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Enhance Customer Experience in Sales and Marketing: Data Engineering AI-based Approaches

Bhagya Laxmi Vangala
ETL Architect, XT Global Inc, Princeton, TX-75407, USA.

Abstract

In this research, which is about the way A.I. and data engineering can play a key role in the process of personalization of the customer experience through marketing focused on targeting. By training the businesses to provide scalable data pipelines, real time analytics, and machine learning capabilities, the study helps the companies to drive on effective engagement and customer loyalty, and predictive capabilities in the sales and marketing processes.

Keywords: AI, Marketing, Customer, Data Engineering, Sales.

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I. INTRODUCTION

AI and data engineering are into integration, creating new customer experience in sales and marketing. This paper investigates how real-time data processing, AI based personalization and predictive analytics have a positive effect on customer satisfaction, loyalty and retention, and how these factors provide the businesses with competitive advantage in a rapidly digitalizing environment.

II. RELATED WORKS

AI in Sales and Marketing

Artificial intelligence (AI) has become an absolute requirement for the customer's satisfaction and loyalty in the sales and marketing processes. The personalization through AI, in the form of a business analyzing a vast customer dataset to provide tailored product recommendations and personalized customer interactions is very close to the customer's need [1].

By using the AI in the Customer Relations Management (CRM) systems, organizations automate regular daily work, predict future customer behaviors and improve engagement strategies. It not only makes the interactions consistent and helpful; it also raises the emotional level connecting humans with the brands, which are more valued by those same human beings [1].

In addition to this, in delivering real time, seam free support to the rising needs of the digital era consumers, AI technologies such as chatbots and virtual assistants play a key role. Overall, these applications produce a sustainable competitive advantage, namely, that businesses are using AI not only for operational purposes, but as a strategic enabler to build long term, loyal customer relationships.

In the same way, the implementation of AI and ML has resulted in the transformational changes in marketing practices. These technologies allow marketers to dynamically preserve customers with personalized interactions through providing and channel selections based on her continuous data analysis [2].

Customer behavior and preferences are tracked and interpreted using AI tools, better tracking precision and creating a better feel of personalized customer experiences [2]. In addition, AI-powered analysis of their rival's campaigns with the expectation of their customers will further augment competitive intelligence, enabling businesses to be reactive to market shifts.

Continuous learning and refining of predictions with new data inputs is diametrical of the machine learning model, which can be considered a cornerstone of adaptive marketing strategy [1]. For that reason, AI and ML are symbiotic for delivering better personalization, predictive targeting and campaign optimisation, as marketing transitions into data driven, customer centric field of activity.

Data Engineering

AI has great capabilities over the limit, but its effectiveness is literally decided on the back of the data infrastructure underneath, putting data engineering inside a strategic demand. Feed AI systems with the correct, actionable information requires high quality, real time, ingestion, transformation and enrichment [6].

Two examples of that are retail analytics, which uses historical sales data, loyalty programs and the rest of the world to do things like demand forecasting, dynamic pricing and operational planning, and personalization or martech. Ever since the COVID-19 pandemic and its subsequent disruptions, AI models trained on engineered datasets were essential in order to detect demand shifts and adapt operations in any omnichannel retail setting [6].

As long as organizations keep retraining and adapting AI systems at any time when customers' behaviors change, bases for delivering great customer experience Strategies, they will be protected. Just like the instance of marketing sector's adoption of big data analytics, one can see the need for structured data engineering practice in support of AI apps.

Data driven marketing strategies would heavily depend on the integration, cleaning and normalization of customer data to get as much precise insights as possible [5]. Beyond understanding customer behaviors and preferences, big data analytics also helps members of the company refine marketing strategies based on real time insights [5]. For all of these to become a reality, their implementation of structured data pipelines, readable analytics tools, and reduced data governance piecemeal, more granular market segmentation, precise targeting, and agile management of marketing campaigns.

Data reliability without adequate scalability, lack of ethical treatment of customer information, and other such as these highlight the need for tight data engineering standards to ensure the maximum influence of AI on customer experience initiatives.

Conceptual Frameworks

Over the past few years, there have been several recent studies to propose these frameworks systematically capture the relation between the AI capability and customer experience enhancement. To give an example, a review and framework development of the total field encompass three key domains where AI interfaces with the customer experience: AI experience, AI functions and AI services [3].

