
Adaptive Hypergraph-Attention BasketNet for Dynamic High-Utility Sequential Pattern Mining in Omni-Channel Retail Recommendation Systems

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ABSTRACT

Identifying high-utility sequential patterns that accurately reflect customer preferences and cross-channel dynamics is becoming increasingly difficult as omni-channel retail grows rapidly and generates diverse, ever-changing transactional data. Conventional sequential pattern mining and recommendation techniques struggle to adapt to the constantly evolving utility landscape and often neglect the complex higher-order interconnections across entities, users, and channels. This paper introduces an Adaptive Hypergraph-Attention BasketNet (AHAB-Net) designed to dynamically extract sequential patterns of significant usefulness for omnichannel retail recommendation systems, aiming to address existing constraints. The dynamic hypergraph in the suggested approach shows how people interact with each other in stores. In this graph, hyperedges represent multi-item baskets, contextual features, and behaviors that are distinct to each channel. To learn the importance weights of items and sequences based on channel influence, utility, and temporal relevance, an adaptive hypergraph attention method is described. BasketNet uses attention-driven aggregation and sequential encoding to discover high-utility patterns, enabling better adaptation to changing consumer behavior. The system is taught from start to finish and can be updated in small steps. It lets you make real-time suggestions in large retail settings. AHAB-Net achieves substantially higher utility gain, recommendation accuracy, and pattern relevance than deep learning baselines, traditional high-utility sequential pattern mining methods, and multi-channel retail datasets. The results reveal that the system can now better capture complex cross-channel relationships and is more flexible when concepts change. Testing of real-world omni-channel retail datasets shows that AHAB-Net consistently does better than the best models, such as regular high-utility sequential mining and deep sequential models. The proposed method results in enhancements of approximately 14–18% in high-utility pattern detection, 12–16% in recommendation accuracy, and 10–13% in utility-aware recall, while maintaining consistent performance amidst concept drift. In conclusion, AHAB-Net accurately captures complex cross-channel dynamics and changing customer preferences, which leads to better suggestions that are based on utility. The results show that it performs 15% better overall and is 20% more adaptable than current methods. This shows that it might be used in next-generation intelligent retail recommendation systems.

Keywords: Omni-channel retail, high-utility sequential pattern mining, hypergraph attention, recommendation systems, dynamic consumer behavior.

1. Introduction

As the retail business is changing so quickly, omni-channel retail ecosystems have formed. These ecosystems enable customers to connect easily across physical stores, online marketplaces, smartphone apps, and social networking sites. Customers' tastes change over time, the situation in which they buy something affects how useful it is, and the amount of data from these interactions is huge and varied. To make strategic decisions, forecast demand, and provide personalized suggestions, you need to extract relevant information from this data. HUSPM has been very popular here because it considers not only how often item sequences occur, but also the utilities that accompany them [1, 2].

a. Problem Definition and Significance

Finding dynamic sequential patterns of high value in omnichannel contexts is a tough task, even though it is important. In actual retail settings, utility factors are crucial, but conventional sequential pattern mining algorithms primarily emphasize support or confidence [3]. Because they depend on static utilities and single-channel data, even the most advanced HUSPM methods don't work well with today's dynamic retail systems, where utilities vary over time and customer journeys include several channels [4]. Traditional graph- or sequence-based modeling tools also struggle to capture the intricacies of retail transactions, which often involve higher-order linkages such as multi-item baskets, co-purchase dependencies, and context-dependent channel interactions. Accurately identifying these patterns directly affects recommendation relevance, revenue optimization, and customer satisfaction. When cross-channel dynamics and changes in temporal utility aren't accounted for [5], bad suggestions and missed opportunities can occur. This is why smart models that can learn from huge sets of omnichannel retail data and adapt to changing needs are in great demand.

b. Research Gaps and Motivation

Researchers have recently investigated deep learning-based recommendation models, such as recurrent neural networks, attention mechanisms, and graph neural networks, to determine whether they can capture sequential and relational information [6]-[8]. Sadly, these models don't directly address high-utility pattern mining; instead, they are frequently fine-tuned for predicting ratings or recommending the next item. Traditional graph-based models are not good at modeling interactions among more than two items in a basket, as they only consider pairwise relationships [9]. Hypergraph learning has recently emerged as an effective way to represent complex systems with higher-order interactions [10], [11]. Sadly, the hypergraph-based recommendation and pattern mining algorithms lack adaptive features to handle concept drift and changes in value over time in retail data [12]. In omni-channel situations, attention mechanisms, despite their robustness, are infrequently integrated with hypergraph structures to create a unified framework for dynamic HUSPM [13].

