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AI-Driven Data Enrichment and Golden Record Creation for Enterprise Customer Data Platforms

Sravan Kumar Kunadi

Independent Researcher, USA

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ABSTRACT: The current digital business environment has demanded the enterprise customer data systems to process massive amounts of disaggregated, inconsistent and duplicated customer data in numerous business systems. This research paper will discuss the concept of artificial intelligence with a view of enriching data, and of the need to come up with golden records as one way of entering data system of customers to enterprises. In the article, the author highlights the use of AI-based solutions to enhance the quality of the data, which includes the detection of missing fields, correction of errors, standardization, a match between records of similar data and linking records that present the same information of heterogeneous entities. Customer profiles can be enriched to be more comprehensive, precise and be context-sensitive through machine learning, natural language processing and rule-based intelligence. Creation of the golden records is one of the most crucial parts of the article as one of the records is coming up with one version of every customer by joining dufferent and contradictory record in to a single trusted and unique record. In the article, we read about the workflow design where the data entry together with the initial processing, feature collection after the data entry, similarity measures, trustworthiness analysis with a file reconciliation is brought up. It further discusses the AI-led enrichment as it aids downstream activities like personalized marketing, customer segmentation, sales intelligence, service optimization, and regulatory compliance. This is the paper thesis: AI implementation in customer data platform does not only do their job in the efficiency of operations and the corresponding enrichment of the decision-making process, but also a more detailed stable look at a customer. Overall, the article unveils that scalable, intelligent and data-intensive enterprise ecosystems, which can be used to support modern customer relationship strategies and business transformation initiatives, need to be built with the help of AI-enhanced enrichment and building golden records.

KEYWORDS: Customer Data Platform; Artificial Intelligence; Data Enrichment; Golden Record Creation; Master Data Management; Enterprise Analytics.

I. INTRODUCTION

As the evolving digital economy, customer information is generated and processed on a grand scale in many platforms and products, including: customer relationship management (CRM) platforms, marketing automation platforms, transactional databases, social networks, third party data platforms. This massive increase in data, which is mostly high velocity, data variety and volume has posed a huge challenge in the data consistency, accuracy and usability. Enterprises are finding customer data platform (CDP) to help bring these far-flung bits of data to a centralized system to assist in analytics, personalization and decision-making. But, the CDPs themselves heavily rely on the quality and completeness of the underlying data. In the real-life scenario, the data on the customers is commonly amalgamated, duplicated, outdated, or not complete, which compromises the quality of the data and decisions taken by the data-driven approaches [1] [2].

Enterprise customer data management has data silos, which are one of the major issues. The storage of the data of various types is kept in different departments like sales, marketing, customer service and finance, which result in the lack of consistency and redundancy. One of the ways in which a customer may occur different across various systems even when it inconsequentially prevalent in firming the name, address or contact information. These discrepancies bring about ambiguity and preventing the creation of integrated customer perception. In addition, the lack of attributes, typographic mistakes, and illogical data formats also make the process of data integration even more complicated. The

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more infrequent traditional data control paradigms have been more frequently so strongly dependent on manual processing and systemic guidelines, and are commonly unable to react to the amount and the intricacies of enterprise overall informational domain [3].

In order to manage these problems, firms are deciding to use more artificial intelligence (AI) to enhance the data management procedure. Application The introduction of AI-used data enrichments has proved to be an efficient tool to enhance the quality of data, completeness of data as well as context of the data that relates to customers. Enriching data may be defined as part of the processes which entails the addition of data to the existing data set as per both the in house and external sources [4]. The AI ways applicable to detecting the missing values, repairing the inconsistencies and standardising the data formats to uniform form would be machine learning, the natural language processing (NLP), and pattern recognition. One such area is that machine learning systems might be used to recreate missing demographics and NLP systems might be used to infer useful information by analyzing unstructured text interfaces (emails, customer feedback and social media interactions). Such abilities greatly minimize the use of manual intervention and make overall data processing processes even more efficient.

The subsequent significant outcome of AI-driven data enrichment is the golden record that turns out to be unique, authoritative and single access to a customer profile. Golden record creation is an intrinsic part of master data management (MDM) strategies and a must to attain a 360-degree customer view. It entails taking away and detecting red duplicated records, filling out the characters of the facts and integrating the data of two or even more information channels so as to produce a reasonable and viable viewpoint. AI plays a fundamental role in that process in that it allows more advanced entity resolution techniques, such as more than just a rule-based matching, like probabilistic and similarity-based techniques. They are able to tackle discrepancies in misspellings records, short forms use and incomplete records thereby having better accuracy in bridging the records.