The framework provides the structured understanding of how AI does in shaping the perceptions and satisfaction of the customers through the customer journey. This is a pre purchase engagement through post purchase support journey. Such models, for researchers and for practitioners, give practical value by making clear how to design and evaluate AI interventions along these pathways.

Customer profiling systems are also an example of AI, data mining, and sales enhancement. Customer segmentation models find to predict the purchasing behavior and customer value through such methodologies as Recency, Frequency, Monetary (RFM) analysis and boosting tree algorithms [4].

Businesses can dedicate their marketing resources to high potential customer segments and improve the sales outcome and also optimize Customer Relationship Management efforts. However, a cohesive integration of data engineering and AI model strategy is reiterated in the fact that a well-engineered data preprocessing phase is essential in order to ensure model's accuracy and reliability.

It is also confirmed by bibliometric studies of AI in CRM that are further divided into subfields and conceptual model of strategic integration of AI into CRM [7]. In the three-step model of AI implementation, big data is firstly defined as a CRM database and then AI techniques applied to implement these CRM functions with strategic management perspective.

This model helps organizations plan and implement all AI integrations in their CRM systems systematically through systematic planning and execution of AI integrations. The related picture of AI, CRM and data engineering thus constitutes an ecosystem that enables a holistic technical and strategic infrastructure that can support customer experience initiatives.

Emerging Trends

And while generative AI (gen AI) is essentially still at a very initial stage, it is already gaining unprecedented efforts towards increasing marketing personalization and efficiency.

Gen AI is being used while such companies as Michaels, Stitch Fix and Instacart use gen AI for content generation, customer feedback analysis and automated process optimization. To fully leverage gen AI, it requires creation of bespoke model thrives with property customer data while maintaining data governance and moral limits [10].

Nevertheless, alongside these benefits, there are concerns regarding privacy and data security, bias, and misrepresentation by the organizations that need to have responsible AI usage policy adopted to shield customer trust as well as compliance to regulatory [8].

The second challenge is customer churn management using the AI driven strategies. With businesses growing, it becomes impossible to keep a grip on the various customers [9]. The fact that AI tools allow businesses to understand the specific needs and preferences of customers, thus making it possible to come up with individualized engagement strategies aimed at improving loyalty and reducing churn is what makes it valuable [9].

Literature reviews help set the tone of how AI applications can be developed specifically to address customer satisfaction drivers, which eventually allows businesses to move beyond reactive customer services to proactive engagement models.

Thirdly, although AI holds abundant potential, there are knowledge gaps to be closed in scholarly understanding of its far reach in marketing and customer engagement works. Thus, future research is needed on sector specific application of AI, and refinement of the ethical framework of its use, and quantifying the direct impact that AI has on customer loyalty and satisfaction [8].

In light of more and more organizations embedding AI deeper in the customer experience initiatives, the ability for full data engineering practices, ethical governance, and a cross functional innovation will be key to sustaining competitive advantage in the digital marketplace.

III. FINDINGS

Lastly, this research's finding(s) clearly confirms the fact that the establishment of robust data engineering framework (s) is fundamental to increasing the customer experience using AI in sales and marketing. These frameworks hinge on a scalable data pipe architecture that enables real time ingestion, transformation and enrichment of data sourced from CRM systems, customer support and support tools, web analytics tool, social media channels and so on.