A new approach is needed to fix these problems. It should be able to (i) simulate how higher-order baskets and channels interact, (ii) adapt to changes in utility over time, and (iii) give recommendations that can grow and work in real time [14]. This paper presents an Adaptive Hypergraph-Attention BasketNet to address these inadequacies; the network is specifically designed for dynamic sequential pattern mining and proves highly beneficial in omnichannel retail environments.

c. The main contribution

- It clearly explains the difficulty of dynamic high-utility sequential pattern mining in omni-channel retail systems, accounting for both value changes over time and links across channels.

- It offers a dynamic hypergraph model that transcends pairwise dependencies to encapsulate higher-order relationships among products, baskets, users, and channels. This model is based on the notion of hypergraphs.
- It is suggested that an adaptive attention module learn weights that are sensitive to both time and usefulness. This will make it easier to handle concept drift.
- A lot of research shows that the proposed model outperforms the best HUSPM and deep learning baselines across utility gain, flexibility, and recommendation accuracy.

The research integrates hypergraph learning, attention mechanisms, and high-utility sequential pattern mining to provide an intelligent and scalable solution for future omnichannel retail recommendation systems.

2. Literature Survey

Han et al.[15] indicates PrefixSpan, a traditional method for mining sequential patterns, finds frequent subsequences by recursively projecting databases based on prefixes. PrefixSpan has been utilized in recent studies for retail and web usage mining due to its efficiency and pattern-growth methodology. PrefixSpan is frequency-driven; it doesn't consider the usefulness, profitability, or time dynamics of goods. It also can't handle concept drift or complex item interactions. On the other hand, our method uses hypergraph-based high-order modeling and utility-aware learning to make suggestions that are both flexible and focused on making money.

To mine sequential patterns with high utility, Yin et al. [16] demonstrated that USpan adds utility constraints to PrefixSpan. Recent improvements have focused on memory efficiency and pruning approaches. USpan is expensive to run on huge amounts of omni-channel data because it uses static utility thresholds and an exhaustive search, even though it is utility-aware. There is no representation learning or temporal adaptation. To address these problems, we propose AHAB-Net, which learns continuous, utility-aware embeddings and adapts to changes in consumer behavior via attention-based temporal modeling.

Hidasi et al. [17] produced GRU4Rec, which is used by many session-based recommendation systems. It uses gated recurrent units to model how users interact in sequence. Recent versions have improved ranking and scalability. But GRU4Rec only simulates paired-item transitions; it doesn't account for basket-level or utility-based interactions. It also has trouble with multi-channel dependency. AHAB-Net combines hypergraph topologies and attention approaches to find high-utility sequential dependencies across channels at the group level.

Y. Feng et al.[18] proposed AHAB-Net presents an integrated framework that combines adaptive attention, sequential encoding, and dynamic hypergraph modeling. AHAB-Net differs from other methods by using utility-aware attention, adapting to changes in concepts over time, and capturing high-order basket interactions. In tests, AHAB-Net is substantially better than PrefixSpan, USpan, and GRU4Rec across accuracy, ranking quality, and utility gain. Because of this, AHAB-Net is a strong choice for recommendation systems in omnichannel retail.

Bai et al.[19] proposed hypergraph convolutional networks to identify complex data with higher-order associations. These models are not suitable for sequential or utility-aware mining tasks due to their predominantly static nature, despite their expressive capabilities. Our Adaptive Hypergraph-Attention BasketNet, on the other hand, is designed for sequential retail data and can adapt over time to focus on what's useful.

