# OmniBERT: Transformer-based approach for Omnichannel Next Best Action Recommendation with heterogeneous dataset

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### Introduction/Problem Statement

Why does this matter in the pharma commercial/

What were traditional approaches lacking?

Poor integration of promotional and non-promotional

Traditional Deep Learning and original BERT-based

NLP models can't capture the heterogeneous,

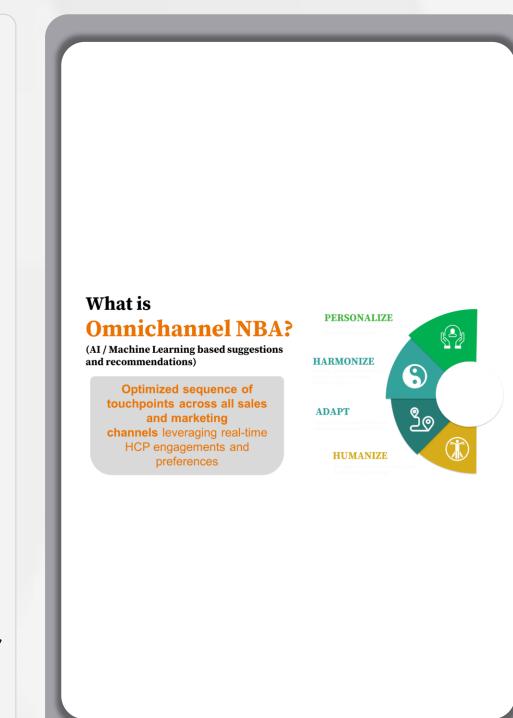
touchpoints leads to suboptimal recommendations in

#### What challenge are we solving?

In the pharmaceutical industry, building HCP trust and engagement requires understanding not just promotional activities but also Non promotional events like patient events, competitive landscape, formulary control etc. Traditional omnichannel Next Best Action models often struggle to account for these dynamic influences

medical/analytics context?

the HCP journey.



# **OmniBERT** Methodology/Architecture

OmniBERT uses longitudinal customer data promotional and non-promotional—anchored to a key date and ordered by event sequence (Figure 2)

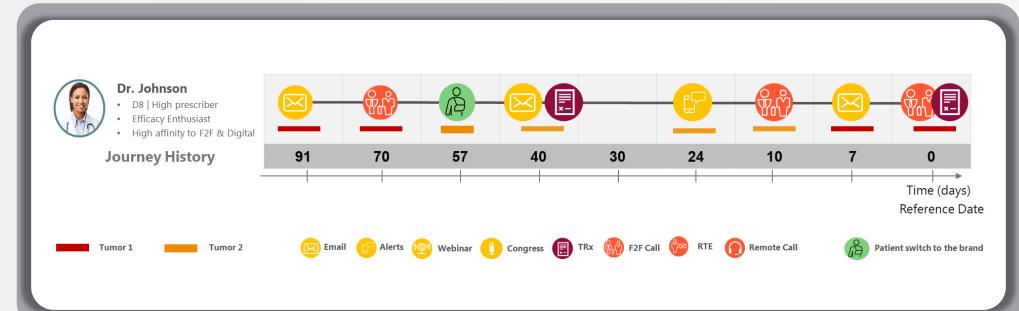
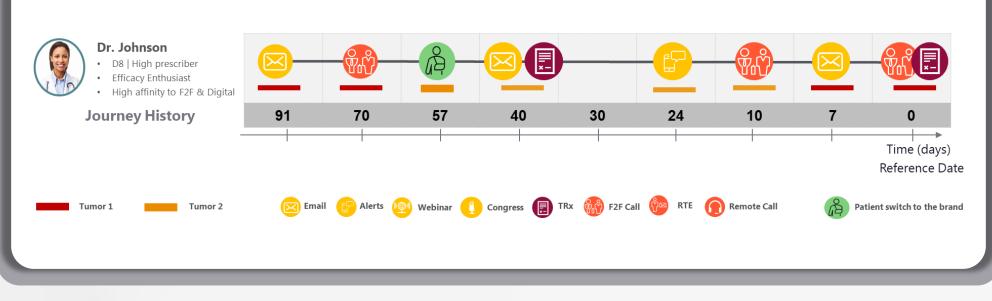
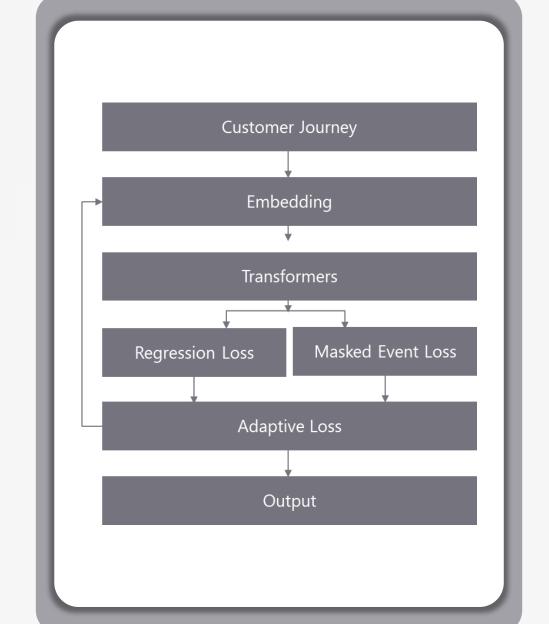


