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# Chapter 6: Delivering tailored financial solutions through hyper-personalization enabled by machine learning algorithms

## 6.1. Introduction

Emphasizing hyper-personalization enabled by Artificial Intelligence (AI) algorithms that drive meaningful engagement with the clients in the production of state-of-the-art investment strategies and advice to leverage the sensitivity of client portfolios to systematic risks – provides asset management firms with potentially unprecedented differentiation opportunities. However, practical implementation challenges require execution through a multi-faceted approach – enhancing back-end data, systems infrastructure, and data science capabilities; re-purposing client engagement models and front-end tools; refining talent requirements, workflows, and processes; as well as addressing important ethical considerations regarding data usage, advice quality, and client privacy. Such differentiation initiatives can be fueled by embedding lower-cost AI-driven data collection and processing techniques that channel and sort the digital exhaust created by clients in their high-frequency interactions with the broader world – and tie them to actionable dynamic financial strategies that aim to translate the AI-enhanced understanding of their motivations and triggers into timely portfolio repositionings to protect the upside and downside for both aggressive and defensive investors during "normal" and "bad" market regimes respectively (Susskind & Susskind, 2015; Tapscott & Tapscott, 2016; Treleaven et al., 2019).

As such, this chapter offers a present-day reflection on how sector players, at the leading edge of such industry transitions, are addressing these new avenues for differentiation, illustrating lessons from best practices, and discussing the challenges encountered, through the lens of client engagement models and front-end tools, as well as the back-end challenges associated with creating the required predictive data science infrastructure. However, traditional providers of asset management services that are considering enhancing existing offerings face a conundrum. On the one hand, amidst declining revenues, greater regulatory scrutiny, and rising competitive pressures – from the proliferation of index tracking portfolios to direct platforms that allow clients to craft their own portfolios to robo-advisors with varying degrees of digital and human assistance and increasingly lower fees – these new avenues of differentiation programs create opportunities to position against investing services geared towards existentially different client needs and preferences, and have the potential to enhance loyalty, retention, and revenues (Vaidya & Kumar, 2020; Zeng et al., 2020).

### 6.1.1. Background and Significance

The feverish pace of technological development has brought about significant changes in many aspects of humanity. Consumers are increasingly becoming demanding for products that cater to their individual needs. The shift from traditional banking to more innovative FinTechs is an indubitable step the financial services market has undergone. Traditional banks, once the monopolists of consumer finance, are now not only facing fierce competition from FinTechs, but also from other unconventional players entering their space. These competitors are coming from different sectors such as Travel Agencies that now offer consumers the possibility to take advantage of tailored financial products for travelling purposes, such as insurance, currency exchanges and gateways, and e-Commerce Players that are starting to partner up with conventional banks in order to offer consumers installment payments on their e-Purchases.

Fashion retailers are offering credit on a revolving basis for consumers to pay for their fashion purchases via the retailer's website. Insurance is sold over the internet by insurance companies. Consumers can open accounts with Liquidity companies for better return on their money deposits. Retailers and locations are appearing everywhere – both physical and e-physical platforms – which are heavily investing in technology to provide users and consumers with a memorable unique shopping experience. Urban businesses, such as street and companies, are appearing everywhere, both physical and mobile-based utilizing the ease of access of smartphones that have transformed how users choose to engage with their surroundings. All players are fundamentally focused on datapreneurship, gathering consumer transaction data pairs and utilizing technology-based processes to monetize vertically on all aspects of consumer life, which leads them to offer targeted, meaningful, contextual based offers. With the emergence of big data technology-based platforms, supported by machine learning algorithms, players are ready to embrace hyper-personalization as the new Differentiating Value Proposition among competitors in a tailored financial solutions market.