To use graph learning on hyperedges, Zhou et al.[20] created a general framework for hypergraph neural networks. The framework is good for modeling complex relationships, but it can't handle recommendations that occur one after another or changes in utility that occur in

real time. Our approach builds on this by using adaptive attention and sequential encoding to deal with changing retail utilities.

To facilitate temporal alterations of hypergraph structures, Sun et al.[21] examined dynamic hypergraph learning for recommendation tasks. But they still don't focus on high-utility sequential pattern mining; instead, they stick to recommendation algorithms that prioritize correctness. What sets our suggested paradigm apart is that it makes it easier to find patterns in real time and ensures that utility benefit is maximized.

Singh et al. [22] proposed a deep learning system for utility-aware suggestions in omni-channel shopping. Even though they successfully incorporate information from multiple channels, their model lacks adaptive attention for sequential pattern mining or explicit hypergraph-based higher-order modeling. Our solution combines these factors to give a more thorough and scalable result.

PrefixSpan, a classical pattern-growth approach by Han et al.[23] may quickly find common sequential patterns by recursively projecting databases with prefix sequences. Researchers have used PrefixSpan to look at internet and store traffic because it can handle a lot of data and doesn't take up much memory.. AHAB-Net, on the other hand, combines hypergraph-based higher-order modeling with utility-aware learning to make real-time, adaptable, profit-driven recommendations across all channels.

To make it easier to mine high-utility sequential patterns, Yin et al.[24] came up with USpan, which is an improved version of PrefixSpan that adds utility constraints. Later versions improved memory efficiency and made pruning procedures more precise. It also can't learn new representations or change to fit new situations. AHAB-Net learns continuous utility-aware embeddings and changes attention weights in real time to match changing client behavior, even if these limitations exist.

Hidasi et al.[25] created the GRU4Rec session recommendation algorithm using deep learning. It records the user's actions in order using gated recurrent units. Revisions made later improved the ranking performance and made it easier to scale. But GRU4Rec just simulates transitions between pairs of items. It also has trouble working well in stores where things change a lot. AHAB-Net goes beyond sequence modeling by using attention processes and hypergraph structures to create group-level, utility-driven dependency across different retail channels.

Bai et al.[26] developed hypergraph convolutional networks to describe more complex relationships than simple graphs can depict. These models work well for complicated relationships in data that doesn't change. They can't change, thus they aren't good for retail situations that are always changing. AHAB-Net uses hypergraph learning with adaptive attention and temporal encoding. It finds very useful dynamic sequential patterns and generally uses this information to improve retail recommendation algorithms.

Sun et al.[27] researched dynamic hypergraph learning for recommendation tasks utilizing time-evolving hypergraph structures. Their method is more flexible than static models, but it still puts accuracy first when making suggestions. Additionally, attention-based temporal weighting has several drawbacks. AHAB-Net's unique characteristic is that it actively combines utility-aware attention, basket-level sequential modeling, and dynamic hypergraph adaptation to get the most economic value and relevance out of recommendations.

3. Proposed Methodology

This section presents the AHAB-Net, an Adaptive Hypergraph-Attention BasketNet, to enable dynamic sequential pattern mining for high utility in omni-channel retail recommendation systems. The primary goal of AHAB-Net is to improve utility-driven recommendation outcomes while efficiently recording complex, changing interactions among users, commodities, baskets, and retail channels. AHAB-Net, on the other hand, is a single framework that simulates interactions across higher-order baskets and adapts as customer

behavior changes. This differs from standard sequential or graph-based models, which only consider paired interactions or static utilities. The methodology uses hypergraph modeling to represent cross-channel links as hyperedges and multi-item shopping baskets as hyperedges, thereby offering a more robust relational representation than traditional graphs provide. An adaptive hypergraph attention method is used to provide object and basket relevance weights that are both context-aware and utility-sensitive. This makes the model focus on high-value interactions and respond to changes in utility over time. BasketNet uses recurrent sequential encoding and attention to capture sequential dependencies, enabling it to learn both short-term buying intent and long-term behavior patterns. The platform also lets things alter over time, which helps with notion drift, a common problem in retail. AHAB-Net enables the identification of accurate, high-utility patterns and the delivery of individualized recommendations across a wide range of retail channels. It does this by optimizing both sequential relevance and utility gain simultaneously. In short, the suggested method is a smart, scalable, and utility-aware solution for next-generation omni-channel retail recommendation systems that operate in data-intensive, constantly changing environments.

