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Hyper Personalization in Wealth Management powered by Medallion Architecture

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Abstract:
Hyper-personalization is transforming the Wealth Management industry, enabling Financial Advisors to reach their clients more effectively with the help of innovative technologies, such as artificial intelligence (AI), machine learning (ML), and the Medallion Architecture. The role of financial advisor(s) would be the first casualty of the technology. Autonomous robo-advisors are increasingly threatening to replace human financial advisors. This paper, therefore, examines how a Financial Advisor can put to work Medallion architecture, a scalable data lakehouse platform, to offer customized financial services to the affluent sector (requiring assets of between 1 million and 5 5million dollars) by processing large volumes of data, including transaction logs, market feeds, behavioral data, and lifestyle preferences. The Bronze, Silver, and Gold levels of the Medallion Architecture enable the creation of an effective data pipeline, facilitating data integrity, scalability, and cost minimization through the use of tools such as AWS S3, AWS Glue, and Databricks. By optimizing the process of data ingestion, transformation, and enrichment, this paper explains how the computational costs of hyper-personalization and advisor margins can be balanced, especially with mass affluent and affluent clients. It suggests the use of such strategies as Change Data Capture (CDC), parallel processing, and micro-batch methods, which would increase the performance without violating compliance and regulations. The article will present the practical consequences of using AI-based predictive analytics and multi-channel client interaction systems to provide scalable, context- sensitive financial advice and, thus, promote trust and customer loyalty within a competitive online ecosystem.
Keywords - Dataware House, Medallion Architecture, Extract Transform Load (ETL), Extract Load Transform (ELT), Data Value Chain, Wealth Management, Hyper Personalization, Cost Optimization.

1. Introduction

Artificial intelligence is transforming every sphere of our lives, and wealth management cannot be an exception. The past five years have seen an increase in net new assets and a low-utilized margin amid competition with other investment products. Clients are also becoming cost-sensitive and would like greater visibility into the costs of investing. The current transformation in the wealth management business is more radical, moving toward client- focused, personalized service delivery. Hyper- personalization is the consequence of artificial intelligence, CRM, data science, and analytics, and it is sure to bring a new meaning to the traditional task of a wealth manager, once seen as a personalized service provider to a diverse client base. The opportunities and challenges that face wealth managers are in efforts to stand out in a more competitive environment. With AI and machine learning, wealth managers can handle large volumes of client

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data and understand their spending habits, investment behavior, and life goals. The needs of clients can be foreseen and solutions developed in advance using predictive analytics and other tools. The complexity of wealthy clients' needs is leading to hyper personalization as wealth managers are gravitating towards personalized insights into their interactions with the customers to offer differentiated services. The customer is now being catered through multiple channels and there is a need to integrate digital interactions with the in-person interface. To differentiate, they must provide a multi-channel omnichannel experience along with the desired efficiency and results.

1.1 The Problem Statement

How do we cater to different segments of the Wealth Band which is typically segmented into 4 broad categories [1]:

- Mass Affluent - $100-250K
- Affluent - $250-$1MN
- HNWI - $1MN-$25MN
- UHNWI- >$25MN

Different levels of customers require different levels of digital solutions and their idea of personalization varies. Understanding of lifestyle and customer preferences would allow the advisors to offer relevant products and a valuable partnership in achieving life goals such as education, health care, real estate, retirement, legacy etc. How can we achieve this through an appropriate data architecture, which allows us to offer customized and personalized services to different segments in the wealth band and achieve an optimum level of personalization for the bands.

Hyper-personalization comes at a cost and therefore the advisors are unable to provide an optimum level of personalization to the Mass and Affluent segment as the cost of acquiring technology and the know-how to offer personalization ends up impacting the Advisors margins. In the absence of a cost effective hyper-personalization model, they are unable to decide between asset-based pricing or subscription fee based model of engagement which creates a win-win scenario for both the parties. This is another area that requires analysis and further research on how wealth advisors can capitalise on this opportunity and create a niche for themselves.

In today's age and time, data is the foundation on hich rests the capability of wealth advisors to offer personalization to their clients while at the same time maintaining trust and integrity in their relationship. This is the balance the advisors must maintain to forge a personalized relationship and address the paradox- the more personalization is enabled through use of different types of structured and unstructured data being processed through several cutting edge technologies such as Wealth AI tools, lesser the personal interface with the customer resulting in a loss of trust with the customer. How do we retain this trust?

In the modern era data has become the most priced commodity. The hyper connected digital ecosystem is based on the foundation of data. The data produced by this digital ecosystem over the past 5-7 years have grown exponentially. The volume of data isn't the only construct; its complexity has also evolved tremendously. Therefore, it is essential for us to develop innovative methods for managing and analysing data. As the data complexity has increased, there has been an evolution in data architecture patterns. Data Architecture, which transports, refines, and contextualizes data for use, is called Medallion Architecture. Such a trend suggests that data

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should grow and develop, eventually reaching a plateau. The lowest level begins with Bronze, then Silver, and lastly, Gold. Similar to the Olympic medal system, where Gold, Silver, and bronze medals represent first, second, and third place, respectively, this system symbolizes the progressive division of achievement, value, and rarity.

The following sections explore hyper- personalization, a strategy poised to transform the experience of wealthier customers with assets between $1 million and $5 million, who are often underserved compared to ultra-high- net-worth clients. This paper explains how a strong data lake house solution, the Medallion Architecture, enables financial advisors to explore a wide range of data, including transaction history, tendencies, behavioural trends, and lifestyle preferences, to provide highly personalized strategies. The architecture offers data integrity, scale, and cost-effectiveness by simplifying data processing and reducing operational overhead. This will optimize client satisfaction and loyalty in the long term, allowing advisors to deliver proactive, contextually oriented advice and fill the gap between traditional robot-advisory platforms and high-quality human advisors.

1.2 Purpose of the Study

This paper examines the different types of data wealth advisors can use to maximize advisory services, supporting scalable personalization without undermining client trust or strategic expertise. The objectives are:

- Provide actionable insights to wealth managers to differentiate their offerings and justify their premium services.
- Offer a more in-depth examination of how hyper personalization in Wealth Management for the affluent sector could be augmented by Medallion architecture.

2. Literature Review:

As the world is evolving into more digital centric, the amount of data generated is not growing linearly, rather it is exploding rapidly. It is not just the sheer amount of the data, but the data complexity of the data is also growing exponentially. Data is not just limited to structural data sources providing the information, it has gone far into semi structure and non-structural data sources. Images, Videos, Excels, JSONs aren't just digital assets, they're part of the datasets that are managed, stored and reported on.