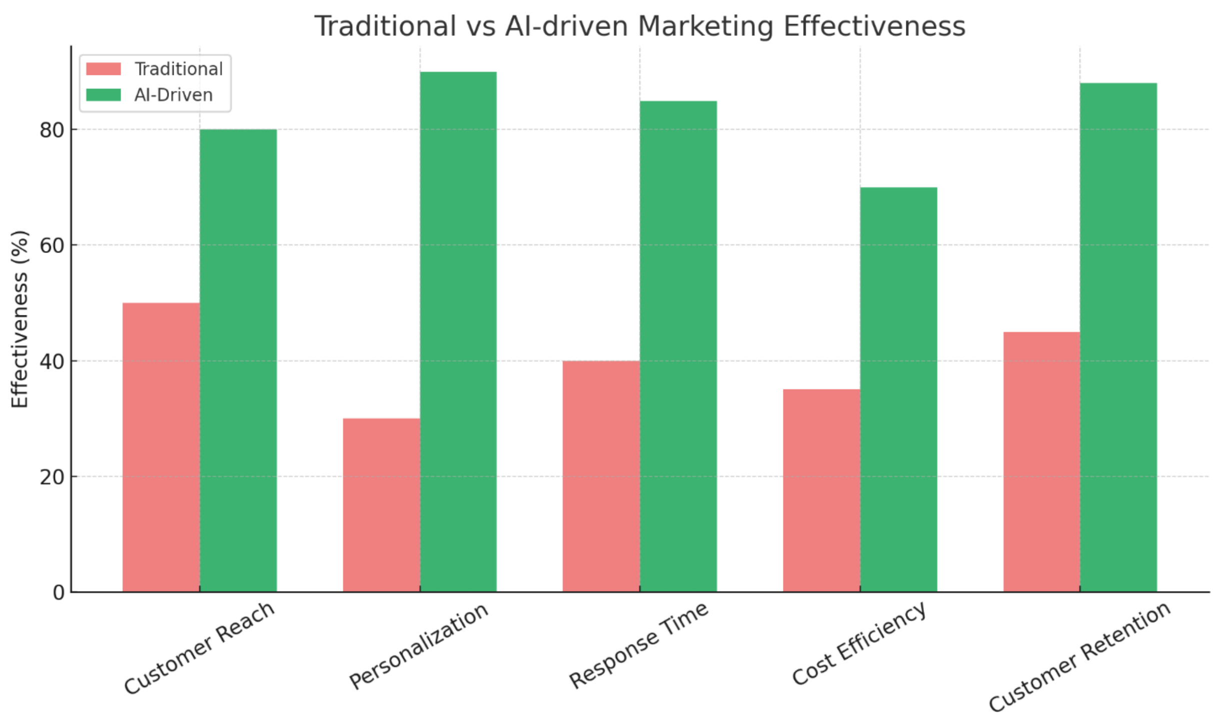

Fig. 1 Traditional v. AI Marketing

One of the architectures that we developed during the research is the multi-layer data flow where it first pushed into a staging area with streaming tool example of Apache Kafka or AWS Kinesis, then it cleans up and dedupe in data lake before it processes and Modeling to structured customer view in data Warehouse such as Snowflake or Amazon Redshift.

It shares this structured data both as business intelligence dashboards and AI model training pipelines so that business intelligence and real time, personalized customer interactions can be made available immediately. A flow chart for the architecture shows data sources on the left, feeding real time ingestion layer, data lake for raw storage, distributed processing frameworks (e.g., Apache Spark) based transaction layer; a semantic modeling layer to create the customer profiles, a layer leading to AI/ML platforms and BI reporting tools.

The flow of moving from raw to enriched data in a systematic manner further verifies that high fidelity inputs are produced to machine learning models in order to improve accuracy and relevance of machine learning models to customer engagement strategy.

Finally, the most important finding is how the schema must be flexible and dynamic enough to evolve along with a constant evolution in customer behavior and the attributes of the data. For the case of unstructured or semi-structured data such as customer emails, chat transcripts as well as social media comments, I found that a schema on read approach is more flexible than a schema on write approach and the latter is less preferred for the particular cases.