## 6.2. Understanding Hyper-Personalization

Today, many institutions accept that providing better and faster service is not enough to compete in a crowded, competitive market. To be distinctive and stay ahead of the pack, they must provide a unique, hyper-personalized experience, a thought that pervades their entire customer relationship proposal, from their front-end communication to the back-end procedures for planning and executing product development and service delivery. Hyper-personalization creates a new standard for performance in customer communications across channels. Customers want proactive and personalized interactions that are aligned with their wants and needs, whether that be through a bank's website, a mobile app, an email or direct mail, or by calling a service representative. Hyper-personalization relies on real-time data analysis and artificial intelligence technology to deliver tailored, relevant, and timely messages to customers. By generating actionable insights from the vast troves of data accumulated from historical transactions and target-specific behavioral analysis, hyper-personalization enables a more tailored experience for each customer and their unique interests, characteristics, and personal circumstances. Financial services organizations can use hyper-personalization throughout the entire customer lifecycle, from the first marketing contact, opening an account, or signing up for a service, through the newest product offers, promotional deals designed for the next purchase, or notices of suspicious transactions or system outages.

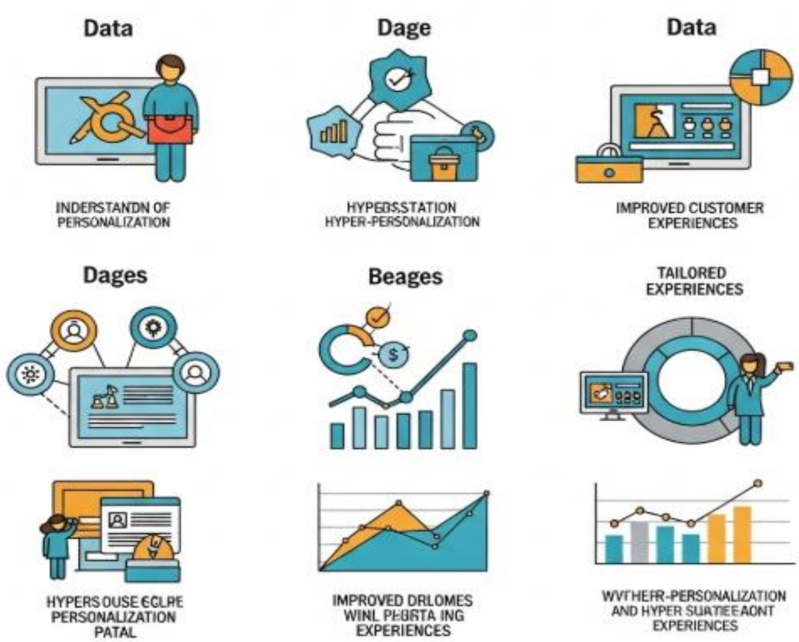


**Fig 6.1 :** Understanding Hyper-Personalization.

### 6.2.1. Definition and Importance

Hyper-personalization enables brands to deliver individualized product or service suggestions at the ideal moment to drive sales and customer satisfaction. Hyper-personalization enhances personalization with additional relevant information around individuals' shifting desires, preferences, needs, circumstances, habits and behaviors. It enables organizations to go deeper into customer demographics, how customers feel about its products/services, how customers behave or interact with them, how customers feel while interacting with brands, and how long customers have been with corporations, anticipating the ideal moment to provide each customer individualized offerings in order to close the gap between brand intent and customer expectations and prevent loss of fidelity in loyalty programs. Hyper-personalization capabilities improve companies' sensitivity and capability in managing customer relations. Particularly during the pandemic, many brands increased their communications and interaction efforts with consumers, which often dissociated them from their core values, therefore sharing relevant content for target audiences while considering contextual situations is more critical than ever. The goal of hyper-personalization is to make interactions more relevant. Marketers need to define the strategies that derive the best results to evaluate if added relevance is worth the extra cost. New technologies have a central role in commitment hyper-personalization and help companies gain an edge over competitors. Personalization has been demonstrated to increase customers' purchase intention, brand loyalty, and perceived value and reduce their perceived risk with tracking, security and payment.