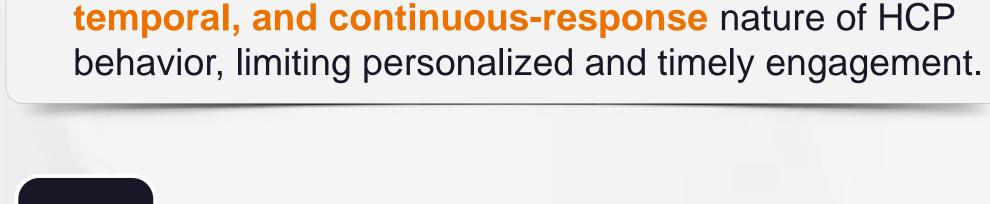
Figure 2: Customer's journey across promotional and non-promotional events



Customer sequences are processed by OmniBERT (Figure 3), generating embeddings by token, event type, position, and time from anchor events.

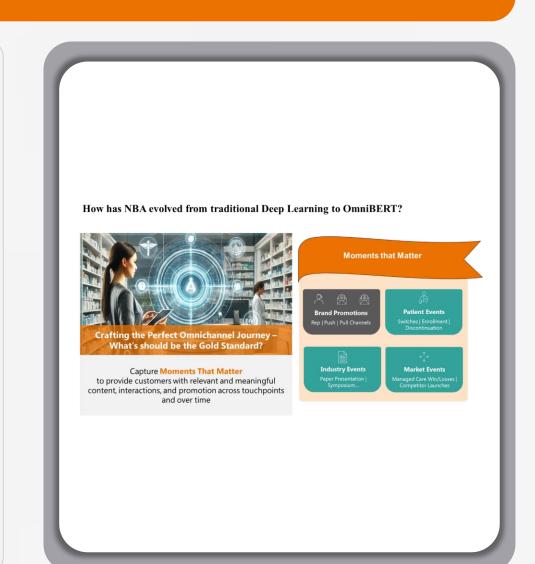
Figure 3: OmniBERT Architecture





# Objective

To showcase OmniBERT, a novel transformer-based architecture combined with Genetic Algorithms, designed to generate optimized next-bestaction (NBA) strategies by learning from diverse, multi-dimensional HCP engagement data