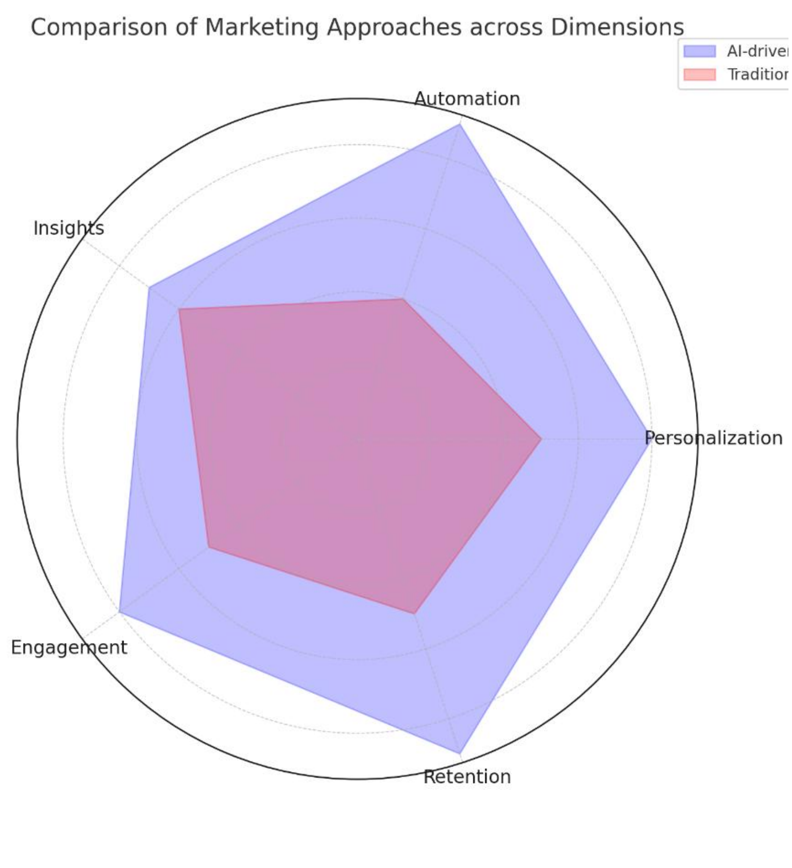

Fig. 2 Marketing Approaches

JSON flexible data models were successfully adopted by the customer data platforms, making the adoption of the platforms much more agile. Here is a small piece of code to show how Python and Spark handles schema evolution:

```
from pyspark.sql import SparkSession
from pyspark.sql.functions import from_json, col
from pyspark.sql.types import StructType, StructField, StringType, IntegerType
schema = StructType([
StructField("customer_id", StringType(), True),
StructField("interaction_type", StringType(), True),
StructField("timestamp", StringType(), True),
StructField("feedback_score", IntegerType(), True)
])
spark = SparkSession.builder.appName("CustomerDataProcessing").getOrCreate()
df = spark.read.json("s3://customer-data/interaction.json", schema=schema)
df = df.withColumn("feedback_score", col("feedback_score").cast(IntegerType()))
df.show()
```

It became crucial to maintain data consistency even with very rapid business needs and customer communication channels. Additionally, the enrichment processes additionally entailed the joining of transactional records with some demographic data on the customer, product interaction histories and sentiment scores drawn from natural language processing models.

