The Role of Artificial Intelligence in Enhancing Business Intelligence Capabilities for E-Commerce Platforms

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***Abstract*—This research focuses on the application of BERT (Bidirectional Encoder Representations from Transformers) and Graph Neural Networks (GNNs) to improve business intelligence (BI) capabilities on e-commerce platforms. The main aim of the research is to develop automation methods for the classification of customer interactions and to create a more effective product recommendation system. In this study, BERT was used to analyze and classify customer interaction texts, including questions, complaints, and reviews, with accuracy reaching 97% and sentiment analysis accuracy of 93%. GNNs are applied to model complex relationships between customers and products based on transaction data, then used to provide product recommendations. The evaluation results show that the GNNs model achieved a mean average precision (MAP) of 0.92 and a normalized discounted cumulative gain (NDCG) of 0.88, indicating high relevance and accuracy in product recommendations. This research concludes that the integration of BERT and GNNs improves operational efficiency through classification automation but also provides added value in marketing strategies with better personalization of recommendations.**

Keywords*—Bidirectional Encoder Representations from Transformers (BERT); Graph Neural Networks (GNNs); business intelligence; e-commerce; product recommendation

I. INTRODUCTION

In recent years, the e-commerce industry has experienced a significant surge in growth, resulting in the generation of vast and intricate amounts of data [1]. This dataset contains comprehensive information regarding customer transactions, shopping patterns, customer engagements, and more relevant data. In order to stay competitive, e-commerce platforms must create advanced business intelligence (BI) systems to evaluate this data and extract practical insights. In this situation, it is critical to enhance business intelligence (BI) skills using artificial intelligence (AI) technology [2], [3].

Bidirectional Encoder Representations from Transformers (BERT) and Graph Neural Networks (GNNs) are two advanced AI algorithms that have the potential to greatly improve business intelligence capabilities for e-commerce systems [4-6]. Google created the sophisticated transformer model known as BERT. This paradigm has transformed the field of natural language processing (NLP) because of its ability to comprehend bidirectional context in text. Natural language processing tasks such as natural language interpretation, text classification, and information retrieval can all benefit from the versatile application of BERT [7], [8]. BERT can enhance the study of customer interaction in e-commerce. By leveraging its advanced capabilities in comprehending conversations and context, BERT has the potential to enhance customer service by delivering more prompt and tailored assistance [9]. Graph Neural Networks (GNNs) represent a distinct class of neural networks designed to process and analyze data structured in a graph format. This algorithm is highly efficient at analyzing intricate linkages and interactions among diverse elements. By representing products, customers, and transactions as graphs, we can employ Graph Neural Networks (GNNs) to detect intricate patterns and correlations in e-commerce. This is highly beneficial for constructing more precise and pertinent product suggestion systems by utilizing data on the correlation between products and client preferences [10-13].

The objective of this study is to investigate the utilization of BERT and GNNs in enhancing business intelligence capabilities on e-commerce platforms [14]. This research aims to analyze customer interactions and make product recommendations, with the goal of gaining new insights into how artificial intelligence (AI) can enhance customer experience and boost business performance in the e-commerce industry [15]. It also seeks to evaluate the effectiveness of different algorithms in real-world situations, offering guidance for implementing improved business intelligence (BI) in the future [16].

II. RESEARCH METHODOLOGY

A. *Methodology*

The research commences by examining consumer interactions utilizing the BERT (Bidirectional Encoder Representations from Transformers) paradigm [17]. The initial stage is gathering conversational text data, reviews, and client inquiries from e-commerce platforms. Subsequently, this data undergoes pre-processing to eliminate any unwanted interference and make it ready for subsequent analysis. BERT models undergo fine-tuning with these datasets to perform tasks like text categorization and comprehension of conversational context, resulting in more profound characteristics and a better grasp of consumer preferences and requirements [18].

Following the study using BERT, the research proceeds by constructing an association graph between customers and items with graph neural networks (GNNs) [19]. Graphs are constructed using transaction data and BERT analysis outcomes to depict intricate connections among entities. Graph Neural Networks (GNNs) are subsequently utilized to represent and examine relationship patterns inside these graphs, with a specific emphasis on producing precise and pertinent product recommendations [20], [21].