In 2024, the global volume of data created, captured, copied, and consumed is 149 zettabytes, according [2]. By 2025, the global volume of data is projected to rise further to 181 zettabytes by the end of 2025. This growth is driven by the increasing use of IoT devices, real-time data processing, and cloud-based storage. To put it in perspective, a zettabyte equals 1 sextillion bytes (1,000,000,000,000,000,000,000 bytes), or the equivalent of storing 250 billion DVDs. As per IDC [3] approximately 90% of the world's data has been generated within the past 3-4 years, and the volume of data stored globally is doubling approximately every four years. Organisations and individuals are not shying away from storing the data and keeping it for long, because storage of the data is becoming affordable. Thanks to Moore's law that has contributed to the reduction in storage costs. Moore's Law is a concept that has shaped the tech world for over five decades, and its implications extend far beyond just computing power. In fact, Moore's Law has also played a significant role in the evolution of data storage.

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Moore's Law (named after the co-founder of Intel, Gordon Moore) is the rule according to which the number of transistors on a microchip doubles approximately every two years, and the computing power doubles in the same time period [4]. The resulting exponential growth has led to the blistering development of data storage facilities. Some of the key impacts the Moore Law has had on data storage include rising storage capacities. The doubling of transistor count in microchips has enabled the creation of smaller and more powerful storage devices, including hard disk drives (HDDs) and solid-state drives (SSDs). This has resulted in a significant increase in the amount of information that can be saved in a particular gadget. Several megabytes of storage were viewed as something huge just a few decades ago, when nowadays terabytes are regarded as standard [5].

As data size and complexity continue to grow, data structure patterns have evolved. Previously, centralized data warehouse-centric structures were used to manage structured data; now, extensive, heterogeneous data are handled in data lakes and lake houses. This type of data architecture has been popularized in this series, the term Medallion Architecture, where the data is filtered, specified, and reused by the data consumer. Medallion architecture ensures a high level of atomicity, consistency, isolation, and durability as data undergoes several stages of validations and transformations before being stored in a layout optimized to be used with efficient analytics. The quality of the data in each of these layers is referred to as bronze (raw), silver (validated), and gold (enriched) [6].

The most essential advantages of Medallion Architecture can be linked to the use and data processing to a considerable extent [7]. One of its advantages is greater information. This architecture will ensure that high-quality, clean, and enriched data is used in the decision-making process, supported by validation and transformation processes that eliminate errors and improve information quality. By engaging in such a systematized process, the accuracy of the data increases, making it reliable at all levels. Scalability is another strength that should be in place. The modular design facilitates data expansion, allowing organizations to scale their infrastructure as more data is generated. This scaling also means the architecture can effectively process both structured and unstructured data without affecting performance or quality.

Medallion architecture also plays a vital role in data governance, where data lineage and validation must be maintained at all levels of the pipeline. This guarantees compliance with regulatory provisions and enhances transparency, enabling organizations to trace how data has been transformed and remain in compliance with relevant regulations. The integrity and accountability of data are needed in intricate systems that integrate machine learning and AI into decision-making processes, as they enable tracking and validation of data at every stage. The structure will not incur any unnecessary computation or storage costs because the strata will perform consecutive data refinement. Only relevant, improved information is transferred to end processing, reducing storage and processing costs. It is also elastic and scalable, allowing the organization to start with the simplest implementations and expand to a diverse range of data sources and processing needs. Lastly, Medallion Architecture has been a pioneer in enhancing data pipeline performance: data is divided into raw, cleaned, and enriched datasets, and complex workflows are simplified. This helps develop pipelines that the organization can use to scale, increasing data processing speed and efficiency and streamlining workflows [8].

Easy to understand and embrace.

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The ease and simplicity of Medallion architecture make it straightforward to formalize the processes data teams are likely to perform [9]. The three levels of data organization (bronze, silver, and gold) provide a clear, rational way to process information, with data teams having a specific list of actions to transform raw data into a range of beautiful datasets that can be analyzed. This transparency and user-friendly structure allow hiring new team members without any inconveniences, and the data processing process is easy to learn and expand within a very short time.

Enhances Data Quality and Governance.

The mere fact that three progressive layers of data processing are formed instantly will enhance data governance and data quality, since companies will have to trace the information on its way back to transform it into gold. The stages serve as a filtering system, and only tested and proven information is forwarded to the next stage, where the silver layer is highly in demand as a filter. The formal procedure will reduce the likelihood of flaws in the analysis process, enabling organizations to easily define data lineage and perform audits in accordance with industry rules and/or the organization's policies.

Scalability and Flexibility.

Medallion was developed using a data lakehouse architecture, which means it can be extended and meets business requirements as they emerge. The architecture of the medallion provides a platform for handling different types and indicates that the organization can begin with a simple implementation and expand as data requirements change.

Extra Access Control and Security.

The availability of data in the medallion architecture, with data broken down into layers, permits the application of access control policies and restrictions that limit exposure to data, which can be more readily prevented and data breaches resolved. In particular, access control can be implemented in such a way that only data engineers have access to bronze data; data scientists and analysts, in general, can access silver data; and only a few individuals or end users can access gold data, as determined by a role-based access policy

Funds the Data Pipeline Construction.

The most suitable architecture for building data pipelines is the medallion architecture, which an organization should possess to create real-time, frequent AI and BI applications. Because the medallion architecture provides a structured, predefined pipeline, it is easy to integrate it into larger data pipelines. The bronze layer is also flexible, making it easy to add new data sources when necessary. This structural and elastic composition can be used to build reusable, scalable data pipelines [10].

2.1 Advances in Intelligent Wealth Management

This research has found that the innovation of intelligent wealth management systems has brought about a revolution. Traditional financial advice is usually based on rational decision-making, whereas intelligent systems apply heuristics and behavioral economics to predict human behavior and discourage bad decision-making habits. This democratizes wealth management and makes it less of an exclusive reserve of the high-net-worth. Such systems are the center of the fintech revolution, combining machine learning, big data, and behavioral insights. [11; 12].

There is another inflection point in the development of financial advice, achieved through the introduction of novel systems of wealth management. The robo-advisor, older generations were

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more concerned with the automation of the passive portfolio construction process. With artificial intelligence, behavioral analytics, and algorithmic processing, these digital platforms are transforming the environment of financial planning and investment advisory. Contrary to previous centuries of robo- advisors, new-age intelligent systems provide highly personalized, adaptive, and changing financial advice [13]. Harris also summarizes the main distinctions between Traditional and new-age intelligent wealth management [13].

Features	Traditional WM	Intelligent WM
Advisor Interaction	Human-only meetings	Real-time + hybrid support
Personalization	Advisor's discretion	Data & behavior-driven
Portfolio Construction	Manual selection	Algorithmic optimization
Risk Profiling	Static questionnaires	Low or zero advisory fees
Cost Structure	High management fees	Low or zero advisory fees
Accessibility	HNWIs, in-person	Mobile-first, mass market
Compliance & Reporting	Manual, advisor-led	Automated, KYC/AML-ready

Figure 1: Features Comparison Between Traditional and Intelligent Wealth Management, Source [13].