### 6.2.2. Historical Context

Despite being a key area of customer service in B2C communications, businesses offering financial products were slow to adapt to the emergence of digital technologies and exploit the opportunities they offer. In fact, geographical barriers and distance dictated the terms and provided natural monopolies to large banking institutions that needed only to be able to service a large population with a standardized offering to achieve profitability objectives. This lack of agility was compounded by the supplier-led product design and placement efforts by many financial institutions, blind to the needs and desires of consumer segments. Traditional marketing techniques were invaluable for discovering the best brand messages for targeted groups of customers in order to drive potential shoppers in-store. Technological advances in the economics of production meant a gradual diversification of consumer tastes and increasing competition for banks' limited spending. This pressure meant spending moved earlier in the buying cycle from post-purchase information, transaction and purchase to comparison, evaluation and search stages. Exploiting the technology to drive customers in-store or to a bank's Call-

Center became essential for financial institutions, leading to the introduction of Data Warehouse technology enabling the storage of transaction data for Decision Support Systems. These acted as strategic weapons for banks with the foresight to transfer resources and competencies from traditional product development and placement to Decision Support and Direct Marketing Systems. These amassed a wealth of information accessible to marketing and sales staff to start the trend towards tailor-made selling of financial services products. Marketing campaigns could at last be based on conversions rather than merely on brand recognition for sending qualified leads to the retail network.

## 6.3. Role of Machine Learning in Finance

Machine learning (ML), a subfield of AI, has a potential to automate large parts of the data extraction, transformation, loading, and modelling work done today by human teams, significantly speeding up technical delivery of business solutions. ML enables identification of hidden patterns in the data and using these patterns to generate predictions. A useful machine learning algorithm should be able to exploit hidden patterns to make predictions. Making predictions is the essence of all machine learning algorithms. The algorithms optimized for prediction performance, so-called predictive machine learning algorithms, are increasingly being used by traditional business intelligence tools. The readily available predictive machine learning algorithms represent only a small subset of the available ML algorithms. Predictive ML algorithms include both parametric models, for example, linear regression, logistic regression, and neural networks, and non-parametric models like decision trees and support vector models.

Despite their unique theoretical advantages, the simple parametric models have somewhat underperformed the readily available non-parametric algorithms, specifically decision trees, on prediction accuracy. The ready-to-use implementation of bagged and boosted trees which extensively use the underlying decision trees for making predictions, specifically Extreme Gradient Boosting and Random Forest, currently represent the best off-the-shelf predictive ML algorithms in terms of prediction accuracy, in multiple competitions. The core functionality of supervised and unsupervised machine learning algorithms is on extracting business insight from data which is directly useful for business decision-making.

### 6.3.1. Overview of Machine Learning Techniques

Machine learning offers a wide range of mathematical processing techniques by which machine learning systems, trained on previously gathered data, internally derive prediction or decision rules. The goal of this section is to provide a brief description of some of the most interesting algorithms, which are relevant in terms of predictive power. However, it is very important to note that, depending on the available data sets and the context of the research question, many other machine learning techniques might be readily available.

The term machine learning refers to a family of algorithms that produce a prediction or decision rule based on examples of desired input-output pairs. A conventional statistical approach would elaborate on the rationale for a certain functional form, provide estimates of the parameters, and validate the specifications based on goodness-of-fit measures. In a machine learning approach, researchers would simply take a family of algorithms and variably implement the fifth-best recipe on their specific data set, blindly relying on out-of-sample prediction power to justify their choice of algorithm.

Over the past few years, a number of specific algorithms has garnered popularity among non-statisticians, several of whom have achieved excellent predictive performance. Their popularity stems from the increasing amount of structured and unstructured data available for analysis, a coinciding increase in computing power, and the development of flexible implementations that appeal to practitioners.