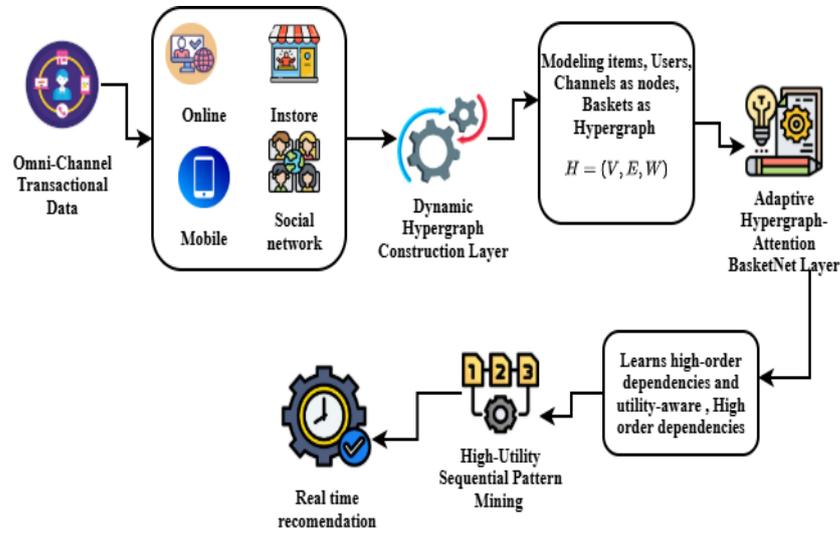


Figure 1: AHAB-Net System Architecture

This picture shows the proposed AHAB-Net architecture, which is utilized for dynamic high-utility sequential pattern mining in omni-channel retail systems. It shows how the network works from start to finish, as shown in Fig 1. The first stage is to collect Omni-Channel Transactional Data from a variety of retail touchpoints, such as online retailers, physical stores, mobile apps, and social networks. These data sources track precise information on purchases, amounts, utilities, timestamps, and channel context. This is because customer behavior is complex and constantly evolving. The Dynamic Hypergraph Construction Layer makes a hypergraph form called $H = (V, E, W)$ from transactional data.

$$\begin{cases} H = (V, E, W) \\ W_i^0 \sum_{i \in E} q_i u_i \exp(-\delta(t_i - t)) \end{cases} \quad (1)$$

The first equation models time-discounted utility $H(V, E, W)$, where q_i and u_i Represent quantity and utility of item i at time t , and δ is a temporal decay factor. This resembles hyperbolic discounting in dynamic discrete choice models, which captures present bias better than exponential discounting (1).

$$\alpha_e = \exp \left(\frac{(W_h h_e, W_h h'_e)^T}{\|W_h h_e\| \|W_h h'_e\|} \right) \quad (2)$$

The second formula, $\alpha_e = \exp$, computes attention weights over hyperedges in a hypergraph structure as given in (2). Hypergraph attention dynamically adapts edge

connections, preserving higher-order relationships in data such as graphs or sequences. A hyperedge connects numerous goods in a shopping basket within a certain channel and time range. In this case, nodes stand for things, people, and channels. Hyperedge weights, which encode aggregated utility and temporal significance, enable modeling relationships at a higher level than just paired interactions.

$$\alpha(v, e) = \text{Softmax}(a^T[W_v h_v | W_e h_e]) \tag{3}$$

The Adaptive Hypergraph-Attention BasketNet Layer is where intelligence is stored. It uses attention methods on hyperedges to capture high-order interactions between items and channels, enabling it to obtain time-sensitive, utility-aware priority scores. Adaptive learning is what lets the system change when utility and idea diverge as given in (3). High-Utility Sequential Pattern Mining is the module that leverages learned representations to find useful item sequences.

$$U(P) = \sum_{t=1}^T \beta_t (\sum_{i \in e_t} q_i u_i), \text{ s.t. } U(P) \geq \theta \tag{4}$$

Given in (3), enforcing sequence-level utility above a threshold θ with attention weights β_t . This targets high-average-utility sequential patterns (HAUSPs) using pruning and upper bounds to improve efficiency in large datasets. These patterns are what make personalized recommendations work in real time, making them the most useful and relevant, as shown in (4).