Research indicates that the democratization in the financial services sector was achieved through an Intelligent WM system. In a more general sense, AI and robo-advisors' solutions to these issues help overcome traditional financial problems, such as high operational costs, inaccessibility, and the need for a human middleman. These technologies democratize financial services by providing targeted solutions to a wide range of customers, including retail investors and large entities [14].

2.2 Use Technology to Get Deep Client Insights.

AI can assist wealth managers in analyzing client data to gain insights into their investment behavior, including preferences, consumption habits, and aspirations. More and more, predictive analytics are used to forecast the needs of clients and provide suitable solutions [15]. One of the studies points out that Predictive personalization goes further to anticipate the needs of the customer before the customer even makes a request, based on information gathered in the previous interaction and financial trends. All these innovations in NLP and AI are moving to a future of financial personalization, adaptive, emotionally intelligent, and highly anticipatory, that ultimately defines a new standard of customer engagement and satisfaction [16]. Behera et al. argue. Argue that financial personalization will make considerable progress, driven by greater information availability, more complex algorithms, and the need to provide users with better experiences [16].

The figure below shows that AI-driven trends such as conversational agents, sentiment analysis, and emotion recognition are significantly influencing the generation of personalized wealth

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management. Predictive analytics, together with these technologies, provides wealth managers with sufficient insights into clients' needs, enhancing interactions and satisfaction.

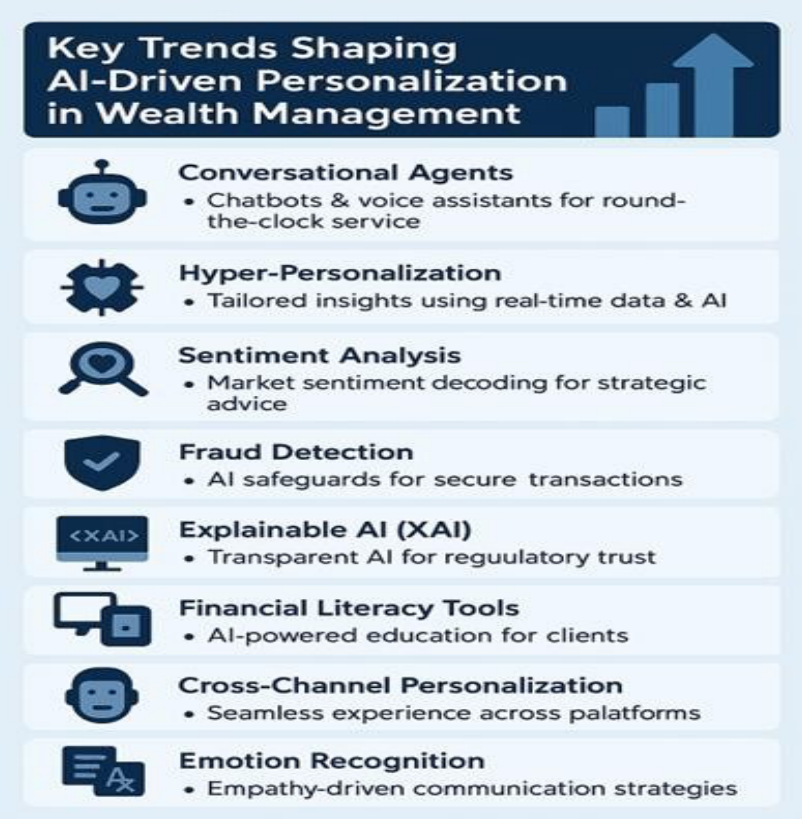

Figure 2: Trends In Hyper-personalization in Wealth Management, Source [16].

The other article examines the transformative principle of hyper-personalization and has extensive consequences for enhancing customer loyalty and satisfaction within a CRM system. It also touches on the instruments on which hyper-personalization strategies are grounded and the importance of making decisions based on data. Customer data platforms (CDPs) are considered key for aggregating disaggregated customer data into an enriched profile. In addition, advanced customer segmentation systems can segment customers based on multiple factors and treat them in a personalized manner. [17].

That way, they are supposed to understand how to use hyper-personalization to build customer loyalty and satisfaction with CRM tools. To provide an example, Rane et al. explain how Natural language processing (NLP) may enhance the perception of customer moods and enable CRM systems to not only personalize content but also tailor communication styles to the preferences of specific individuals [17].

3. Research Gaps and Novelty Aspect

The innovation of this work is based on standard data sets used to develop highly individualized financial plans for different groups within the upper-income population with varying financial needs, goals, and objectives. Though conventional wealth management methods rely on a broad, one-size-fits-all approach, this paper proposes hyper- personalization. Here, customers with varying levels of wealth, including the Mass Affluent, Affluent, High Net- Worth Individuals (HNWI), and Ultra High Net-Worth Individuals (UHNWI), will receive tailored, specialized

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financial advisory services. This very high level of personalization is possible because of the massive volumes of data, including transaction history, lifestyle data, behavioral trends, and market data, which will help wealth managers better understand each client's preferences, risk-taking abilities, and long-term goals. This means that wealth advisers are better placed to tailor their services to the needs of their wealthy clients, thereby being more valuable and, consequently, more satisfied and devoted [18; 19; 20].

The data-driven approach to wealth management has its potential, though it has particular gaps that can be addressed through research. One of the most critical gaps is the lack of client microsegmentation. Today, wealth managers divide their clients into general wealth segments, such as Mass Affluent, Affluent, HNWI, and UHNWI. Nevertheless, these sections are likely to ignore minor distinctions. These segments have yet to be subdivided further into smaller, more specific microsegments, enabling more precise financial measurements. The foregoing can be seen in clients whose wealth is similar but may have very different life objectives, expenditure habits, and investment decisions. Micro-segmentation is also related to the practice of wealth managers taking their portfolio management a step further, offering more detailed financial solutions that are more effective at addressing customers' needs.

Another research gap that warrants critical attention is the distribution of tailored investment plans within hyper-personalized wealth management plans. The article focuses on data architecture and personalization. Still, the author fails to explain how to customize investment strategies to a client's individual needs, including asset allocation, portfolio construction, and tax optimization. These play vital roles in the financial well-being of wealthy clients, and there should be extensive research on how investment policies can be adapted to suit these clients, leverage the abundance of available information, and help them manage their investments more effectively. The article does not identify the data structures or deep learning algorithms that could be used to personalize wealth management further. Although models such as the Medallion architecture were discussed in terms of data processing and refinement, the development and implementation of predictive models, recommendation engines, and machine learning algorithms have not yet been undertaken. These models may serve as variables for forecasting client requirements, optimizing financial guidance, and automating investment decisions. The research should acknowledge that these models can be constructed, trained, and deployed based on the richness of the data. They should be practical, economical, and applicable to real-world scenarios.