### 6.3.2. Applications in Financial Services

Finance is one of the most data-driven industries and is a natural candidate for the use of machine learning algorithms for pattern discovery, identification of hidden relationships, and prediction of financial behavior. The predictive quality of machine learning models tends to be superior to that of traditional statistical methods in many instances, particularly for structured and unstructured big data. As finance moves toward greater automation and customer focus, machine learning will play an ever-firmer role. Various applications of machine learning are discussed below. Predictive modeling with machine learning is one of the most prevalent areas of machine learning application in finance. Most financial decisions are based on predicting some economic quantity, whether interest rates, stock prices, or credit risk.

Predictive modeling is mostly conducted using structured financial data. In a supervised learning scenario, algorithms are trained to predict cash flows to take place in the future using historical financial variables. At a high level, using financial statements to forecast cash flows and business performance is similar to predicting stock prices, although the information set used in accounting forecasting is usually more constrained than that used in predicting stock prices. Financial risk prediction is a crucial aspect of the financial industry. Financial institutions, including banks, rely on evaluation models to determine the risks associated with lending money to individuals and businesses. These models are usually derived using logistic regression but, more and more often, machine learning techniques are being tested and employed for this purpose.

## 6.4. Data Collection and Management

Data collection is probably the most critical step toward enabling the hyper-personalized solutions explored in this research. The focus of the hyper-personalization is to offer the right solution, to the right person, at the right time, and via the right channel. Achieving this however requires large amounts of both qualitative and quantitative data, relevant to address the factors that can enable a suitably informed and contextualized financial advisory experience. This part considers the types of data that can be adopted to enhance the hyper-personalization experience, as well as its ethical implications. While financial transactions of users can provide considerable quantitative insight, qualitative data can also be procured through third-party websites and secondary data collection, mainly in a scraping format.

Types of Data Required

The existing literature on financial advisory services provides several elements for financial advisory, varying from basic demographic, financial need, risk tolerance, saving and investment preferences, country of origin and residence, religion (for Sharia-compliance), as well as wide-reaching psychographic information to name just a few. However, only a limited number of the mentioned insights are frequently adopted by both automated advisory solutions and human advisors. Data privacy is also a key topic in this practical implementation discussion, and machine learning methods have been shown to be able to process sensitive user data in a suitable manner, however still needs to be carefully researched when it comes to providing respective solutions.

### 6.4.1. Types of Data Required

We apply hyper-personalization to the three mutually exclusive types of available data, thus, we require large amounts of qualitative and quantitative for every Client Segment. Aggregated data will be provided by internal sources before engaging with clients. To advance our business model, we need to get more granular data from existing and future Clients. Internal private data sources will provide qualitative data. Some potential sources of personal quantitative data are Industry Groups and specific websites, including social media platforms and high net worth individual targeting companies. Qualitative data can pertain to behavioral determination, Empathy, values, beliefs, interests, life stages, life events, and need for social approval in terms of need for expensive products and/or support for climate change and/or collaboration to help in both Clients' home and business locations. Quantitative data can be both Personal, related to Shareholders, Stakeholders, Beneficiaries, Board Members, Employees, and Management, Staff, such as number of people, total personal net worth, income, occupation, time to live, and time to succession real and nominal, up to Income Tax or Inheritance Tax, Temperament paragraph, and Non-Personal, related to targeted vacation spots, Startup business funding for technology areas to be covered, normal economic, fiscal, and monetary policies, based on utilizing real GDP growth rate, inflation rate, total Tax Revenue, people pay and balanced Budgets, Export Growth, and Foreign Direct Investment, natural product cycle, and Major Currency Partnerships that the Clients directly compete with.

### 6.4.2. Data Privacy and Ethics

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Even though consumers have given consent and companies are using the provided data with a sincere intention, a critical issue arises when such data is used to manipulate their behavior without their awareness. Financial institutions using hyper-personalization for target marketing need to be aware of how their customers will react to being disturbed by identifying customer pain points, emboldening the trigger that inspires their client to become a buyer. It is essential to be focused on the intent of those messages for that particular type of offering as well as to be focused on establishing trust with consumers. Such reactions can also be directly related to the intent behind the delivered message and the time point that the customer or consumer organization has been messaged.