The customer data platforms offer another chance to implement AI and achieve real-time data processing and learning. Unlike the traditional models which are built on solid rules, AI models can adapt to the altered data trends and improve their performance, over time. This proves to be highly beneficial in the fast moving business world whereby, customer behaviour and information source is continuously changing. Additionally, AI based solutions can give a confidence score and explainability measures, which will help companies to determine the probability of more data and records that get collected and consequently, will be reliable. This will elevate up trust on the system and assist in adherence requirements to data governance and regulation requirement.

Quality customer information is a necessity not only to various aspects of the business. Marketing The refined and merged customer profiles would further target, promote and execute on customers more precisely besides providing more personal customer experiences. Effective data in sales facilitates scoring of leads, dealing with opportunities, as well as in building customer relationship. The image of the customer interactions in general in customer service will be what will enable tackling the issues more efficiently and treat the customers more gratifyingly. The need to have correct and regular customer information on regulatory compliance to fulfil the demands of data protection laws, and prevent legal liabilities, is also a priority.

Despite the benefits of AI-powered data enrichment and forming golden records being huge, several problems exist. The most topical issue is still privacy and security of the data, especially when it comes to integrating data of various sources. The other essential step to be taken is mechanisms that ensure that data processing processes undertaken by the companies align to the respective legislation and ethics. Also, AI systems require significant capital in infrastructure like large-scale capital, skills and data management systems, to be installed. It is also determined by the need to address the problems, which are pegged on the artificial bias and openness to be able to guarantee the data processing obtain results that are objective and objective.

The suggested research paper will respond to the following research question: what would the use of AI be to supplement the data provided and to generate gold records on enterprise customer data platform? It takes into consideration the architectural concerns, workflows and algorithms to convert the unstructured, disaggregated information to quality, integrated profiles of customers. The article also discusses how AI- based solutions may affect the data quality, business and operations performance. This research will help to create smarter, more scalable and more reliable data management systems by offering an intensive analysis of the existing practices and emergent trends.

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In conclusion, in the context of the digitalization of organizations, customer data management and maximizing its use are one of the main success factors. The data creation and improvement using AI to construct the golden records and data is a viable solution to this problem since data can be non-consistent and divided. This way, by helping to construct trustful, whole and credible profile of the customers, the technologies are going to enable the enterprises to be in a position to tap all the potential of their data resources and generate long-term expansion of their business in a world that is already highly competitive.

II. RELATED WORK

Artificial intelligence with the customer relationship management, creation of data values, and organizational governance became an object of more new research and provides a solid conceptual framework within the frames of which the literature on AI-enhanced data enrichment and the creation of golden records in enterprise customer data platforms can be framed. Starting with incorporating the formation of AI-linked CRM study and understanding the growing input of intelligent systems into customer-analysis, customer-personalization, robotization and decision-making is a good start, which is delivered by Ozay et al. [1] in a colossal bibliometric and methodical survey. They have discovered that in their analysis AI in CRM is no longer about automation but about an even more strategic AI, including predictive analysis, customer segmentation and service optimization. This article is highly timely in that it makes it clear that enterprise CRM is quickly becoming reliant on quality customer data, but less concerned with how precisely the technical aspect of the technical processes is implemented in order to integrate dislodged records into a plausible golden record. Therefore it leaves a wide gap to the enrichment of the literature on data enrichment and identity resolution.

Even the strategic value of data, in its turn, is increased, which is what Ritala et al. [2] add to what the firms will be selling and monetizing in B2B markets relying on the value propositions of that type in particular. Their work, however, does not restore data as the by-product of the operations but rather as a low-cost resource that would make it possible to create a competitive advantage, service-innovation and new business trends. The same perception is relevant in case of enterprise customer data platforms as better and better dependable customer information boosts the usability, market worth and strategic value of the company data resources. However, [2] is not filled with technical process of empowering, unifying and harmonizing the raw and rigid data on customers in detail, no matter how much the data needs to be monetized and made valuable. This creates a void to a model that correlates data value with data ready and improved by AI and generation of a golden record.