An imminent gap in the research area of client trust and the human element of technology integration emerges as wealth managers continue to hyper-personalize with the help of data-driven tools. The human relationship between the consultant and the client is one of the most essential elements of trust building that may be lost in the wealth management industry in the era of AI and machine learning. The research should be extended to include the use of technology to enhance these personal interactions, rather than substituting for them in future studies. The balanced use of automated information and the human touch will be paramount in ensuring that technology does not erode clients' confidence in their advisors; hence, no advisory experience will be lost at the expense of the human touch. Research is needed on regulatory and compliance issues related to hyper- personalization in wealth management [21]. Since the financial services business will also be data-intensive, wealth managers will be forced to comply with privacy, data protection (including the GDPR), and economic regulations. The art is to balance the use of client information to personalize it without violating regulatory requirements. The research on wealth

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managers' ability to develop adequate compliance and provide personalized services to customers without undermining the integrity of the advisory process and the relationship between clients and advisers also requires further research.

Despite the potential of hyper-personalization in the wealth management industry, these research gaps need to be addressed to advance the field. Further development of microsegmentation for clients, incorporation of investment strategies, data modeling and machine learning algorithms, and the establishment of trust with clients regarding the technological integration environment and the regulatory process are among the areas that can be improved. It must also entail further research to develop realistic, holistic methods of providing personalized, data-driven financial solutions that would cater to the needs of affluent clients [22; 23].

4. Tools recommended:

- AWS S3
- AWS Managed Service of Kafka
- AWS Glue
- Databricks or Snowflake
- Data Band for data quality
- Quicksight/Looker

The table below summarizes the tools used for hyper-personalization in wealth management, highlighting their applications in data collection, processing, predictive analytics, optimization, and reporting. It outlines the role of AWS services, Databricks, and visualization tools in enhancing personalized financial strategies.

Table 1: Tools and Their Application in Hyper-Personalization for Wealth Management

Step	Tools Used	Application in Study
		continues the ETL process.
4. Predictive Analytics & Machine Learning	Databricks, Snowflake	**Databricks** is leveraged for ML model building and predictive analytics. **Snowflake** is used for storing processed data and supporting large- scale analytics.
5. Data Optimization	AWS S3, Data Band	**AWS S3** stores optimized data for faster access. **Data Band** ensures data quality by monitoring and managing the data pipeline.
	Quicksight/Looker	**Quicksight** and **Looker** provide dashboards and visualization of client data for advisors to monitor performance and make data-driven

The figure below illustrates the process of populating an AWS Lake with data, monitoring data quality using DataBuckMonitor, and handling data exceptions. The cleaned data is then moved to Amazon S3 output buckets and Amazon Redshift for further analysis and processing. This flow ensures data integrity throughout the process.

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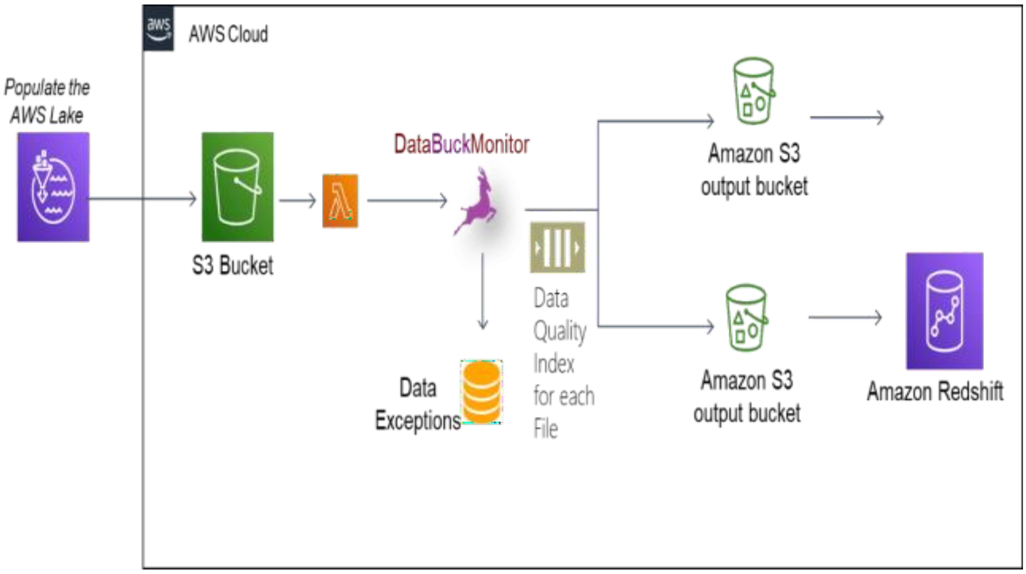

Figure 3: Continuous, Autonomous Data Lake & Warehouse Observability

5. Methodology

The article is based on an actual process in which an architectural perspective on how wealth advisors can utilize Medallion architecture to offer highly customized wealth management to wealthy clients is provided. It uses a Step

1. Data Collection & Segmentation
2. Data Processing in Bronze Layer
3. Transition to Silver Layer

Tools Used
AWS S3, AWS
Managed Service of Kafka
AWS Glue, Databricks
Databricks, AWS Glue

Application in Study
AWS S3 is used to store large amounts of raw data (parquet format). Kafka streams real-time data. AWS Glue is used for ETL processes to clean, validate, and process raw data. Databricks is used for data transformation and processing.
Databricks is used for data processing and transformation in the Silver layer, enriching the data. AWS Glue single primary technique that leverages current technologies, such as artificial intelligence (AI), machine learning (ML), and the Medallion Architecture, to build a scalable and efficient data pipeline. One methodology applied in this work could be divided into the following steps:

Data Segmentation and Data Collection.
Data Collection and Segmentation are the initial stages of making individual financial plans with customers in this research study [24]. The mediation in this case means obtaining information from different sources — transaction records, market data, and behavioral data — and classifying

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clients into wealth bands (Mass Affluent, Affluent, HNWI, and UHNWI). Micro-segmentation and behavioral objectives will establish specific needs of the groups, which will be met using other methods. This approach aligns with the work of Koneru, who states that the structure is the key to managing complex systems by data segmentation [25; 26].