One thing that financial institutions should avoid is a tendency to over-indulge and bombard their customers with personalized offers, as it would have the opposite effect. Having said that, data-sharing practices should be extremely transparent, clearly outlining what data will be collected, for what purpose, and how it will be used for the advancement of the customer or client experience. Customers ultimately need to be made deeply aware of the benefits that come with sharing their data. Sharing needs to be positioned as reciprocity — what are the mutual benefits they can derive from it. Cyber security breaches have continuously been brought to public concern in the past few years. Unfortunately, as people have gotten more aware of the value of their data and what breaches can mean for their personal and professional lives, organizations have done little to stem the tide of such breaches. This has created an atmosphere of distrust between consumers and organizations that are empowered to provide hyper-personalized services.

### 6.5. Building Hyper-Personalized Financial Models

Users in proprietary banking often feel neglected as many banks claim to offer personalized wealth management but create financial models that ignore the specificity of individual user situations. In addition to approval criteria, professionals have to consider risk premiums and exposure to get an evaluation. Assuming a static asset-living correlation and robust models that do not depend on portfolio-specific asset price behaviors, the analytics suggest a quantitative model that captures the degree of correlation between life events and assets based on available events and thresholds of the portfolio and events using past asset information. However, it is not enough to obtain a user's demographic data and estimate the timing of different life stages. There is a notable user disequilibrium across the life cycle and very few users actually move into the different trigger stages as they grow older. Utilizing event data, data on portfolio sizes and risks, and events, we can build bespoke models to support advice across the wealth cycle. This hyper-personalized model can estimate a user event likelihood for the next few years, taking the available user data, different risk thresholds, and alternative event probabilities into account.


**Fig 6.2 :** Building Hyper-Personalized Financial Models.

The entry of the younger generations into wealth building, while the older generations enter juicing, and if the succession plans of affluent families are not consulted, there is a probability of wealth going undeclared and with it the fee opportunity. Banks are also reluctant to rely on data that is not internal due to reputational risks, resulting in cookie-cutter wealth models that merely enhance product margins. Events that are uncommon are associated with long tails and banks could use data to refine their own risk. This is an opportunity, not a risk. For building a hyper-personalized financial model, we need to select the design algorithms and enable cumulative data usage for training. Cumulative exposure to clients' life cycle events will enable mastering the appropriate algorithms that are beyond the normal toolkit. Ensuring for sustained results takes documenting when models overperform other model approaches. Any example of outperformance becomes especially relevant, as it may lessen concerns related to model drift and brittle model performance if the different algorithms have to process momentous shifts in focus over time.

### 6.5.1. Algorithm Selection

A wealth of predictive algorithms has been developed in the last couple of decades, and with them has emerged a pressing concern: which algorithms to include in the heads of AutoML tools? The problem is that there is no single best answer, for many reasons. First, it is impossible to draw a general conclusion that holds for all datasets. Thus, one reason why a huge variety of predictive algorithms are made available from different AutoML systems is that it is not easy – from a practical standpoint – to anticipate the kind of predictions that users would like to automate: there will probably be always datasets that deserve a predictive approach that is not yet available in a specific AutoML tool, even if it is possible to specialize in a domain. Second, computing time is certainly an essential factor in any practical machine learning application, including AutoML. As a consequence, it is not wise to consider all algorithms available. Rather, it seems to make sense to limit the choice to implement specific subsets of algorithms for the underlying prediction problem. Typically, the models deemed most influential in terms of prediction accuracy are the most promising candidates to put in the heads of an AutoML tool, or a selection of nominative algorithms that research and experience have shown to be profitable for the instance of problems.Moreover, the algorithm selection problem is part of a broader issue in machine learning, usually referred to as algorithm selection. The idea is that for a specific problem, different algorithms might yield different results in terms of accuracy. Thus, there exists a different methodology for determining which model could be the optimal one for a dataset, using meta-learning techniques. These techniques leverage previous learning experiences to build a model capable of predicting the relative performance of algorithms applied to unseen data. The final question that remains open is if we can leverage the above methodology to reduce the methodology applied by Auto-ML tools.