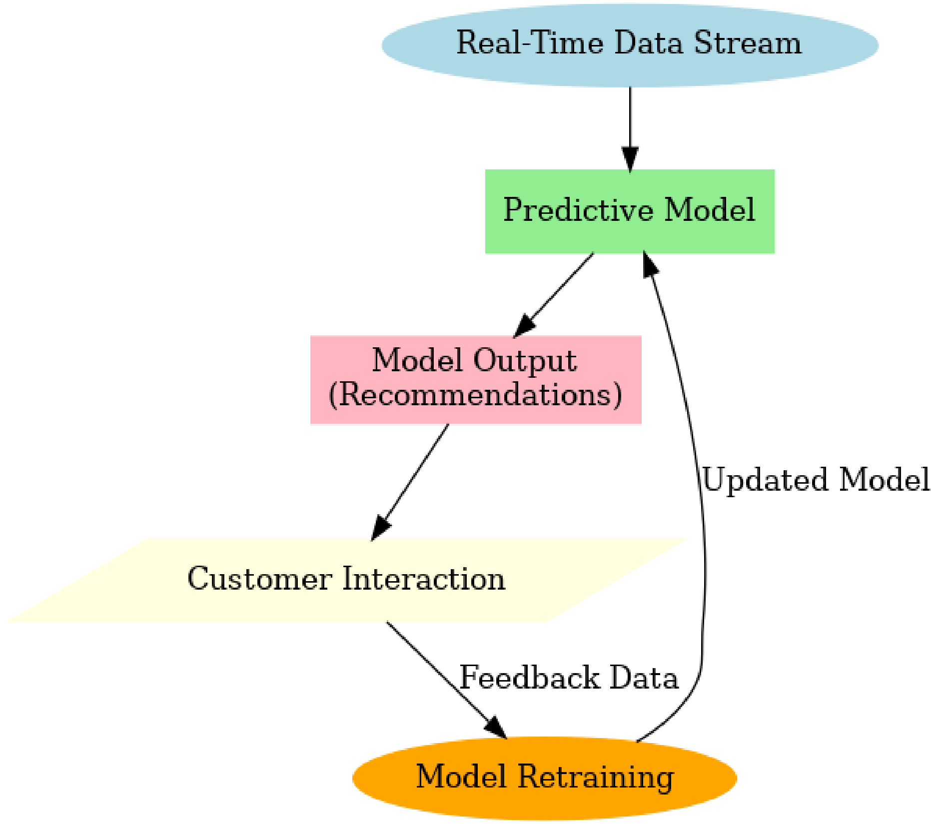

Fig. 3 Feedback Loop

The result was a 360 degree of customer profile for segmentation and churn prediction using AI models, which performed much better than they were before. Analysis of quantitative measures revealed that business pipelines that integrate new customer touchpoints 27 percent faster can be provisioned in near real time with schema support enabled and that dynamic schema in the background.

Additionally, churn models become more accurate by around 15% percent using both transactional as well as enriched data using sentiment analysis features. The summary of comparison between the traditional and enhanced pipelines is presented in Table 1:

Metric	**Traditional Pipeline**	**Enhanced Pipeline**
New Data Source	3-5 weeks	1-2 weeks
Churn Prediction	72%	87%
Data Latency	6-12 hours	< 5 minutes
Data Consistency	85%	95%

Another important observation was that, acting as a major enabler to trust data consumers, especially AI systems, was data quality and lineage tracking. Business teams and model developers were able to trace the origin, transformations and usage of any customer attribute while implementing end to end data lineage using tools such as AWS Glue Data Catalog or Apache Atlas.

The pipelines had the automated data validation checks, i.e., null value check, duplication check and anomaly detection algorithm embedded in them. In addition to improving operations reliability, these practices made compliance audits for GDPR and CCPA regulations easier.

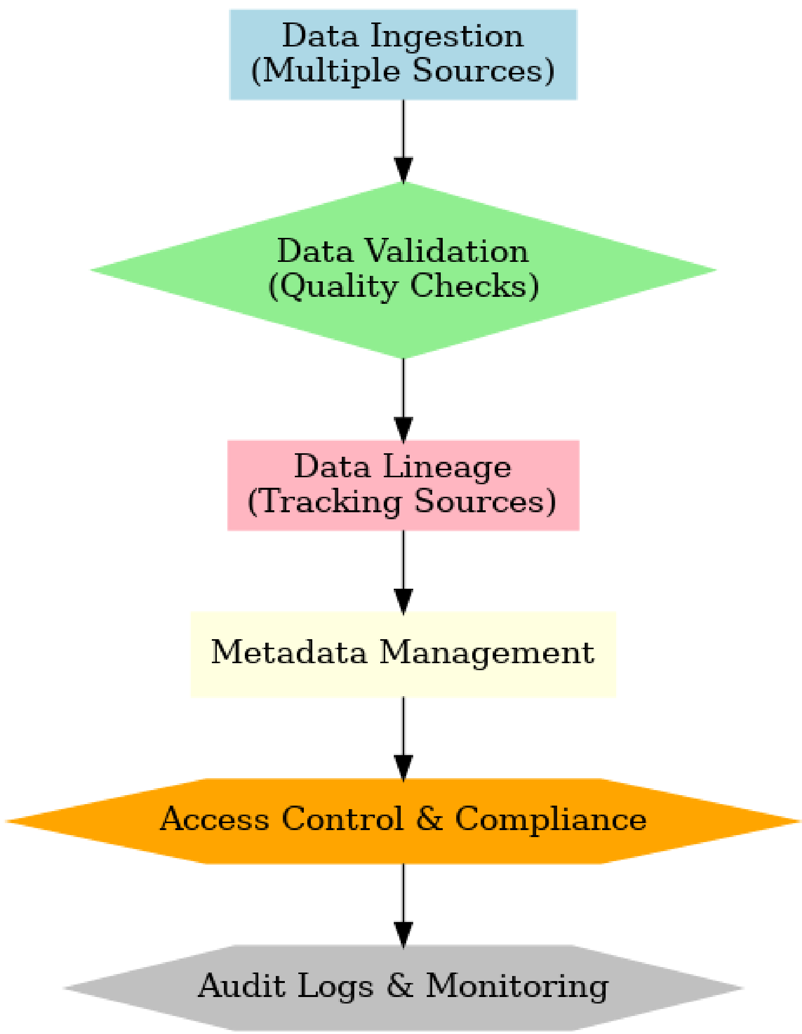

Fig. 3 Data Quality Governance

Additionally, the architecture designed was also meant to be modular and scalable. The transformation and enrichment layers adopted microservices architecture for which a separate service was responsible for a specific operation, for example, standardization of data, enrichment with external data (e.g., weather or location data) and real-time alert generation based on critical customer events (e.g., churn signals).