On the aspect of implementation, the contribution of Laato et al. [3] is to discuss the creation of machine learning systems within the information systems development praxis. They use their work to imply that AI implementation is the modeling exercise, and are a socio-technical process, which is made up of design decisions, lifecycle integration and infrastructure preparedness and organization adaption. It has a direct dependency to the enterprise customer data platform in which AI-based enrichment solutions and matching solutions would have to be reconciled with greater amounts of data engineering processes and data governance systems. What makes this [3] study interesting is that the emphasis has merely changed towards the novelty of the algorithm and the practice of operation of machine learning. However, it is not confined to the customer data management and domain specifics that would be pertinent to customer identity unification and the development of record quality would potentially be in order.

The other theme within LAI literature is that of governance. Birkstedt et al. [4] discuss the sphere of AI governance and outline the most significant themes, gaps in the literature, and research agendas related to the aspects of oversight, accountability, risk, fairness and organizational control. Enterprise customer data platform is one of the most camouflageive to AI, as the data enrichment and entity resolution provided by AI may affect the customer image, classification and targeting. In cases where the processes are opaque, or where they are not very regulated, they can introduce the biasing effect or bring about inconsistencies or compliance risks. The article by Birkstedt et al. [4] is an excellent introduction to the governance perspective yet falls short of giving real analysis of customer data platform or golden record system and would have to project governance perspectives to the customer data integration landscapes.

Dastjerdi et al. [5] explain how CRM area-specific has been shifted and suggest a framework to study the shift towards use of AI-integrated CRM systems in medical industry with the help of hybrid fuzzy decision-making approach. Their studies will be valuable because they will consider the fact that AI-CRM application will be implemented subject to conditionality based upon various technological, organizational and environmental variables. Their level, however, is

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healthcare, the investigation provides us with operable information regarding the intricacy of the process of adoption, priorities of decision tendencies, and the readiness of the institution. One can discuss the same issue with that of the enterprise customer data platform with the golden record that cannot be built based solely on the algorithms but organizational investment, data care and platform incorporation are also required. However, [5] is very appalling on the aspects of adoption, rather than technical architecture definition and de-duplication.

Bonetti et al. paper [6] provides a practice-based at-theory conceptualization of how AI is jointly instantiated in retailing practice by co-evolution of technology, and organizational routine practices. They have learnt that AI is not entrenched in the company, that it is growing and growing to become a new form based on how they operate, the relationship between the stakeholders and decision making cultures. This observation holds great significance to the customer data platform of the enterprises as the application of better customer records influences marketing influence, service and sales processes of the various departments. Topicality of [6] as the fact, which demonstrates that AI-intelligent system needs to be business practice oriented, however, the research does not directly examine the issue of customer master data, record linkage and logic of unifying data.

Merhi [7] goes further to comment on the implementation by considering critical success factors which determine the implementation of artificial intelligence. In the paper, leadership support, the data availability, organizational culture, technical capability and strategic alignment are cited as a factor. These dimensions can come in handy when analyzing AI-driven customer data platforms as the data enrichment process and the establishment of the golden records will demand solid data pipelines, governance dedication, and preparedness of the institution. Even though [7] has a solid implementation point of view, it can be applied in any AI area, and is actually unconcerned by the data quality, and entity resolution challenges, which dominate customer data platforms.

Ledro et al. in their review on CRM [8] are particularly critical since they not only chart out the literature of artificial intelligence in customer relationship management, but also identify the key themes, opportunities, and future trends. A review of their clarifies the presence of AI in the knowledge creation of a customer, customer interaction automation, and decision support, making intelligent customer systems rise in the popularity. But, like [1], this analysis is more focused on AI application at the CRM level, Compared to the engineering problem of the problems that led to those, which can be formulated as the necessity to create a homogeneous and realistic system-level system identity of customers. This is one of the most important loopholes since most of the benefits at the higher level CRM could be confined in the absence of well kept golden records.

Mäntymaki et al. [9] indicate that they relate narrower regarding the perception of governance and introduce organizational AI governance and emphasize on structures, roles and control systems that are required in regulating the use of AI. Their labor beautifies the normative foundation of relying on enterprise customer platforms, namely, automated reasoning enhances and incorporates the customer identity. Ranking of source and scoring of confidence, clarify explainability, privacy and accountability in such situations require a system of governance. However, [9] might not be data-platform-specific architecture to how governance ought to be mandate under customer record management although it is conceptually comprehensible.

Lastly, Saura et al. [10] deal with the issue of AI-based online marketing-business-to-business CRM. The timeliness of their work is in their emphasis of the AI goal of customer targeting optimization, business market intelligence and relationship strategy. This is in tandem with the downstream worth of enhanced customer data and platinum records. Akin to other literature on CRM oriented literature though, [10] is more oriented towards the strategic and marketing outputs as opposed to the technical underlying data base of such outputs.