### 6.5.2. Model Training and Testing

The data used to create models for predictive analytics, which would finally generate normalized scores for the base user information, consisted of users' credit behavior who had applied for fast user personal loans and UPI-linked merchant transactions for Dec 2023. Data for 449 customers who had a payment default have been assigned +1 in the y-label (classified as a user for generating negative scores or labels as expected). The remaining data for 22,926 are non-defaulters, assigned with -1 in the testing and training model label. Models for training will have the active Y-label set as +1 (for defaulters) and balanced by setting the input of 2201 records for defaulters normalized with an equal weight of 2201 for -1 label records. The rest of the y_label set has been down-sampled, which is the method of handling class imbalance. The statistical method of handling model imbalance by stratified sampling is also used in the function, which for better results uses the bore score, correctly classifying each class through a likelihood function. Each of the model's hyper-parameters defining the model are tuned for best output scores through a function, which does a grid search and uses predictive scoring through K-fold cross-validation method, outputting the best score using the following model performance metrics of the accuracy loss function or likelihood output estimated errors with a probabilistic approach along with the F-beta score, Matthews correlation coefficient, area under the precision recall curve and the indicator function which integrates ROC AUC and average precision to be maximized.

## 6.6. Case Studies of Successful Implementation

Many banks and financial services companies are already realizing the operational and business value of hyper-personalization. Since 2012, we are helping clients develop personalized experiences by maximizing their data assets and embedding data analytics and AI capabilities across the enterprise. Our clients have leveraged our maturity model, which considers existing capabilities and goals to provide a roadmap. Our advisory services span all four steps of the analytics journey – strategizing, building the foundations, piloting and productionalizing hyper-personalized experiences in function and enterprise. With implementation, we extensively partner with technology majors. The use of algorithms, real-time processing capabilities and embedding of hyper-personalization in enterprise software is key to productionalizing exceptional experiences. One of the largest banks in Asia scripted a successful new customer acquisition process. Uncovering valuable insights from customer transaction behavior, it developed and tested seven machine learning models per product to identify new customer demand with an 85% or more hit rate. Demand for 25 banking products was scored and ranked for 2.5 million new customers. From these, the bank selected three products per customer on average which were most relevant for their onboarding journey with the objective of increasing new account activation rates and cross-selling transaction service fees. Personalization permitted marketing cost savings of 60% over conventional methods. Two-way personalization increased new account openings more than three-fold, and generated increased transaction service fees. Now, the bank has plans for expanding application of hyper-personalization to product recommendations for new and existing customers, along with friction-free journeys.

### 6.6.1. Case Study 1: Retail Banking

With the advent of e-banking, customers find it easy to operate bank accounts through applications. Banks can conduct transactions at lesser ownership costs while enhancing customer service and experience. Banks have also begun to invest in AI and Machine Learning to capture more customers and reduce operational costs. Leveraging alternatives, retail banks can drive more artificial intelligence and machine learning adoption.