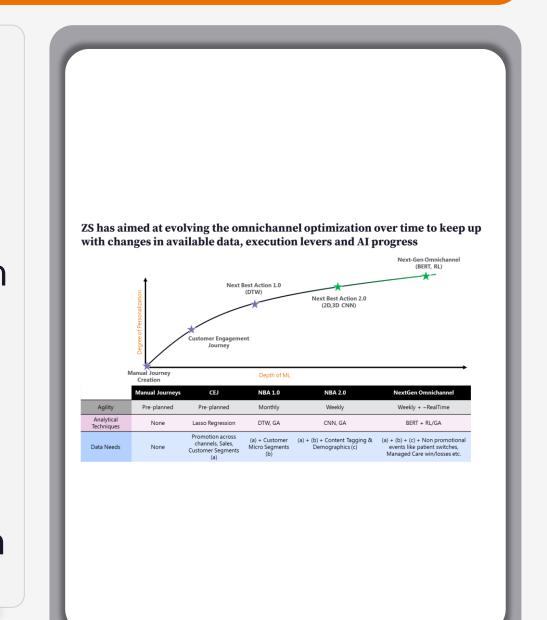


#### Background

In pharma, faster, richer capture of nonpromotional data opens the possibility to link such events to Rx behavior beyond traditional promotion and profile data. However, mining this data is complex. Figure 1

high-dimensional sequential shows how ZS has evolved its omnichannel optimization over time.

Figure 1: Omnichannel Optimization Evolution



- Token embedding
- Type embedding
- Position embedding
- Temporal embedding

Figure 4 illustrates this using the customer journey shown in Figure 2.

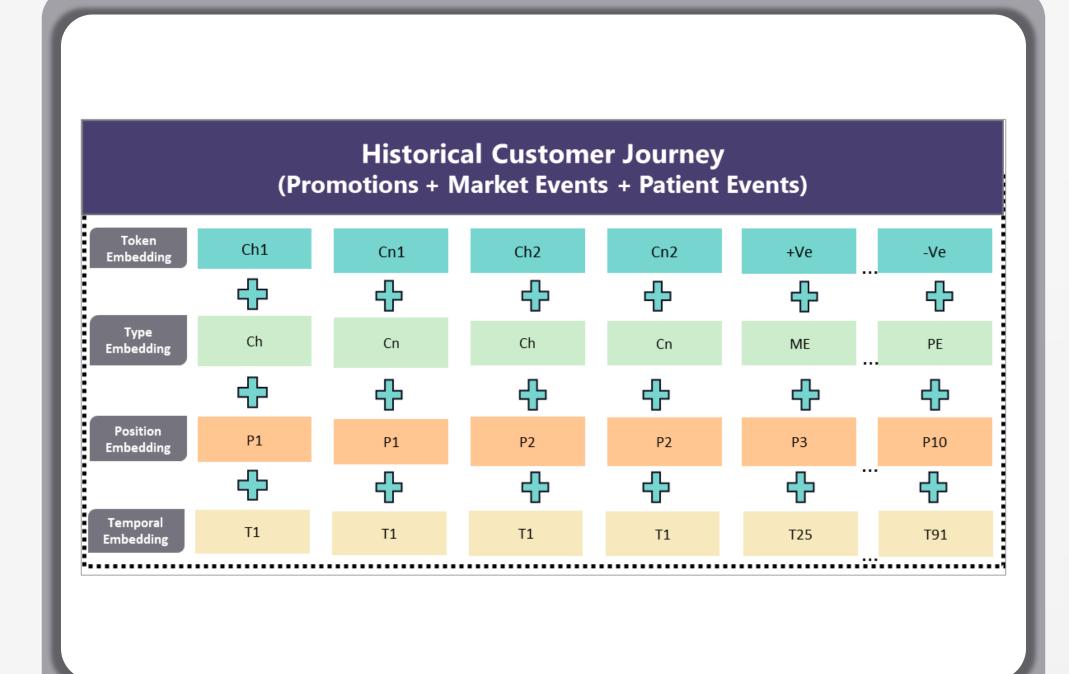


Figure 4: Illustration of input data for OmniBERT

OmniBERT optimizes two loss functions:

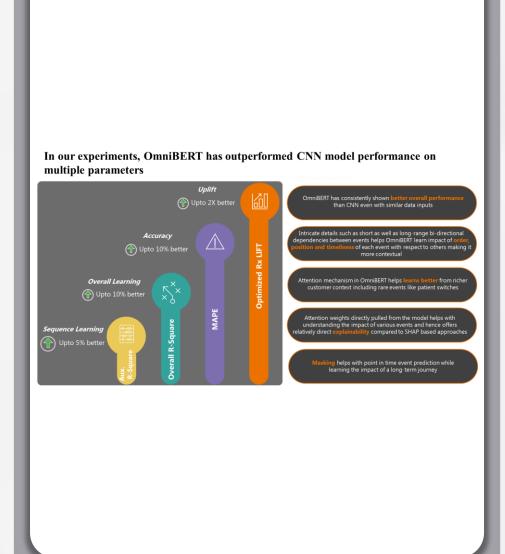
- Masked Event Modeling
- Event Prediction (Regression Loss

Adaptive weighting of the two losses enhances training convergence



## Results/Impact

- Up to 90% reduction in model training time
- Upto 5% improved performance through architecture tuning and incremental ~5% via additional data ingestion





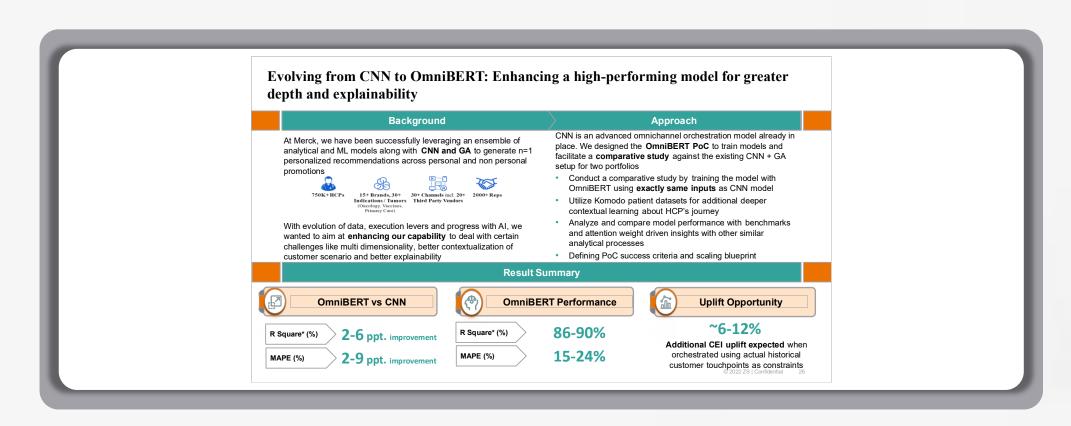
# **MERCK & ZS Partnership on OmniBERT Implementation**

Merck has been a leading partner in adopting ZS's omnichannel Next Best Action (NBA) innovations. Building on this strong foundation, We collaborated on the OmniBERT implementation initiative.

#### Together, we:

- Co-defined objective, approach, success criteria, and timeline
- Identified target franchises and incremental datasets to be used
- Developed a comprehensive implementation blueprint and scaling roadmap

This joint effort reflects a shared commitment to advancing Al-driven, customer-centric decision-making at scale





#### **Innovation Highlights**

- 1. Enhanced Model **Performance**
- 2. Better topline uplift opportunities
- 3. Improved **Explainability**
- 4. Scalability and **Adaptability**
- 5. 360° Customer **Context Integration**
- 6. Optimized Journey Design



#### Some of the benefits over traditional DL models:

Key Criteria	OmniBERT	CNN
Handling Journey Multi Dimensionality	Easy	Complex
Model Performance	Very High	High
Model Explainability	High	Low
Journey Dimension Scaling	Easy	Complex
Optimization Opportunity	Very High	High



#### **Conclusion/Key Takeaways**

- OmniBERT outperforms traditional models in NBA
- Integrates promotional and non-promotional data for better personalization
- Attention based explainability builds trust and adoption
- Scalable for future pharma engagement needs



#### **Future Roadmap**

- Integrate GenAl based explainable module
- Leverage Market research and other unstructured data (like rep notes) to augment HCP's context
- Integrate with GenAl-based content generation for hyper-personalized engagement
- Leverage Reinforcement Learning (RL) based approach for journey optimization