Taken altogether, the literature proves the high level of evolution of AI-CRM, data monetization, implementation and governance [1]-[10]. A large gap at the intersection of these streams persists, though, namely the necessity to have a shared framework that would allow to apply AI to harmonise the fragmented enterprise customer data, deal with overlapping identities and build goldens in customer data platforms. The current research fills this gap by adhering to strategic CRM value to technical data unification and AI implementation, which is mindful of governance.

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III. FRAMEWORK: ENRICHING DATA WITH AI AND CREATING GOLDEN RECORDS

The section will include the overall design of the AI-prescribed data enrichment and selection of the golden record over the enterprise customer data platforms (CDPs). The advanced artificial intelligence techniques will be applied in the model to solve the problem of disaggregated and uncoordinated and incomplete customer information. It establishes end to end architecture, basic components as well as methodological processes required to transform raw and heterogeneous data into one, high quality and reliable customers data.

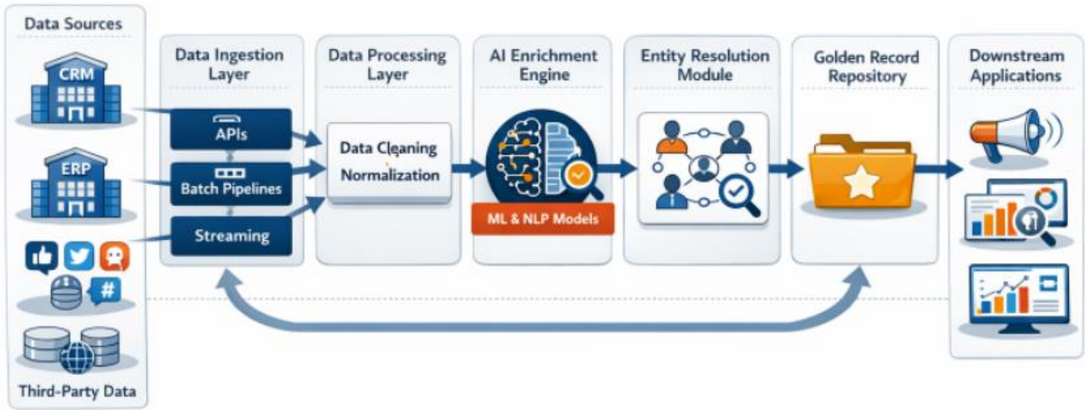

Figure 1: End-to-End AI-Driven Customer Data Platform Architecture

3.1 Overview of the Framework.

The system suggested is based on the multi-layered structure that includes data ingestion, preprocessing, feature engineering, AI-enhancement, resolving of entities and the creation of golden records. The layers are all connected to each other thus enabling easy flow of the data and continuous improvement with feedback loops. It can also scale up, automate and flexible framework and is thus capable of dealing with large volumes of structured and unstructured data in dynamism enterprise environments.

To put it into simple terms, the corner stone of the construct is the fact of turning the isolated customer data into intelligence. It does so by training and solving rule-based ones with machine learning models in a way that enhances the quality of the data and report to a single source of truth, than to a customer. This modular design enables the organizations to scale some of its modules to its business need, level of data and capabilities of the technology.

3.2 Data Ingestion Layer

The initial step of the framework is the assembly and gathering of data of a variety of sources. These sources are located in the tools in the category of customer relationship management (CRM), enterprise resource planning (ERP) systems, billing, and customer support database, and the category of outside sources, social media, third party data vendors and publically available data sets.

The data ingestion can either be in batch form or real time streaming. A batch processing can be used to integrate large-scale historical data and real-time ingestion can be used to process incoming data streams. The technologies that allow a smooth flow of data to the central location are webhooks, message queues and APIs.

The heterogeneity of data is also a major issue with this layer where various sources can be different in their format, schema and/or standards. To overcome this, the framework will be founded on algorithm mapping and normalization in data that will guarantee consistency in datasets. Metadata is ingested as well and to provide the context and help with the downstream processing.