Performance evaluations are conducted by utilizing metrics like precision, recall, F1-score, and NDCG (normalized discounted cumulative gain) to assess the efficiency of the recommendation model [22]. The outcomes of these two phases are merged to offer a more all-encompassing business intelligence solution and enhance the e-commerce platform's abilities in comprehending and catering to its customers can be seen in Fig. 1.

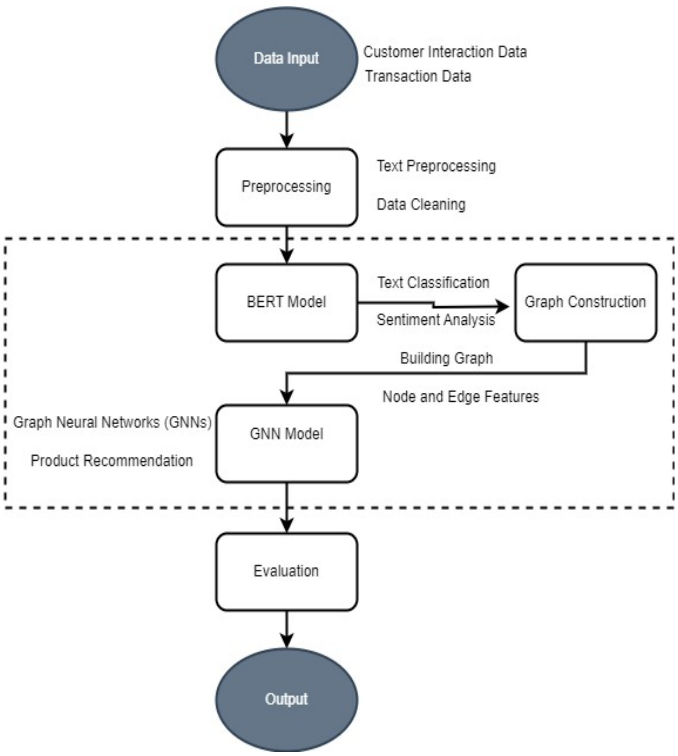

Fig. 1. Research methodology.

B. Problem Solving Approach

1) Artificial Intelligence (AI) in Business Intelligence (BI) for e-commerce: Artificial intelligence (AI) plays a crucial role in advancing business intelligence (BI) systems [23]. Within the realm of electronic commerce, business intelligence (BI) converts unprocessed data, including sales transactions, customer activity, and user interactions, into significant insights that influence company decision-making [24]. By integrating artificial intelligence (AI), business intelligence (BI) systems may analyze vast quantities of data, uncover concealed patterns, and offer highly precise, predicted insights. This integration significantly improves an e-commerce platform's capacity to comprehend and cater to its clients in a more efficient manner [25].

2) Bidirectional Encoder Representations from Transformers (BERT): BERT possesses the capacity to comprehend bidirectional context in text, enabling it to analyze words in sentence context from both the left-to-right and right-to-left orientations. These tasks, such as text classification, information retrieval, and natural language understanding, are particularly crucial [26]. In the realm of e-commerce, BERT is employed to scrutinize client interactions, including product evaluations and dialogues with customer care, to extract profound insights into customer requirements and inclinations. Utilizing this comprehension of consumer interactions helps enhance customer service and customization. Below are the sequential instructions for utilizing BERT. The following main components underlie BERT [27-30]:

Phase 1→ Input Embeddings

$$mbedding\ (x_i) = TokenEmbedding\ (x_i) + ESegmentEmbedding\ (x_i) + PositionEmbedding\ (x_i) \quad (1)$$

Phase 2 → Self-Attention Mechanism

BERT's key component self-attention allows the model to focus on different parts of the input sequence when processing each token.

Scaled Dot-Product Attention

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (2)$$

Where:

Q query matrix

K key matrix

V value matrix

d_k dimensions of the key

Multi-Head Attention

$$MultiHead(Q, K, V) = Concat(head_1, head_2, \ldots, head_h)W^O \quad (3)$$

Where:

$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$

W_i^Q, W_i^K, W_i^V weight matrix for the i th head

W^O output weight matrix

Phase 3 → Feed-Forward Neural Network

$$FFN(x) = \max(0, xW_1 + b_1)\, W_2 + b_2 \quad (4)$$

Phase 4 → Layer Normalization

$$LayerNorm(x) = \frac{x - E[x]}{\sqrt{Var[x] + \epsilon}} . \gamma + \beta \quad (5)$$

Where:

$E[x]$ the average value of the input

$Var[x]$ variance of the input

ϵ small constant to prevent division by zero

γ and β parameters that can be studied

Phase 5 → Loss Function

$$Loss = -\sum i \in masked\ positions\ LogP(x_i|x_{<i}, x_{>i}) \quad (6)$$

Phase 6 →Training Objective

BERT is trained in masked language modeling (MLM) and next sentence prediction (NSP).