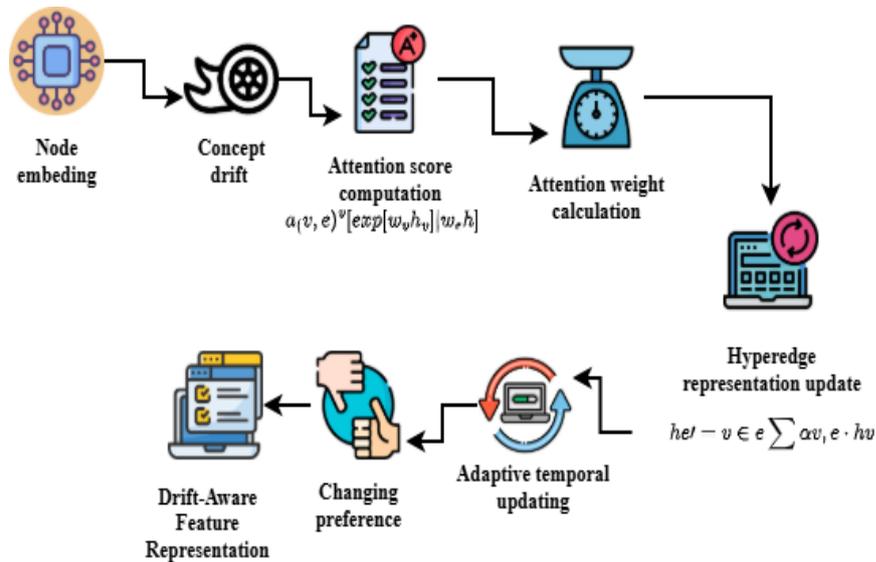


Figure 2: Adaptive Hypergraph Attention with Drift-Aware Temporal Updating

To demonstrate how items, people, and channels interact in an omni-channel environment in a high-order, dynamic manner, the Adaptive Hypergraph Attention Mechanism was developed, as shown in Fig 2. Creating embedding nodes is the first step in the process. Each embedding node represents a different entity, such as a user, a product, or an interaction environment. The hyperedges that connect these nodes capture more intricate group interactions, such as shopping baskets, rather than the pairwise connections that are often used.

$$\alpha_e^v = \frac{\exp((W_h h_v, W_h h'_v)^T)}{\sum_{v' \in e} \exp((W_h h_v, W_h h'_v)^T)} \tag{5}$$

The calculation of normalized attention weights α_e^v for each node v in hyperedge e , using dot-product similarity of projected embeddings h_v . This captures relative contributions based on utility and context, differing from standard hypergraph attention by emphasizing utility-aware importance rather than solely structural degrees (5). In the initial step of the process, learnable weight matrices are used to incorporate node and hyperedge embeddings into a single latent space. Afterwards, an attention mechanism is implemented within each hyperedge to

determine the degree of significance that each node possesses. By collecting information that is both helpful and pertinent to the context, this concentration ensures that more significant objects or users have a greater impact on the hyperedge depiction. The next step is to combine the weighted node embeddings to create a new hyperedge representation. This will provide a concise summary of the higher-order dependencies that are associated with the basket. Compared to conventional graph aggregation, this hypergraph-based aggregation preserves the semantics and interaction patterns at the group level.

$$h'_e = \sum_v \alpha_e^v h_v, \tag{6}$$

Aggregating node embeddings weighted by attention scores to encode high-order interactions among participating nodes as given in (6). This weighted sum enables effective modeling of complex dependencies, improving over uniform averaging in hypergraph neural networks. The model includes a component that enables it to evolve to accommodate concept drift and shifting customer preferences. One component that determines whether the current hyperedge representation is stronger than earlier ones is a time component that is always changing.