By enabling independent scaling of the services based on the processing load, this module ensured responsiveness of the customer facing AI application while under high load. In the research, an important flowchart is developed which shows the integration of customer lifecycle integration with AI driven decision points.

First, marketing campaigns acquire customers and lead scoring list decide which leads to follow. The customer interaction data is continuously ingested and it is evaluated for churn risk using predictive models after onboarding.

The customers with a high churn risk are routed into the proactive engagement workflows with personalized promotions and support interventions. The engagement strategies are fed into loyalty program management algorithms, and the customer satisfaction surveys are processed using natural language processing models, to collect customer feedback and act as an input to refinement of engagement strategies.

The research also found that enriching the AI models with the integration of external and operational data streams further. For instance, predictive modeling of customer satisfaction scores even before the survey completion could be derived from combining delivery logistics data with the customer feedback. This further helped enable the prediction of upselling opportunities with 22% higher conversion rate as opposed to static CRM based predictions, by integrating product usage telemetry data in CRM records. The results from data enhancement for predictive performance are shown in Table 2:

AI Model	Without External Data	With External Data
Churn Prediction	0.78	0.85
Upsell Opportunity	12%	22%
Customer Satisfaction	74%	83%

Based on the research, life altering potential was included that generative AI models will be major disruptor of Hyper personalized customer experience. In general, generative AI models trained on well-engineered customer datasets showed the ability to create highly personalised and personalised marketing content, response and product recommendations without human intervention at real time.