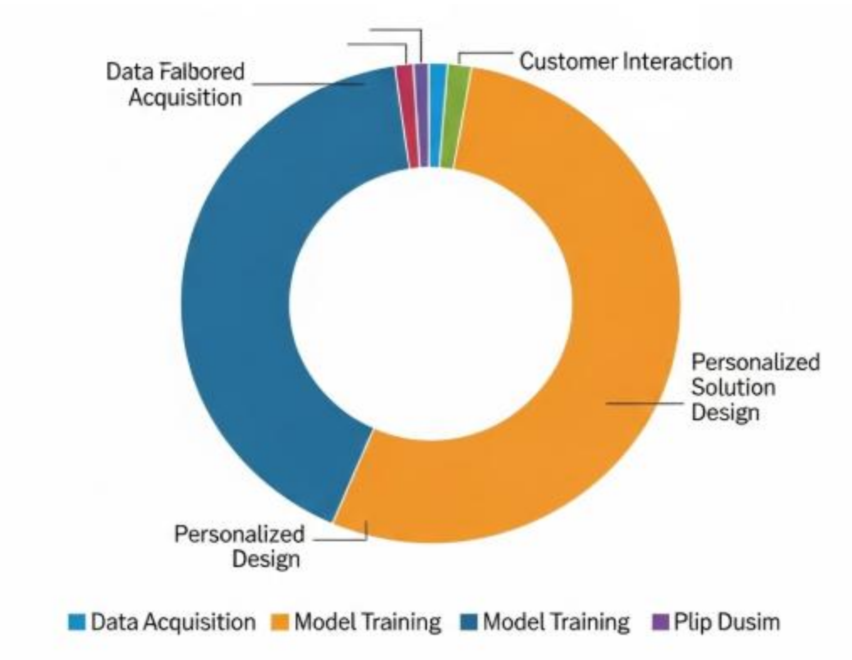


**Fig :** Delivering Tailored Financial Solutions Through Hyper-Personalization Enabled by Machine Learning Algorithms.

Changes in customers' preferences toward communicating through video, email, and texts rather than in person or by phone have reinforced marketing efforts to announce new options and expand existing automated preferences. These changing preferences, along with the advent of new distribution channels, enable organizations to acquire and retain new customers and maintain existing customers more effectively and efficiently. The growing demand for personalized products and services is pushing organizations to raise the ante by trying to match individual needs with the right products and services more quickly, smoothly, and accurately. Technology is making mass customization cheaper, faster, easier, and less risky. But few organizations are using the technology to automate what the market is capable of doing – deliver customized banking.

Umpqua Bank, headquartered in Portland, Oregon, proudly calls itself a "community bank" and has become one of the fastest-growing banks in the Northwest. Umpqua is trying to change not only how community banking devices customers and the branch banking model, but also how banks and customers view each other. For Umpqua, who the Bank is and what it stands for is as important as the product and services the Bank offers. Products, services, and technology are merely the means for achieving a higher ideal – turning banks into communities that are good for both the banker and the banked. Accordingly, the Banks tagline – "A Bank for People, Not a Bank of People" – is intended to remind Umpqua employees continuously about this higher ideal.

### 6.6.2. Case Study 2: Investment Management

The joint research report on key considerations for private wealth management (PWM) innovation and development states the following challenges for the global PWM industry: (1) Slow growth of the PWM sector as compared to the overall asset management industry, (2) Highest customer mix risk, (3) High reputational and commercial risk, and (4) High distributions and servicing costs. With 77 % of investors prepared to pay for a PWM service where a proven value is offered in return, and with 700 billion in assets already transacted from PWM to more customized investment and retail choices, customers are sensitive to price differentiation. And equally, industry leaders have recognized that additive-discovery through a higher level of deliverables is essential to their PWM business.

In this context, a major player in the PWM industry has recently transformed its long-only fund-processing and operational infrastructure. By leveraging advanced technology in its core private investment and liquidity fund product lines, it has turned its product into an institutional quality offering, whilst enabling radical customization on the level of individual fund share classes. The impact of machine learning algorithms is being deployed to handle the deluge of private account transaction messages, whether made by restricting banks, credit lines, or client lifecycle events. Thus, machine learning algorithms help with the product customization, whilst delivering cumulative operating leverage.