Medallion Architecture of Data Structuring.
The data obtained is processed using the Medallion Architecture and converted into three large layers: Bronze, Silver, and Gold. The information consumed in the Bronze layer is unstructured, semi-structured, and raw, and is in various forms, such as transaction and social media feeds. AWS S3 buckets contain this information in this format, so that sufficient storage of this information in Parquet is guaranteed. Data processing tools such as AWS Glue and Databricks are used to clean, validate, and filter raw data in the Silver layer. This would entail removing redundant and misguided information and categorizing it to support additional analysis. The information is up to date and correct because the change is captured by Change Data Capture (CDC), and only the required changes are recorded. The data is also enriched and integrated at the Gold layer to support decision-making and predictive analytics. This stage involves generating actionable insights from a client profile using advanced data models. These lessons are being applied to popularize individual financial planning and customer participation.

Machine Learning and Predictive Analytics.
To enable hyper-personalization, machine learning is applied to model the enhanced information. The clusters are models used to group clients based on their behaviors, preferences, and financial objectives. It is an excellent relief, as it enables microsegmentation, allowing wealth managers to provide an array of advisory services. Predictive models are also used to forecast future outcomes (e.g., investment preferences, risk tolerance, and life event triggers, such as retirement or healthcare needs). These models will use the information provided before to project the future and provide more accurate, individualized information. The recommendation engines offer personalized financial products, strategies, and advice to clients based on their dynamically changing needs. The process will also ensure that the best and most timely financial recommendations are made to all clients.

The Multichannel Customer Interaction.
Due to the increased pressure on the channeled multichannel interaction, the research has been utilizing several tactics to reach clients. Through CRM and multichannel communication systems, advisors can offer personalized advice to their customers via online applications, mobile apps, email, and customer portals. Another critical aspect of the study is the omnichannel experience, which affects both online and offline communication. AI-powered bots and virtual assistants also provide real-time support, enabling clients to get any aid at any time and through any channel, thereby enhancing the client experience.

Knowledge. Continuous Improvement and Measurement.
Client satisfaction, loyalty index, and ROI will be the performance measures employed by the current study to determine the effectiveness of the hyper-personalized strategies. Moreover, the paper is cost-effective, as it continually lowers operational costs through parallel and micro-

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batching. The specified approach is connected to the research by Kumar, Malik, Brahmbhatt, and Prashasti, which emphasizes the significance of predictive analytics and AI- oriented optimization for enhancing business performance and reducing costs [27; 28].

Compliance and Security

The industry rules are followed in the methodology. The article focuses on privacy and data security to protect clients' data. Medallion Architecture implements role-based access control to ensure only authorized personnel can access sensitive data, thereby maintaining integrity and confidentiality.

The following figure illustrates how hyper- personalization can be implemented in wealth management, step by step. It describes key initiatives such as data capture and segmentation, Medallion Architecture transformation, predictive analytics, multichannel customer communications, and performance analytics, all of which are necessary for individualized wealth management.

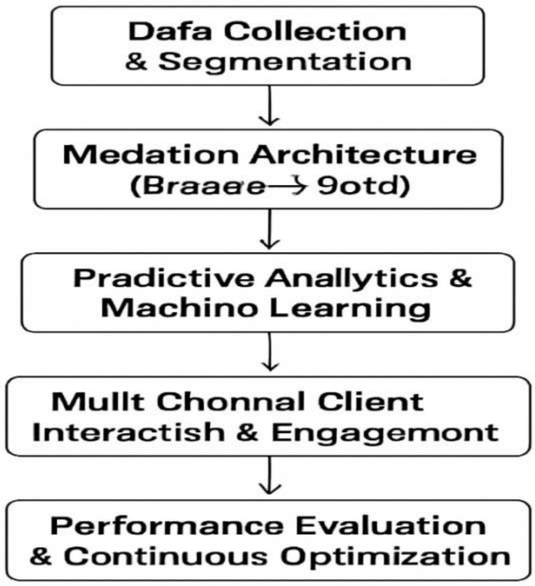

Figure 4: step-by-step methodology for hyper- personalization in wealth management

The table below outlines the process of hyper- personalization in wealth management, including data collection and segmentation, as well as compliance and security. It also emphasizes the application of Medallion Architecture, predictive analytics, multi-channel engagement, and performance optimization to deliver personalized financial strategies without sacrificing data integrity and compliance.

Table 2: Steps for Hyper-Personalization in Wealth Management

Step	Description
Data Collection & Segmentation	Collect various types of data (client data, third-party data), segment into wealth bands (Mass Affluent, Affluent, HNWI, UHNWI), and create micro-segments.
Medallion Architecture (Bronze -> Gold)	Data undergoes transformation through Bronze (Raw data), Silver (Cleaned & validated), and Gold (Enriched, analysis- ready data) layers.

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Predictive Analytics & Machine Learning	Apply machine learning models (clustering, predictive models, recommendation engines) to analyze data for hyper-personalization.
Multi-Channel Client Interaction & Engagement	Use digital platforms and omni-channel strategies (CRM tools, chatbots, mobile apps) for client engagement and personalized guidance.
Performance Evaluation &	Measure effectiveness via client satisfaction metrics, advisor efficiency,
Continuous Optimization	and cost-effectiveness. Continuously optimize the strategies.
Compliance & Security	Ensure compliance with data privacy and regulatory standards, applying role-based access and data governance.

6. Medallion Architecture:

When discussing the development of the data architecture, the history of data capture must be studied. Information that had been buried in data was revealed with the advent of relational databases in the 1980s. It was, however, soon discovered that the databases created to accommodate transactions were not well-suited for higher- order analytics. This architecture served as the foundation for future data architecture. This concept aligns with the research on innovations in asset tracking and communication that have transformed industries like fleet management through advancements in technology and data usage [29].

There was a paper published by IBM back in 1988, where it was coined that the transaction-processing environment in which companies maintain their operational databases was the original target for computerization and was then well understood. On the other hand, access to company information on a large scale by an end user for reporting and data analysis was relatively new. Within IBM, the computerization of informational systems was progressing, driven by business needs and by the availability of improved tools for accessing the company data. It was then apparent that an architecture is needed to draw together the various strands of informational system activity within the company. IBM Europe, Middle East, and Africa (E/ME/A) adopted an architecture called the E/ME/A Business Information System (EBIS) architecture as the strategic direction for informational systems. EBIS proposes an integrated warehouse of company data, firmly based in the relational database environment. End-user access to this warehouse is simplified by a consistent set of tools provided through an end-user interface and supported by a business data directory that describes the available information in consumer terms. [30]

- Transformation: Transformation involves taking that data, cleaning it, and putting it into a common format, so it can be stored in a targeted database, data store, data warehouse. Cleaning typically involves taking out duplicate, incomplete, or obviously erroneous records.
- Load: Load is the process of inserting that formatted data into the target database - data warehouse.

The challenge with ETL is the high coupling with the target state data model, which is the consumer-centric data model of DWH. With complex data structures, creating the dedicated pipeline for every consumer will delay time to market and present a challenge as well. To address this, it is recommended to centralize the data into a repository, where it can be parked and then

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processed based on the requirements of the data consumer. This model is referred to as "Extract, Load, and Transform (ELT)" [33]. In ELT, the pipeline is built with all the source systems, where the raw data is sourced from the disparate systems. Once the data reaches a sink, called "Data Lake". Then the consumer centric product can be built on it, via simple Transformation of the data sets.