Masked Language Modelling (MLM)

$$MLM\ Loss = -\sum i \in masked\ positions\ LogP\ (x_i|x_{masked}) \quad (7)$$

Next Sentence Prediction (NSP)

The model is trained to predict whether two input sentences appear sequentially in the original text.

$$NSP\ Loss = -(y \log P\ (IsNext) + (1-y) \log P(NotNext)) \quad (8)$$

Where y Binary labels indicate whether two sentences are sequential or not.

3) Graph Neural Networks (GNNs): Graph neural networks (GNNs) proficiently examine intricate connections and interactions among diverse elements. Graphs consist of nodes that can represent various entities, such as consumers and items [31]. The connections between these entities, such as buy transactions, are represented by edges. Graph Neural Networks (GNNs) have the ability to acquire knowledge about these graphs and are employed for tasks such as predicting connections (e.g., suggesting products) and categorizing nodes. E-commerce platforms can enhance the precision and relevance of their product recommendation algorithms by leveraging graph neural networks (GNNs) to analyze intricate relationship patterns between products and customers [32-34].

Phase 1 → Graph Representation

Graf G defined as a pair (V, E), where V is the set of nodes and E is a set of edges.

Phase 2 → Basic Notation

h_u Features of neighboring nodes u

W Learnable weight matrix

σ Non-linear activation function

$N(v)$ Set of neighbors of node v

Phase 3 → Propagation Rule

General Message-Passing Framework

$$h_v^k = \sigma(W^k.AGGREGATE^k(\{h_u^{k-1}: u\epsilon N(v)\})) \quad (9)$$

Phase 4 → Output Layers

After the propagation layer, the node representation is updated and ready to be used in predictions

C. Data Classification and Analysis

The primary data consists of customer interactions, product transactions, product details, and relationship networks connecting customers and products. We evaluate customer contact data, including chats, reviews, and feedback, using the BERT model to gain a comprehensive understanding of customer preferences and wants [35]. We utilize data on product transactions, including client purchases, to construct graphs that illustrate the correlation between customers and products. Product information, such as category and price, enhances the feature nodes in the network. Graph neural networks (GNNs) subsequently examine the graph representing the link between customers and products to identify intricate relationship patterns and deliver precise product suggestions. The analysis procedure entails extracting features, gathering information from neighboring nodes in the network, and using a non-linear activation function to generate node representations [36] that can be seen in Table I.

TABLE I. NODE REPRESENTATIONS

Data Type	Description	Analysis Method	Objective
Customer Interaction	Customer conversations, reviews and feedback.	BERT	Understand customer preferences and needs
Product Transactions	Information about product purchases by customers.	Transaction Analysis and GNSs	Building customer-product relationship graphs and pattern analysis.
Product Information	Product details include category and price.	Data Enrichment & GNNs	Node features in a graph.
Relationship Graph	Graph representation of the relationship between customers and products based on transactions.	Graph Neural Networks (GNNs)	Detect relationship patterns and product recommendations.

III. RESULT AND DISCUSSION

Data in Tables II, III and IV include customer interactions, product transactions, product information, as well as additional features used in the customer-product relationship graph and data in Tables V, VI and VII include information for analysis, from customer interactions to product transactions and relationship graphs. Each parameter in the data, such as Text Length, Transaction Frequency, Edge Weight, and Node Features, provides context for understanding how customers interact with products on an e-commerce platform. This data provides the basis for in-depth analysis and implementation of algorithms to improve Business Intelligence on e-commerce platforms.

TABLE II. CUSTOMER INTERACTION DATA

Interaction ID	Customer ID	Text
1	101	"What is the return policy for this item?"
2	102	"Do you have this product in size M?"
3	103	"How long does shipping take?"
4	104	"Can I change my order after placing it?"
5	105	"Are there any discounts available?"
6	106	"I received a damaged item, what should I do?"
7	107	"Is this product available in other colours?"
8	108	"I need help with tracking my order."
9	109	"Can I get a refund for this purchase?"
10	110	"What is the warranty period for this product?"

