable for fit explanations without risking stereotyping, and how are edge cases redacted or rephrased?
3 Store handoff	Ch.5–6. How should the hand-off to store pickup or a fitting appointment be designed so that it increases confidence without creating pressure?
4 Conflicting metrics	Ch.7–9. If return rates fall but opt-outs rise among specific cohorts, what design or consent adjustments are warranted, and how is success re-measured?
5 Minimum data	Ch.1–2–8. What is the minimal data required to deliver meaningful fit guidance, and how is that minimal set communicated to users to reinforce trust?

Co-funded by the European Union

9.4. Evaluating AI-Driven Retail Experiences (I)

Conversion and revenue show only part of the customer experience.

Engagement	Conversion	Customer sentiment
Do longer sessions help shoppers progress?	**How much lift comes from the AI feature?**	**How do shoppers respond to the feature?**
Assess the quality of time spent. Identify where AI helps shoppers move toward their goal and where it creates detours.	Compare conversion with a holdout group to estimate the incremental effect.	Use micro-surveys, CSAT, NPS and NLP. Check how tone and clarity correlate with feature adoption.

Guardrail metrics	Enforce limits on latency, errors and returns.

Co-funded by the European Union

9.4. Evaluating AI-Driven Retail Experiences (II)

Trust and autonomy	Track opt-ins, opt-outs and feature disablement. An opt-out after initial consent can signal pressure.
Accessibility and fairness	Test across diverse cohorts. Escalate disparities for correction, even when overall results look acceptable.
Sustainability	Assess model and runtime costs and whether the system can scale.

Review cycle
Before launch
Complete the pre-launch checklist.
After launch
Hold scheduled reviews.
At each review
Use a shared workspace to measure results, learn and adapt.

When a guardrail is triggered, change how the AI behaves (NIST, 2023).

Co-funded by the European Union

10.6. Conclusions – What Endures

Chapter 10 brings together a practical toolset (§10.2), the Carrefour enterprise model (§10.3) and a visitor journey ready to pilot (§10.4).

1 Govern data	2 Launch in stages	3 Measure value	4 Audit operations
Define data contracts (Ch. 1–2, 8). Make consent, explainability, fairness and appeal conditions for launch.	Prototype, test and roll out behind feature flags with a rollback option. Personalize for a clear purpose without pressuring shoppers (Ch. 3, 5–6).	Agree on a balanced CX scorecard: incremental uplift, customer trust and autonomy, and guardrail metrics.	Audit how the service runs and use results to guide the next round of design and testing.

Lasting value depends on how well teams integrate data, design, measurement and governance. A newer model alone cannot deliver it.

Co-funded by the European Union

Skills4Retail
Building sustainable growth



Thank you

Funded by the European Union. Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor the granting authority can be held responsible for them.

Co-funded by
the European Union