As illustrated in the figure below, the difference between ETL and ELT lies in their processing order. ETL extracts, transforms, and loads data, while ELT extracts and loads data first, followed by transformation, allowing for more flexibility and faster data processing.

The need for systems offering decision support functionality predates the development of the first relational model and the introduction of SQL. Market research and television ratings magnate, ACNielsen provided clients with something called a "data mart" in the early 1970s to enhance their sales efforts. [31] Data Warehouse (DWH) is the data sink, providing a unified source of truth, where all the data sources push their data. Historically, DWH is where the data model is prescribed prior to the start of data population in the warehouse. This prescribed format is created with a mindset for a given use case or "Data Product". Therefore, this DWH is often referred to as "Data Mart".

To move the data to this DWH system, Extract Transform and Load (ETL) became a de facto standard, organizations adopted a schema-on-write philosophy: where the data schema was defined upfront and use ETL processes to transform source data to fit that schema before loading. ETL gained momentum and many organizations such as "Informatica" , "Abnitio", etc were formed, by doing ETL in the most optimized way. As defined by Google Cloud [32] -

• Extraction: Extraction is the process of retrieving data from one or more sources—online, on- premises, legacy, SaaS, or others. After the retrieval, or extraction, is complete, the data is loaded into a staging area.

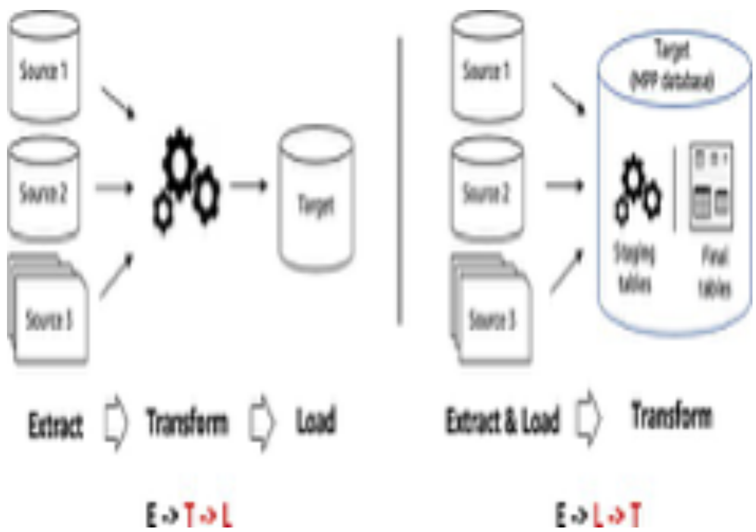

Figure 5: ETL vs ELT - Difference Between Data- Processing Approaches - AWS

Built on a similar concept was a BIG Data Concept, Hadoop implementation, where data was sourced from different systems, and aggregated/computed on demand, making schema on read concept. The challenge with Hadoop was the co-existence of data and computation on the same system. To overcome this challenge, a Data Lake concept was launched, wherein computation is conducted in a different system than data storage. With Medallion Architecture, data increases its

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value by passing through different tiers. This data value chain evolves the data sets for specific use cases. A medallion architecture is a data design pattern used to logically organize data in a lakehouse, with the goal of incrementally and progressively improving the structure and quality of data as it flows through each layer of the architecture (from Bronze ⇒ Silver ⇒ Gold layer tables). Medallion architectures are sometimes also referred to as "multi-hop" architectures [34]. As illustrated in the figure below, the Medallion Architecture organizes data through progressive tiers, enhancing its value. Data flows from Bronze (raw integration) to Silver (filtered and cleaned) and finally to Gold (business-level aggregates), improving its structure and quality for specific use cases.

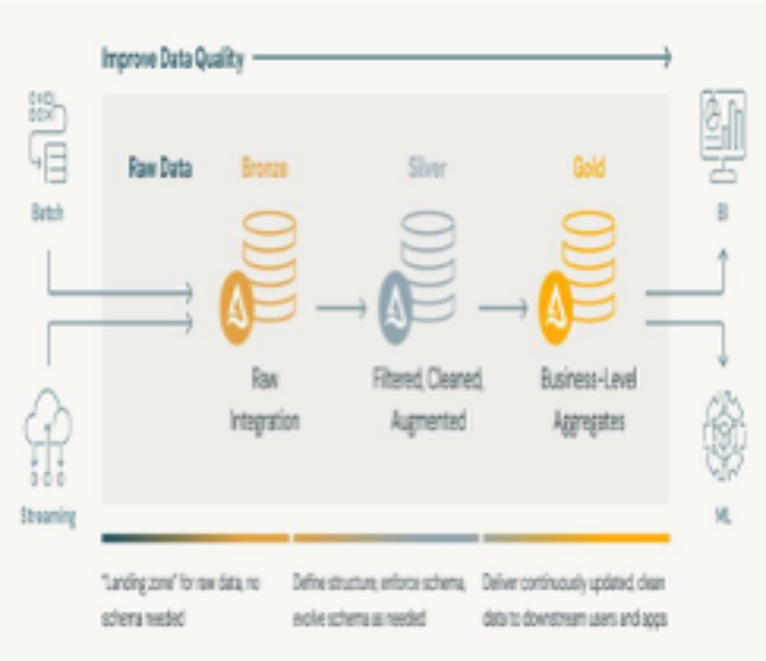

Figure 6: Data Value Chain powered by data lake pipeline [34].

7. Role of Data in Wealth Management:

The application of data from different sources to contemporary wealth management practices that underpin both personalized client service, risk assessment, and regulatory compliance. This helps a long way as it is now possible to provide wealth managers with the capabilities to offer individual and customized services to their clients:

7.1. Client Profiling & Personalization.

The client persona is created using large datasets and includes demographics, financial history, habits, and life ambitions. Using this data, advisors and wealth management companies can create detailed client profiles that include investment options, risk tolerance, life experiences, and related financial needs, including medical, retirement, and housing. It is a fuel that customizes offerings with a greater impact on improving client experiences and client retention [35].

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Figure 7: Client Profiling and Personalization Framework: Building a Comprehensive Client Persona

7.2. Investment Decision-Making

The decision-making process style as concerns investments. Once again, when information has been gathered, it will provide a clue to how investment decisions are made. Gather market data, economic data, and new-age data that are built in analytics, including ESG score and sentiment analysis. It will assist in constructing an investment portfolio, developing an asset mix and allocation plan, and performing an investment performance analysis. The wealth advisors and managers will be in a position to make sound decisions, not using their gut or intuition.