TABLE III. PRODUCT TRANSACTION DATA

Transaction ID	Customer ID	Product ID	Quantity	Transaction Frequency	Purchase Variety
1	101	1001	2	3	2
2	102	1002	1	1	1
3	103	1003	3	4	2
4	104	1004	1	2	1
5	105	1005	2	3	1
6	101	1006	1	3	2
7	102	1007	1	1	1
8	103	1008	1	4	2
9	104	1009	1	2	1
10	105	1010	2	3	1

TABLE IV. PRODUCT INFORMATION DATA

Product ID	Product Name	Category	Price	Stock Availability	Product Ratings
1001	T-shirt	Clothing	20	In Stock	4.5
1002	Running Shoes	Footwear	50	In Stock	4.7
1003	Leather Jacket	Clothing	100	Out of Stock	4.6
1004	Smartwatch	Electronics	150	In Stock	4.8
1005	Wireless Earbuds	Electronics	30	In Stock	4.4
1006	Backpack	Accessories	40	In Stock	4.3
1007	Sunglasses	Accessories	25	In Stock	4.5
1008	Laptop	Electronics	500	In Stock	4.9
1009	Office Chair	Furniture	200	Out of Stock	4.6
1010	Water Bottle	Accessories	15	In Stock	4.2

TABLE V. NODES (CUSTOMERS AND PRODUCTS)

Node ID	Type	Age	Gender	Category	Price	Product Ratings
101	Customer	25	Male	-	-	-
102	Customer	30	Female	-	-	-
103	Customer	22	Male	-	-	-
104	Customer	28	Female	-	-	-
105	Customer	35	Male	-	-	-
1001	Product	-	-	Clothing	20	4.5
1002	Product	-	-	Footwear	50	4.7
1003	Product	-	-	Clothing	100	4.6
1004	Product	-	-	Electronics	150	4.8
1005	Product	-	-	Electronics	30	4.4

TABLE VI. EDGES (TRANSACTIONS)

Source Node	Target Node	Transaction ID	Quantity	Edge Weight
101	1001	1	2	40
102	1002	2	1	50
103	1003	3	3	300
104	1004	4	1	150
105	1005	5	2	60

TABLE VII. NODE FEATURES

Node ID	Feature 1	Feature 2
101	Age: 25	Gender: Male
102	Age: 30	Gender: Female
103	Age: 22	Gender: Male
104	Age: 28	Gender: Female
105	Age: 35	Gender: Male
1001	Category: Clothing	Price: 20
1002	Category: Footwear	Price: 50
1003	Category: Clothing	Price: 100
1004	Category: Electronics	Price: 150
1005	Category: Electronics	Price: 30

A. Data Processing Results with BERT

Most customers ask about return policies, product availability, and shipping information. This indicates areas need to be clarified on e-commerce sites to reduce customer service burden. Complaints about damaged goods and requests for refunds were most common, indicating a need to improve delivery quality and return policies. BERT successfully classifies customer interaction texts into relevant categories with a high level of confidence. This allows e-commerce platforms to automatically handle various types of customer inquiries or complaints more efficiently, shown in Table VIII.

TABLE VIII. CUSTOMER INTERACTION ANALYSIS (TEXT CLASSIFICATION)

Interaction ID	Customer ID	Text	Predicted Class	Confidence Score
1	101	"What is the return policy for this item?"	Inquiry: Return Policy	0.98
2	102	"Do you have this product in size M?"	Inquiry: Product Availability	0.95
3	103	"How long does shipping take?"	Inquiry: Shipping Information	0.97
4	104	"Can I change my order after placing it?"	Inquiry: Order Modification	0.96
5	105	"Are there any discounts available?"	Inquiry: Discounts	0.93
6	106	"I received a damaged item, what should I do?"	Complaint: Damaged Item	0.99
7	107	"Is this product available in other colours?"	Inquiry: Product Availability	0.95
8	108	"I need help with tracking my order."	Inquiry: Order Tracking	0.94
9	109	"Can I get a refund for this purchase?"	Request: Refund	0.97
10	110	"What is the warranty period for this product?"	Inquiry: Warranty Information	0.96

B. Data Processing Results with GNNs

GNNs identify purchasing patterns and provide relevant product recommendations for each customer. These recommendations are based on historical relationships between products frequently purchased together by other customers with similar purchasing patterns as in the Table IX.