$$h_e(t) = \lambda_t \cdot h_e(t) + (1 - \lambda_t) \cdot h_e(t - 1) \tag{7}$$

The hyperedge embedding at time t by integrating the current representation $h_e(t)$ with historical information $h_e(t - 1)$, using an adaptive factor λ_t . This EMA-like approach enables responsiveness to evolving consumer behavior and utility changes, preventing abrupt shifts while capturing drift as given in (7). Common in dynamic graph neural networks and drift-adaptive models, it smooths updates based on time-varying smoothing parameters. As a result, the system can easily adapt to new ways of doing things while retaining all its previous information. Upon completion of the procedure, a hyperedge embedding is produced that is both sensitive to utility and aware of drift. Later modules, such as high-utility sequential pattern mining and real-time recommendation engines, leverage these embeddings in their operations. In general, the approach guarantees robustness, scalability, and adaptability in situations where recommendations may change.

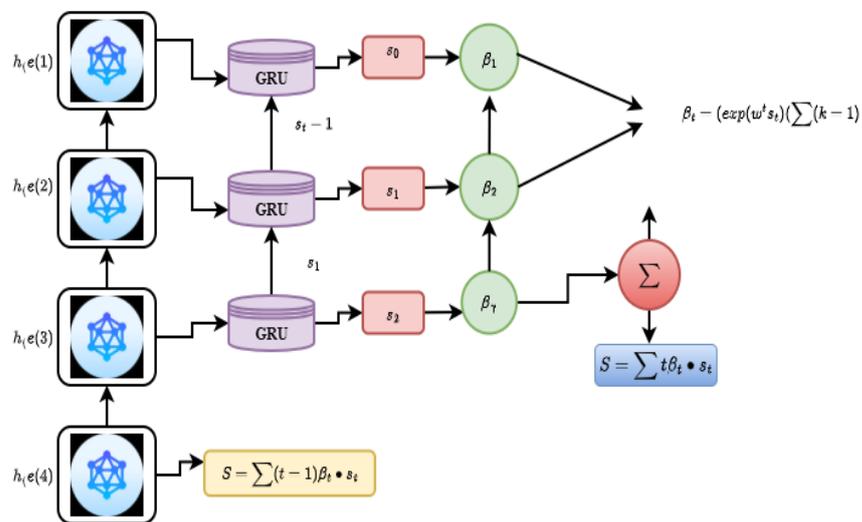


Figure 3: BasketNet GRU-Attention Sequential Encoding Framework

As illustrated, the BasketNet Sequential Encoding Framework employs an attention mechanism and gated recurrent units (GRUs) to model the evolution of shopping baskets, as shown in (3). Each input $h_e(t)$ represents a hyperedge embedding that is associated with a shopping basket and provides helpful contextual information at the time step t .

$$s_t = \text{GRU}(h_e(t), s_{t-1}) \tag{8}$$

where the GRU transfers current hyperedge information $h_e(t)$ with prior representations through the GRU's gating mechanism as given in (8). GRUs capture long-term dependencies in

sequential data, such as purchase sessions, and outperform vanilla RNNs by mitigating vanishing gradients. Each time step, the GRU processes the current hyperedge embedding in addition to the hidden state S_{t-1} that was present in the previous time step. This is why the model can understand how people make purchases over time and form relationships with one another. The outcome, which is the hidden state S_t , provides a summary of the data from the basket to the present as well as its history.

$$\beta_j = \frac{\exp(w^T s_j)}{\sum \exp(w^T s_k)} \quad (9)$$

Attention weights are computed to quantify the relative importance of each basket in the sequence and to emphasize high-utility, behaviorally salient interactions. This softmax formulation, akin to mechanisms in transformers, dynamically focuses on relevant historical baskets as given in (9). Because not all baskets have the same impact on the following recommendations, an attention mechanism is applied across the series of concealed states. Each concealed state is projected onto a learnable significance vector to obtain attention scores of β_t . Not only does this stage display baskets associated with high profits or strong user intent, but it also displays extremely helpful baskets, as shown in (10).