The figure below shows how different data sources, market and economic data, ESG scores, and sentiment analysis are combined to inform investment decisions. The data-driven method enables wealth managers to design customized investment plans, enhancing hyper-personalization and optimizing client portfolios in line with specific objectives and market dynamics.

The figure below shows the key elements of developing a client persona in wealth management. Using a combination of data, including demographics, financial history, and life goals, wealth managers can provide custom investment strategies, improving client experience and retention by hyper-personalizing them.

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Figure 8: Data-Driven Investment Decision-Making Framework

7.3. Risk Management

The practice of risk management is essential, and advisors are expected to engage in it to proactively minimize potential losses and help clients remain loyal to the advisor. This is achieved by using historical prices, client risk ratings, and macroeconomic trend analysis. Risk management can also be performed by reviewing portfolio risk assessments, including volatility, to identify weaknesses. The efficiency of management and the risk-free processing of information will yield these insights and improve client outcomes [36; 37].

7.4. Reporting- Regulatory Compliance.

Ensures compliance with financial regulations (e.g., AML, MiFID II, FATCA). The data utilized will be receivables records, KYC (Know Your Customer) information, and audit trails. The t helps reduce the risk of lawsuits and increases credibility through reporting.

7.5. Performance Measurement & Benchmarking.

Improves accountability and demonstrates worth to clients by advisors. The advisors will be able to track investment performance against the market benchmark and the client's goals. The data that is used is the performance measures (portfolio) and benchmark indices.

7.6. Automation & Efficiency

Cost reduction, human error reduction, as well as releasing advisors to more valuable strategic tasks. Based on the operational and workflow data, advisors can fuel automation in portfolio rebalancing, robo-advisory systems, and client onboarding.

7.7. Predictive Analytics and market insights

Provides companies with a competitive advantage by providing faster and data-driven decision-making. The advisors can foresee the market dynamics, client requirements, and investments. One

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of these large areas is the use of big data, AI/ML-driven insights, and real-time feeds to generate predictive analytics that assist in making investment and portfolio-related decisions.

8. Case Study: Hyper-Personalization Tailored for Wealth Management with Medallion Architecture

8.1 Provision Raw Data in Bronze Layer:

To provide hyper personalization the core part is to know about the client, and there are two ways of knowing about the client -

1. First-hand information - via surveys and/or targeted questionnaire
2. Second had information - via Behavioural and Psychographic Data feeds

Behavioural and psychographic data feed is vital for understanding what clients do, what they like, and how they are driven psychologically. Absorbed into the Bronze layer of Medallion Architecture, these feeds enable advisors to learn about clients' needs, customize strategies, and provide advisory services tailored to each individual (e.g., next-best-action recommendations or life-event-driven planning). Examples of such feeds are -

a. Financial Stature - Source of this information is mainly the feed from client's online banking details, along with activity of number of login. The number of logins can derive the anxiety factor.

b. Lifestyle Feed - Source could be financial data aggregators, such as Plaid. It provides records of spending, savings, or investment transactions, including categories. It also provides information about real time lifestyle changes, such as spending on major home renovation, philanthropy donations, etc.

c. Transaction Logs - Source could be CRM, call logs. It tracks client's preference, and concerns. For example, if the client is repeatedly asking for Risks, conveys the risk appetite.

d. Social Media Engagement - Source would be Social Media, such as Instagram, Facebook, X, LinkedIn feeds. These feeds will provide information about the latest likings and inclinations of the client. It could be affinity to crypto, a particular IPO, etc.

e. Credit Bureaus - Source would be any of the credit providers. These feeds provide information about current wealth levels.

Beyond these personalized feed, it'll be critical to
capture -

i. Transactional data - Realtime and historic data access to client's transactions, that includes trades, etc.

ii. Portfolio Holdings Data - Current and Historic Holdings, profit/loss report.

iii. Market Feed - Such as Bloomberg, Refinitiv, FactSet, exchanges, or public sources. This feed provides - Real-time and historical market prices, indices, interest rates, currency rates, and volatility metrics.

iv. Internal Compliance and Tax Systems - To ensure the advisor is compliant, client verification data, anti-money laundering checks, and regulatory filings is required, along with tax returns, capital gains/losses, trust structures, and beneficiary details.

v. External Sources - News API, economic calendars, and government databases for getting real time feed for macro events.

The feeds listed above will help advisors to personalize advice, predict needs, proactive engagement, and be compliant [38]. These feeds must be captured in Bronze layer in AWS S3

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bucket in different files in a columnar data set of parquet format. It has to be ensured that the files are compacts for optimized storage cost.

The figure below illustrates the various layers involved in data processing, such as Bronze, Silver, and Gold, as part of the Medallion Architecture. These layers are essential for organizing and transforming raw data into actionable insights for personalized wealth management, enabling hyper-personalization.

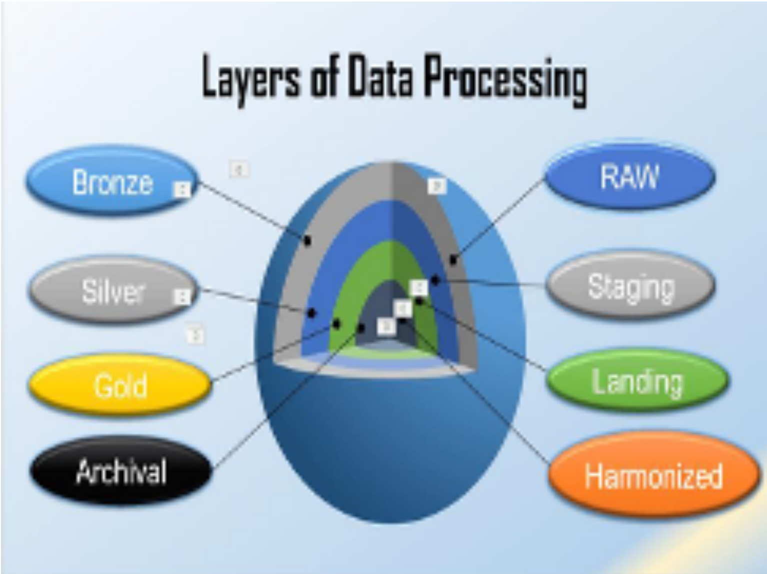

Figure 9: Layers Of Data Processing

8.2 Design of the Silver Tier

The move between the Bronze and Silver layer (raw data and ingested data, respectively) into the Silver layer (cleaned, validated, and enriched data) is a critical step towards the Medallion Architecture to transform data into reliable data to mirror the client profile, transactions, and market data that can be hyper-personalized. Data loss prevention strategies should be prepared in advance of this transformation and will also help achieve compliance (e.g., GDPR, SEC regulations). This aligns with Singh's work, which emphasizes the importance of secure, privacy-sensitive methods for processing data and of adequately controlling human-level access to sensitive information without contravening regulatory principles [39; 40]. An appropriate data model should be used to manage big data. This data model should comply with the determination of the correct facts and dimensions of the data sets. It implies that the data volatility, time sensitivity, and relations should be uncovered and defined. After the data model has been logically defined, it needs to be made available in the physical system.