### 6.6.3. Case Study 3: Insurance Sector

Globally, consumers are by and large unhappy with their insurance. A CEO of a mid-tier insurance company in the south-eastern United States reported that 85% of insurance customers are unsatisfied with their interaction with agents, brokers and other vendors. Over 75% of consumers refuse to renew with their current insurers, preferring to switch to competing vendors perceived to be more attentive to their concerns. One of the factors impacting customer dissatisfaction in the insurance industry is lack of hyper-personalized product offerings. Different generations and ethnicities have different needs with respect to preferable insurance products. Thus, for an insurance company seeking to retain its customer base, understanding diverse customer needs is an important aspect in formulating personalized insurance offerings.Historically, insurance companies have viewed their products mainly as financial services offering protection against catastrophe and disasters. As a result, insurance products have been treated as routine generic offerings, lacking hyper-personalization. Although recent advances have made hyper-personalization more possible to implement, such an approach is still not widely adopted in the insurance industry. The mature state of many insurance markets and the expansion of other financial services have put increased pressure on revenues and market share, making personalized offerings a must-have for competitiveness.

Hyper-personalization enables insurance companies to go beyond a product-driven, transaction-focused business model, and develop deeper emotional connections with customers by responding to their needs on their preferred device during their real-time decision process. We apply the proposed hyper-personalized framework in a case study of the insurance sector, addressing how algorithms can be used to collect and analyze customers' various types of data. The personalized insights gained through data analysis can then be transformed into precise and granular customer segments, which can be used to tailor value propositions for specific segments.

## 6.7. Conclusion

The introduction of ML algorithms have empowered FIs to compete on speed and scale alone. Customers have become accustomed to on-demand service and have developed a low level of brand loyalty. Moreover, the impact of the pandemic has transformed shopper behavior, making personalization even more important. In today’s financial services landscape, hyper-personalization is no longer just a marketing technique; it is one of the most crucial factors for long-term customer engagement and retention. AI algorithms increase the accuracy of decision-making and recommendations while speeding up internal FIs workflows and increasing revenues. Hyper-personalization enables FIs to carve out deeper relationships with customers, understand them better, and translate insights into valuable lifetime offerings and services.

Using ML algorithms, FIs can collect insights and use them to predict the financial needs of their customers when they are making decisions. The prediction of outcomes lets companies pinpoint the optimal time to target customers through the ideal channel and recommend the preferred product or service. Additionally, customer predictions based on data will also update in real-time to provide the most personalized experience possible as customer preferences change. Research has shown that customer-centric firms are more profitable compared to firms that take a product-centric approach, and a significant portion of a company's future revenue will come from just a small percentage of its existing customers. With that impact on the bottom line, it's a no-brainer that customer satisfaction is and will be a differentiator for every FI.

### 6.7.1. Future Trends

Delivering solutions to markets that are not yet explored by any other means is really hyper-personalization. The term hyper-personalization means creating products or services for the individual. The product rating system is used by companies to show interest in what you like, prefer, and even to generate predictions about your behavior in the future. These companies collect various data such as your previously viewed content, digitization of human activity, and more such data to be combined into a single or small number of individuals to have an intimacy level. There are various approaches or techniques to be used for hyper-personalization such as deep learning, self-organizing maps, natural language processing, reinforcement learning, fuzzy semantic viewer, rule-based approach, and more.

With a combined pipeline of creating personalized content using what user has engaged previously, creating improved recommendation using new user in session-based interaction, correcting user interest using NLP, training the recommendations using reinforcement learning, and visualizing the personalized solution pipeline using fuzzy logic system, we have we are able to hyper-personalizing user interest over user agent priority. The future of hyper-personalization may be diverse. This is possible for the individual sharing economy and its part in collaborative consumption. Customers will have a wide and extended choice of brands and products until the companies offering what customers want to buy change their prices and services policies. Company-centered interactions will be replaced by individualized customer-centered interactions by using social networks, artificial intelligence, and hyper-personalization systems that enable creating and maintaining a relationship.

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