TABLE IX. CUSTOMER SEGMENTATION ANALYSIS

Segment	Characteristics	Actionable Insights
High-Value Customers	Customers who buy products at high prices	Focus on personalizing premium product offerings
Frequent Buyers	Customers with high purchasing frequency	Loyalty offers or discounts based on volume
Category Loyalists	Customers who tend to buy from one category	Promote related products in the same category

IV. VALIDATION

A. Performance Evaluation of BERT

BERT is used for customer interaction text classification. Performance evaluation is measured using several metrics [37], [38].

$$Accuracy = \left(\frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}\right) \quad (10)$$

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)} \quad (11)$$

$$Recall = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives\ (FN)} \quad (12)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (13)$$

Table X shows BERT provides excellent results in text classification and sentiment analysis, with high scores in all key metrics. This reflects BERT's ability to effectively understand and process customer interaction texts for customer service automation and data-driven decision making in e-commerce platforms.

TABLE X. BERT PERFORMANCE EVALUATION

Evaluation Metrics	Value	Interpretation
Accuracy	97%	97% of BERT's total predictions were correct, demonstrating a high level of accuracy in customer interaction text classification.
Precision	0.95	95% of the positive predictions made by BERT were true positive, indicating that this model has a low false positive rate.
Recall	0.96	BERT successfully identified 96% of all existing positive cases, indicating that the model is very good at detecting the correct classes.
F1-Score	0.96	A harmonious combination of Precision and Recall, showing a good balance between the two.
Sentiment Analysis Accuracy	93%	BERT was able to classify sentiment with 93% accuracy, demonstrating reliability in determining whether text is positive, negative, or neutral.

B. Performance Evaluation of GNNs

GNNs are used for tasks such as product recommendation and customer-product relationship graph analysis. Its performance evaluation is measured using metrics such as Mean Average Precision (MAP) and Normalized Discounted Cumulative Gain (NDCG) [39]:

MAP

$$MAP = \frac{1}{2} \sum_{i=1}^{n} AP(i) \quad (14)$$

NDCG

$$DCG_p = \sum_{i=1}^{p} \frac{2_i^{rel} - 1}{\log_2(i+1)} \quad (15)$$

$$NDCG_p = \frac{DCG_p}{IDCG_p} \quad (16)$$

Precision@K

$$Precision@K = \frac{Number\ of\ relevant\ items\ in\ K\ recommendations}{K} \quad (17)$$

TABLE XI. GNNS PERFORMANCE EVALUATION

Evaluation Metrics	Value	Interpretation
Mean Average Precision (MAP)	0.92	92% of the products recommended by GNNs are relevant and match customer preferences.
Normalized Discounted Cumulative Gain (NDCG)	0.88	Relevant recommendations tend to appear at the top of the recommendation list, increasing the likelihood of a product being chosen by a customer.
Precision@5	0.93	93% of the top five recommendations are relevant to customers.
Precision@10	0.89	89% of the top ten recommendations are relevant to customers.
Coverage	85%	GNNs cover 85% of the products in the catalogue, ensuring diverse and varied recommendations.
Hit Rate	0.90	90% of all customers find at least one relevant product in their recommendation list.

V. CONCLUSION

This research reveals how the use of BERT (Bidirectional Encoder Representations from Transformers) and Graph Neural Networks (GNNs) can improve business intelligence (BI) capabilities on e-commerce platforms. Through in-depth analysis, BERT was proven to be effective in classifying customer interaction texts with an accuracy rate of 97% and was able to perform sentiment analysis with an accuracy rate of 93%. This enables automation in the management of customer inquiries and complaints, directly increasing customer service efficiency. GNNs show good performance in providing relevant product recommendations, with a mean average precision (MAP) of 0.92 and a normalized discounted cumulative gain (NDCG) of 0.88. GNNs also managed to cover 85% of the products in the catalog, ensuring that the recommendations provided were varied. Customer segmentation generated by GNNs allows the identification of segments such as high-value customers and frequent buyers, which can be targeted with more precise marketing strategies, increasing campaign effectiveness and customer loyalty.

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