Since the data volume is huge, it is recommended to follow the steps listed below to ensure cost optimization, faster time to write and read.

For Data Writing the following strategies must be implemented:

- Data must be partitioned with proper logical keys. This will ensure that the writes are targeted to the correct partition to avoid the full scan.
- Data should be bulk loaded and in parallel processing. This will ensure that there is a burst in the data, and the compute layer doesn't have to be active always. Parallel processing ensures that the data is ingested in a multi-threaded environment for faster insertion.

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- Change Data Capture (CDC) must be implemented to ensure only the changed data is being consumed to be inserted. Kafka must be leveraged for streaming the output. The CDC must be enabled on the required data fields only. Not for all.
- Realtime vs Batch, it is preferred to have batched transaction(s). Only a handful of the data elements must be considered for real time update. This will ensure that full scan is reduced, and time sensitive data is only updated via Kafka streaming services. A happy medium in this approach is following a micro batch data processing technique.
- Row Hash Comparison will ensure the de- duplication is done before the Upset operation starts.
- Though an ANTI PATTERN, it is recommended to follow the “Delete and Insert” construct for large batches, rather than MERGE. This will ensure the Deletes are performed first, then inserts, and finally the data must be committed. This can be achieved by transactional handling done by the processor and not handed over to the data layer to manage. This approach is faster, efficient, and cost effective for large data set merges.
- At the bronze layer, before publishing the data mark the data as insert, delete or update. This will ensure that simple data COPY COMMAND can be leveraged for inserts, whereas Updates and Deletes gets deleted first, and then follow the copy command for update data sets.

For Data Reading the following strategies must be implemented:

- Data must be properly indexed in the logical order. This will ensure the read time spent by the compute is drastically reduced. Note - the indexes should not be very heavy, as it slows the write process. Therefore, it has to be a right balance between indexes.
- Filter data as early in the query as possible. This will ensure the finer queries are executing on the smaller datasets.
- Cache the frequent access datasets to ensure that data storage layer is not being queried for the frequent access datasets.

Though the Medallion Architecture recommends Bronze, Silver, and Gold tier implementation, for better cost optimization, the Gold tier could be skipped. There are certain trade-offs listed below, and if properly governed, the Gold Tier could be reserved for Ultra High Net Worth Individuals and High Net Worth Individuals. For the Affluent category, the value for hyper-personalization could be derived from the Silver Tier. Restricting data just until the Silver Layer reduces transformation costs as Gold layer processing is skipped. It enables faster iterations by directly using Silver data, which can speed up model prototyping, especially for simpler models, reducing development time and compute hours. With smaller data volumes, Silver data is often less aggregated, so smaller, targeted datasets for specific ML tasks can lower costs compared to Gold's broader, analytics-ready tables. However, challenges arise, such as data quality risks in the Silver layer, as it may lack business-specific transformations and could require ad-hoc processing during training. Effective governance and customized data processing are critical for achieving cost-effective scalability in enterprise operations [41]. Using the approach listed above and the subscription of the feeds, a financial advisory will be able to service "Affluent Band” of clients with confidence provisioning hyper personalization without massive technology cost. The more the clients in the band, the better will be the return on investment with this recommended approach. As it targets, quantity more than quality of hyper personalization.

The table below illustrates the Hyper- Personalization Process for Wealth Management Using Medallion Architecture, which outlines key steps such as data collection in the Bronze layer, data

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processing in the Silver layer, and optimization strategies. The Gold layer is optional for cost optimization in the Affluent category.

Table 3: Hyper-Personalization Process for Wealth Management Using Medallion Architecture

Step	Description
1. Provision Raw Data in Bronze Layer	Collect first-hand data (surveys, targeted questionnaires) and second-hand data (behavioral, psychographic feeds) to understand client preferences and needs.
2. Data Types in Bronze Layer	Includes financial stature, lifestyle data, transaction logs, social media engagement, and credit bureau data. Stored in AWS S3 in Parquet format for optimized cost.
3. Transition to Silver Layer	Raw data is cleaned, validated, and enriched for reliability in decision-making.
4. Data Processing in Silver Layer	Includes partitioning, parallel processing, Change Data Capture (CDC), micro-batch processing, and row hash comparison to improve performance.
5. Data Optimization	Use indexing, filtering, and caching to optimize data reading and processing speed.
6. Gold Layer (Optional)	For cost optimization, the Gold layer may be skipped for the Affluent category, relying on the Silver layer for data processing.

9 Conclusion:

The Medallion architecture has been a revolution in wealth management, hyper-personalizing services to serve high-end clients with minimum and maximum funds of 1 million to 5 million. With this scalable, robust data lakehouse, wealth advisers will efficiently and inexpensively handle diverse data, including transaction history, market data, behavioral data, and lifestyle data. Predictive analytics and machine learning models can transform valuable information using the Strategy Medallion Architecture, enabling seamless achievement of this goal. Financial advisors can offer real- time, contextually relevant financial advice to every client, based on their needs, using Change Data Capture (CDC), parallel processing, and micro-batching. This would not only simplify data processing but also allow the company to reduce operational costs and, consequently, offer personalized services without compromising the margins that accrue to advisors. The architectural design criteria of hyper- personalization within the Medallion Architecture have undermined the requirements of informational decision- making and the value of customer trust, as this paper will demonstrate. One of the challenges wealth managers face in standing out from robo-advisors is offering more personalized, data-driven services without losing the human touch.

The market has evolved, and wealth managers can now reevaluate their thinking about financial management, as they are no longer reactive but proactive, facing many competitors and customers who need solutions not only personalized but also practical. These financial technology applications will enable wealth advisors to enhance client loyalty and satisfaction, thereby creating long-term value for both the company and its clients. The future of the research could examine how new technologies, including edge computing and even more innovative machine-learning algorithms, can be implemented in the region as it moves toward even greater hyper-personalization. This will fit human-centered services offered by wealth managers, with AI-based applications that can ensure a completely personalized experience, regardless of wealth

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level. Furthermore, the radical opportunities will come into play once discussing turning Medallion Architecture into a fully AI-based wealth advisory, which will change the future of wealth management for more people. Medallion architecture has a high potential to meet the interests of wealth managers and enable them to hyper-personalize their services (cost-effectively) as it scales. The framework will help the industry offer proactive, individualized guidance to address the needs of high-income customers, making wealth managers the most crucial players in a more digital and data-driven ecosystem.

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