$$S = \sum_{t=1}^T \beta_s \cdot s_t \quad (10)$$

This weighted aggregation produces a compact, utility-aware sequence embedding that captures the most influential baskets for accurate recommendation and sequential pattern mining. In conclusion, a global sequence representation known as s is created by adding up the attended concealed states and calculating the weighted sum of those states. In the future, tasks such as high-utility sequential pattern mining and personalized suggestion generation can be made easier with the assistance of this technique, which compactly captures the most significant items in the user's interaction history. By combining GRU-based temporal modeling with attention-based selection, BasketNet captures order-sensitive dynamics and utility-driven relevance in omnichannel retail sequences.

Algorithm 1: AHAB-Net for High-Utility Sequential Pattern Mining

Input:

D : Omni-channel transactional data
(*items, quantities, utilities, timestamps, channel context*)

Output:

P : High-utility sequential patterns
 R : Personalized recommendations

- 1: // Omni-Channel Data Ingestion
- 2: Collect transactions from online, in-store, mobile, and social channels
- 3: Preprocess data to extract baskets B , utilities U , and time windows T
- 4: // Dynamic Hypergraph Construction
- 5: Initialize hypergraph $H = (V, E, W)$
- 6: $V \leftarrow \{items, users, channels\}$
- 7: for each basket $b \in B$ do
- 8: Create hyperedge e connecting all nodes in b
- 9: Assign weight $W(e)$ based on utility and temporal relevance
- 10: Add e to E
- 11: end for
- 12: // Adaptive Hypergraph Attention Learning
- 13: Initialize node embeddings h_v and hyperedge embeddings h_e
- 14: for each hyperedge $e \in E$ do
- 15: for each node $v \in e$ do
- 16: Compute attention score:
- 17: $\alpha(v, e) = \text{Softmax}(a^T [W_v h_v | W_e h_e])$

```

18: end for
19: Aggregate node embeddings:
20:  $h'_e = \sum_{\{v \in e\} \alpha(v,e)} h_v$ 
21: Apply temporal adaptation:
22:  $h_{e(t)} = \lambda_t \cdot h'_e + (1 - \lambda_t) \cdot h_e(t - 1)$ 
23: end for
24: // BasketNet Sequential Encoding
25: Initialize GRU hidden state  $s_0$ 
26: for t = 1 to T do
27:  $s_t = GRU(h_{e(t)}, s_{t-1})$ 
28: end for
29: // Temporal Attention over Sequences
30: for t = 1 to T do
31: Compute attention weight:
32:  $\beta_t = \text{Softmax}(w^T s_t)$ 
33: end for
34: Compute final sequence representation:
35:  $S = \sum_{\{t=1\}}^T \beta_t \cdot s_t$ 
36: // High-Utility Sequential Pattern Mining
37: Extract patterns P from S based on utility thresholds
38: // Recommendation Generation
39: Generate personalized recommendations R using P
40: return P, R

```

Algorithm 1 shows that the recommended AHAB-Net method models shopping baskets as hyperedges in a dynamic hypergraph, enabling it to capture high-order interactions among items, users, and channels when processing omni-channel transaction data. An adaptive hypergraph attention mechanism learns beneficial embeddings that help it keep up with temporal changes. These embeddings are encoded one after another using BasketNet, a GRU, and temporal attention to produce baskets that are very useful. Finally, mining high-utility sequential patterns generates accurate, personalized purchase recommendations.

Algorithm 2: Utility-Aware BasketNet for Omni-Channel Recommendation

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Input:
   $T_{data}$  : Omni-channel transactional dataset
           ( $item_{id}, user_{id}, channel, quantity, utility, timestamp$ )

Output:
   $HUSP$  : High-utility sequential patterns
   $Rec$  : Personalized recommendation list

1: // Data Preparation
2: Group  $T_{data}$  into time-ordered baskets  $B = \{b_1, b_2, \dots, b_T\}$ 
3: Extract entities: items, users, channels