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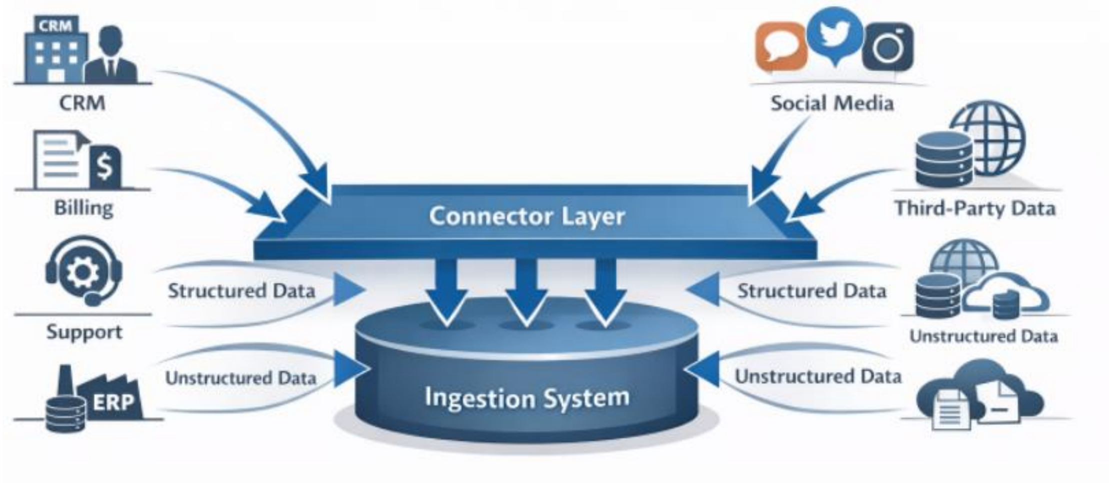

Figure 2: Data Source Ecosystem and Integration Layer

3.3 Data Preprocessing/normalization.

After the data is ingested it undergoes preprocessing to enhance the quality of the data and be ready to be further processed. Some of the important operations that are carried out in this stage are data cleaning, transformation and standardization.

The data cleaning will be directed towards locating and removing the following types of errors: missing values, redundant data and inefficiencies. Some of the methods that are embraced in order to maintain the integrity of data include imputation, outlier detection and normalization. Examples will include; date format aberrancies can be standardised and predictive applications can be used to predict missed contacts.

The concept of standardization is critical in making data between various sources to be successfully compared and fused. This includes the text format to common case, number corrections and normalization. Moreover, categorical variables can be converted to machine readable codes which may be utilized in training a model.

Data validation process also exists in the preprocessing layer to ensure that quality data that is predescribed is processed. Such mechanisms are the rule-based checks, statistical validation and detection of an anomaly via AI models.

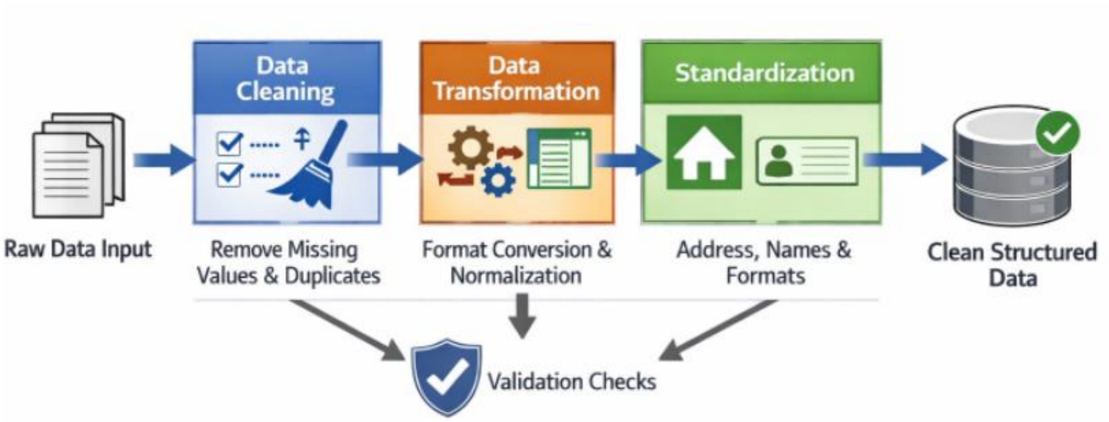

Figure 3: Data Preprocessing and Standardization Pipeline

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3.4 Feature Engineering
The second step in the framework that is critical is feature engineering as it transforms the raw data to meaningful features which may be used to analyse it based on AI. This entails the job of extracting the correct attributes, creating derivation features and giving values to the various values of data.