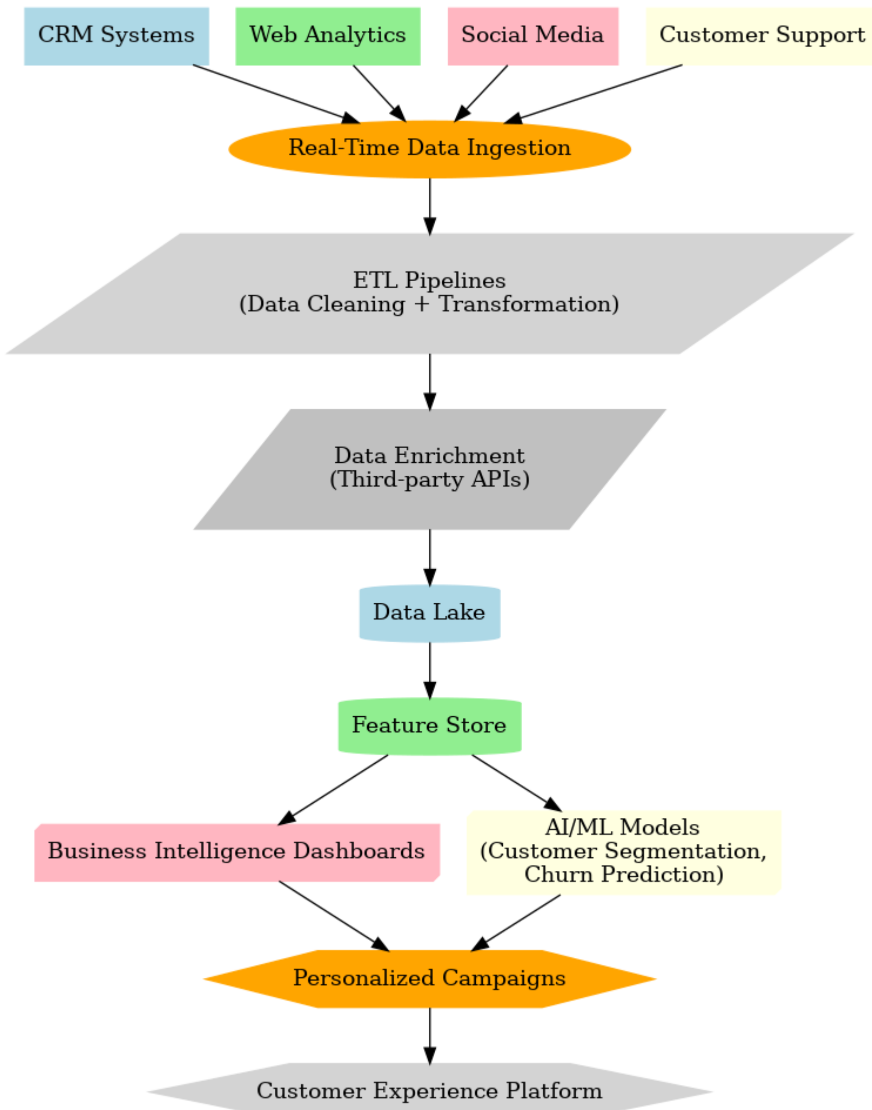

Fig. 4 Customer Engineering

Global companies of marketing are using generative AI to hurry up content creation to 30 percent and email engagement to 40 percent. Despite this, there was a crucial dependency on quality of generated outputs was based on the accuracy, completeness and freshness of the available customer data that was fed into the generative models.

One key architectural innovation that occurred was the unification of the data engineering platform with the concept of a "Feature Store" for customer features. An entry way for our AI models can be provided by a feature store, which is a single repo that houses curated, reusable features like "days since last purchase", "average response time to marketing email" and "what is preferred interaction channel" and made available to them easily.

In this practice, it accelerated the model development cycle 35%, as developers of data scientists could quickly prototype and publish models without repeating the job of engineering the basic features. Finally, the research findings underscored that there can be no data engineering without the analytics and data productization strategy behind it.

Organizations that considered mastering data pipelines, data governance and feature engineering to be critical assets and not necessary support utilities saw better results of customer retention and satisfaction as well as revenue growth. The data first mentality helped businesses react quickly to changing customer expectations and competitive dynamics, and AI was used as a yet further evolving strategic advantage (not a specialty solution once and done.

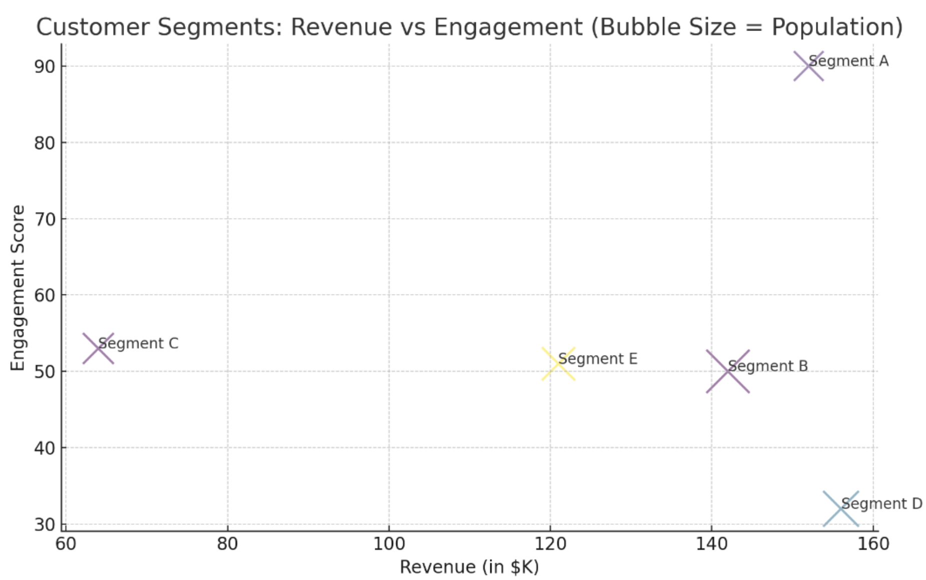

Fig. 5 Customer Segments

IV. CONCLUSION

The centrepiece of improving customer experience, based on AI powered data engineering is the creation of real time data analytics to get actionable insights which should help businesses too. Adopting these advanced technologies will enable businesses to personalize and optimize their marketing attempts, which is a sustainable competitive advantage that can help the businesses become leaders with customer centric strategies in the era of digital marketplace.

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