The characteristics can be a personal(e.g. name, email, phone number), demographic(e.g. age, location), behavioral(e.g. buying history, interaction patterns) and the contextual(e.g. tastes, engagement levels) ones. The features are standardized, so that the feature vectors are a representation of each of the customer records.

The similarity scoring and embedding generation are sophisticated methods, used to give the complex associations among the data attributes. The natural language processing models on the other hand as a representation model, can be used to transform the text based properties into vectors that possess its similar yet not identical representations which are relatively close.

The other issue that is also critical is that of weighting of the features since different features might have different weights when determining record similarity. On email addresses, those addresses can carry a higher mark as compared to names as they are unique. The weights can be assigned, both manually, and in an automating way on the basis of expert knowledge and with the help of a statistical analysis.

3.5 AI-Driven Data Enrichment
The layer of enrichment is grounded on the artificial intelligence which is used to provide completeness and a contextual relevance to the customer data which is availed systematically. This will entail including additional information to the already existing records, by sourcing it internally and externally.

The predictive models are machine learned to provide the missing values (either the demographics attribute or the behavior inferences of the data) of the data, based on the trends observed. The techniques of natural language processing can be used to extract the meaningful information in the unstructured data such as customer reviews, emails and support tickets.

The third party data (such as social media activity, credit score or geographic) is also added to the customer profile by means of integration of external data. This additional information is what enhance the customer insights to be more well defined and precise.

As the new ideas and feedbacks keep being acquired, enrichment is a dynamic and iterative process of learning and the models are learning. This renders the enriched data to be timely and pertinent in dynamic businesses.

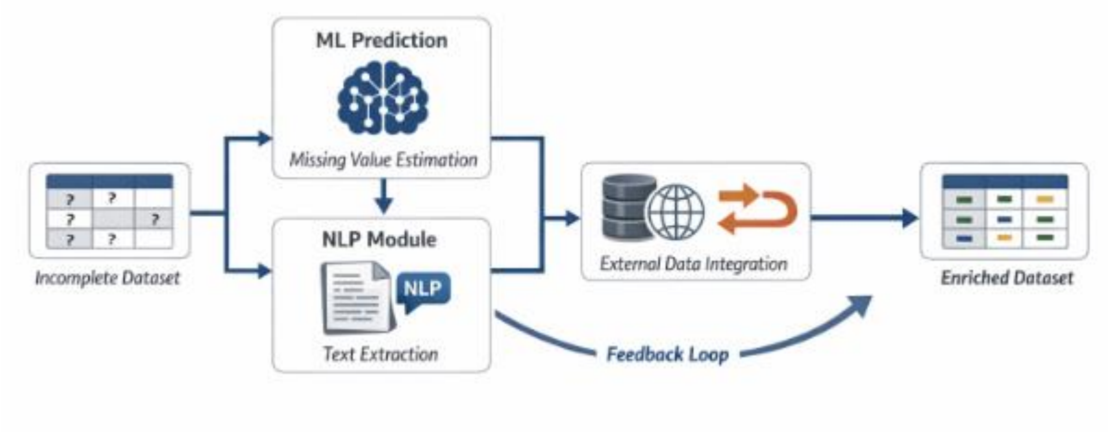

Figure 5: AI-Driven Data Enrichment Workflow

3.6 Compare and find similarities.
The model is founded on entity resolution that determines and lines duplicate records that have the same customer. The usual matching algorithms based on rules are not guaranteed to work well due to the difference in data entries e.g.

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misspellings or the lack of data completeness. Through this, the frame heightens accuracy of the matching thanks to AI-based approaches.

Similarity matching is a comparison of records with the data where the records have a number of compared attributes and their similarity score. Attributes similarity is also compared subscribing to such methods as the levels of similarity between the strings (e.g., the Levenshtein distance, the JaroWinkler), numerical matching and categorical matching. The total of these scores is achieved to get the overall similarity of the records.

Machine learning models, e.g. supervised classification algorithms or clustering algorithms are used to classify pairs of records as either a match or non-match. Labelled datasets are used to train these models which are then able to adapt to complex data trends.

These threshold based decision mechanisms are applied in establishing which records to be merged, which records will be flagged to be reviewed or which records are to be considered an independent entity. This makes there be a trade off between automation and accuracy.

3.7 Golden Record Creation
The last step of the structure is the production of golden records, the official photo of all the customers. This will pool together the records of multiple similar records to one and unique record.

One of the most important things about coming up with the golden records is the conflict resolution since there may be some conflicting values of a single attribute across the sources. The framework uses different approaches to settle such conflicts, such as:

- Priorities of sources: More trust towards certain sources of data.
- Recency-based selection: Selecting the most recent.
- Confidence scoring: Choose the values, most of which are predicted correctly.
- Aggregation techniques: Adding a value to a number when it is needed.

The resultant golden record is a complete and consistent list of attributes, which give a 360 degree picture of the customer. They are centralized and are availed to the down stream applications as such reports.

3.8 loop feedback and life-long learning.
The element of a feedback loop is needed in the framework in order to be able to keep on learning and updating models. The model parameters are updated based on user feedback, performance metrics of the system as well as validation results to achieve more accuracy in the long run.

By the active learning processes, it is possible to find out the cases of uncertainty as well as to put them into a priority list according to which they should be discussed. This can contribute to making quality labelled data to train the model. Key performance indicators such as matching accuracy, correctness of the information and the time of processing are also used to determine monitoring tools.

3.9 security and scalability)
The data governance issues, data security as well as the data scalability are also discussed in the framework. The good governance policies will offer a guideline on information, rule and application of AI ethically. Encryption, as well as access control, which guards valuable information of a customer is a measure of computer security measures.

The distributed computing technologies as well as the cloud-based infrastructure will be open to scalability that will support the effectiveness of the framework to compute a taskful of data. flexible and maintainable Modular design and microservice architecture The design must be grounded on modular design and microservices architecture.

IV. FRAMEWORK EVALUATION AND FUTURE ENHANCEMENT

The proposed framework of the AI in the data and golden record is a highly versatile powerful scheme of rising one of the challenges of the enterprise customer data structure, which have shrouded across the years, i.e., fragmented, bogus, composite and numerous records of a customer. It is effective because it can unify fragmented information sources, carry out clever prior processing, repair flaws or weak points, reshape mishaps on the bodily expression and create a

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solid record of customer as a golden record. In terms of evaluation, the framework could be evaluated on five broad areas that comprises of enhancing data quality, precision of matching, efficiency in operations, scalability and business applicability.

Firstly, the framework is of great importance in improving quality of data. Preprocessing, normalization and enrichment can help in taking advantage of missing data, correcting inconsistencies and harmonization of data that was entered in a businesses system within multiple different systems and standardize such data to fit the new platform. This in itself serves to contribute to completeness, consistency, uniqueness and validity of enterprise datasets. A company like this is practically predetermined with objective reduction of the volume of duplicated documents, similarity of customer features crossplatform and encouragement of trust in bottom-stream analytics. The introduction of AI-based imputation and contextual enrichments, in particular, is quite convenient since it is not restricted to the data purification process but allows the system to come up with more useful and effective profiles of their customers.

Second, the framework works well in the gold record building and entity resolution. Old Deterministic matching Systems Old deterministic systems do not scale to data with typographical variance, abbreviation, non-uniform naming policies and even in data where the names of the identifiers are unknown everywhere. The framework is augmented with similarity scoring, feature weighting and machine learning-based record linkage to increase the likelihood of the correct record identification of records that represent the same real world customer. This not only enhances the feasibility of the final product of a golden record, and a true 360 customer standoff. Its conflict resolution aspect also makes it powerful as in a situation when there are more than one values the most credited value, most current or most statistically value will be picked.

Third, the framework also strives to operational efficiency. The processes involved in cleaning of data and consolidation of records are also labor intensive, time consuming and may give errors. Conversely, a lot of ingestion, validation and enrichment and merging is automated in the proposed model. Not only will it decrease the rate of manual review, but it will also increase the rate of data onboarding and in addition will allow real-time updating of customer profile to be performed (almost in real-time). In large companies the robotic process holds tremendous value, as the data of the customers is generated within the context of the sales scope, service scope, online platform, and network of partners. This will increase better speed and accuracy in managing the data.

Fourth, the framework is very scalable to enterprise. It is stratified allowing it to process structured data and unstructured data that exist within different systems within organizations as well as is modular. It would mean that the optimization or upgrade of every of the layers such as ingestion, preprocessing, enrichment or matching can be optimized independently. The model can be applied both to distributed systems and high volume processing environment and cloud based customer data systems. Scalability is though not only technical but organizational as well. The framework has to be augmented with powerful governance, the ownership of customer data and integration of business workflows to be successful in the actual deployments.

Fifth, it is a pertinent business framework. The personalization, segmentation, scoring leads, targeting campaigns, customer service, recognition of fraud and compliance of the reports will be done with the right golden records. Improved Customer data, equally improves the executive decision making since the analytics and predictions are done based on a more realistic bind of master profiles. Therefore, the framework is not just a technical solution with the system but a customer apprehension and digitalisation strategist.

These benefits aside, the structure must be enhanced in the future that will make the structure more flexible, full and open. Among the developments that can be considered important is the elucidating AI mechanisms. The decisions matching and enrichment have the potential to make difference when it comes to treating the customer there is need to ensure that auditability is taken care of. The future systems should be able to provide justifications which can be construed as to why records were matched, why a value was selected or why an attribute was attributed. This would create an enhanced trust of business users and it will assist in religious conformity.

The second improvement is the streaming intelligence in real-time. Most of the already existing frameworks have been restructured to suit a batch-based method; the operations of our time businesses have to suit the operation of the identity discovery and synchronization of the profiles in the continuous mode. Subsequent versions ought to adopt low latency streaming pipelines that will optimize and equalize the records obtained. This is particularly true when it is considered

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in association with such types of industries as retail, banking, healthcare and telecommunications where the customer environment evolves very quickly.

The third enhancement is associated with the privacy preserving and federated learning methods. Minority information are highly sensitive and any compelling justification which may lead to risk is to be mitigated in future designs involving any measure of risk that comes with the centralized model training. Intelligent matching and enrichment with privacy-aware entity resolution and secure multiparty computation might be made possible by federated AI, privacy-aware entity resolution, and secure multiparty computation.

Fourthly is the adaptive confidence management which is a part of a work. The systems of tomorrow have to be capable of dynamically calculating match using reputation of a source, past performance, relevance of various properties and circumstance of the domain in comparison with hard coded limitations. This would enhance the accuracy in the decisions made in unclear matching situations.

Finally, domain-specific knowledge graphs and semantic intelligence ought to be included in the future structures. The inclusion of interactions between customers, households, organizations, products and interactions would enable the system to generate more golden records and open up more information on the pattern of customer ecosystems. This would not only transform mapping the simplistic record conglomeration, but excellent customer cognizing co-ordination.

Overall, the given framework proves to be useful, practical and practical in enterprise customer data platform. Through its analysis, it has been revealed that it has a tremendous potential on enhancing the data quality, determine resolution, efficiency and customer insights.

V. CONCLUSION

This paper has discussed the roles that the increasing importance of AI-based data enrichment and the incumbency of the golden records in customer data platforms in business play. Weaknesses of disaggregated, partial, inconsistent and duplicate data have been compounded by the increased requirement of an organization to utilise the customer data to serve marketing, sales, service, analytics and strategic decision-making. Gone are the traditional approaches of managing data when it comes to the volume, complexity and dynamism of the present day enterprise environment. This use of artificial intelligence represents a ground-breaking path of customer data quality and creating a united, trustworthy and sensible customer outlook.

The paper has revealed that AI-data enrichment enhances enterprise datasets by filling blank spaces, correcting mistakes, standardization, and incorporating relevant data in terms of different types of structured and unstructured databases. Machine learning, natural language processing and similarity analysis and intelligent matching methods can be used to enhance the customer profile as an automated, scalable and adaptive process. This improved data is the foundation of appropriate development of golden records where similar and conflicting records might be merged into a single authoritative record about every customer.

Consistent with the proposed framework, different layers, i.e. data ingestion, preprocessing, feature engineering, enrichment, entity resolution and conflict-sensitive record merging layers can work together to enrich customer data platforms. The level of personalization, precision, the level of intelligence of leads and accounts, customer support and compliance with regulations are now within greater reach of the business by creating credible golden records. Also, the framework can be used to propel efficiency in operations since it lowers the levels of manual labour and would also create an easier process to manage customer data more frequently and in a timely manner.

At the same time, the study observes good governance, data security, transparency and scalability are also included among the elements that characterize a successful implementation. Real-time processing, elucidable AI, privacy-sensitive learning, adaptive confidence scoring, as well as semantic integration of knowledge can be stepped up a notch in order to make such systems functional.

Finally, besides being optional anymore, data enrichment and creation of golden records through AI is in fact a necessity of an enterprise customer data platform. They offer technical and strategic background of constructing clever,

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faithful, and client-centric information ecosystems that might persist to create a competitive edge in the all-data-driven globe.

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