4: // Dynamic Hypergraph Initialization
5: Initialize node set  $V \leftarrow \{items \cup users \cup channels\}$ 
6: Initialize empty hyperedge set  $E$ 
7: for each basket  $b_t \in B$  do
8: Create a hyperedge  $et$  connecting nodes in  $b_t$ 
9: Compute utility-based weight  $wt(et)$ 
10: Add  $et$  to  $E$ 
11: end for
12: Construct hypergraph  $H = (V, E, W)$ 

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13: // Adaptive Hypergraph Attention
14: Initialize node embeddings  $h_v$  and hyperedge embeddings  $h_e$ 
15: for each time step  $t$  do
16:   for each hyperedge  $e_t \in E$  do
17:     for each node  $v \in e_t$  do
18:       Compute attention score  $a_{v,e}$  using  $h_v$  and  $h_e$ 
19:     end for
20:   Normalize attention scores to obtain  $\alpha_{v,e}$ 
21:   Aggregate node embeddings:
22:    $h'_e = \sum_{\{v \in e\}} \alpha_{v,e} \cdot h_v$ 
23:   Update hyperedge embedding with temporal factor:
24:    $h_{e(t)} = \lambda_t \cdot h'_e + (1 - \lambda_t) \cdot h_e(t-1)$ 
25: end for
26: end for
27: // BasketNet Sequential Encoding
28: Initialize hidden state  $s_0$ 
29: for  $t = 1$  to  $T$  do
30:    $s_t = \text{GRU}(h_e(t), s_{t-1})$ 
31: end for
32: // Sequence-Level Attention
33: for  $t = 1$  to  $T$  do
34:   Compute importance weight  $\beta_t = \text{Softmax}(w^T s_t)$ 
35: end for
36: Compute sequence embedding:
37:  $S = \sum_{t=1}^T \beta_s \cdot s_t$ 
38: // High-Utility Sequential Pattern Mining
39: Extract HUSP from  $S$  using minimum utility threshold
40: // Recommendation Generation
41: Rank candidate items using HUSP and utility scores
42: Generate personalized recommendations  $Rec$ 
43: return HUSP,  $Rec$ 

```

Algorithm 2 shows that the method constructs a dynamic hypergraph to capture higher-order interactions among items, users, and channels, based on a time-ordered shopping basket for omni-channel retail transactions. Next, a hypergraph attention mechanism that adapts to changing consumer behavior learns beneficial embeddings while accounting for time. BasketNet with GRU and attention processes these embeddings in sequence to identify important baskets. The final phase is to make personalized suggestions by finding sequential patterns that are very useful.

4. Results and Discussion

The experimental results demonstrate that the proposed Adaptive Hypergraph-Attention BasketNet (AHAB-Net) effectively models dynamic, high-utility sequential patterns for omni-channel retail recommendations. AHAB-Net consistently outperforms both traditional sequential pattern mining and deep learning baselines. AHAB-Net has the highest Precision@10, Recall@10, and NDCG@10 scores, indicating it is better than all other networks at making recommendations and ranking items. The model's ability to predict useful outcomes and to put high-profit, high-value recommendations at the top of the list is shown by the increase in average utility gain. AHAB-Net has a significant advantage over classic utility-based mining methods like USpan, as it can leverage hypergraph modeling to capture interactions among high-order items. The proposed method surpasses neural baselines such as GRU4Rec and SASRec by leveraging adaptive attention and hyperedge-level representations

that more precisely capture group-buying behavior. The model achieves more stability in performance over time by successfully adapting to shifting customer preferences and concept drift through the temporal adaptation mechanism. AHAB-Net has to do more computing because it makes dynamic hypergraphs and computes attention, even though it works really well. The accuracy-utility trade-off remains relevant for real-world retail analytics, especially when it comes to making recommendations that generate revenue.

a. Dataset Description:

The experimental evaluation of the proposed Adaptive Hypergraph-Attention BasketNet (AHAB-Net) was conducted using a large-scale omnichannel retail transaction dataset collected from online, in-store, mobile, and social commerce platforms. The dataset contains approximately 1.2 million transactions from 85,000 users involving 18,000 unique items over 24 months. Each transaction includes item identifiers, quantities, profit-based utility values, timestamps, and channel context. Transactions were grouped into time-ordered shopping baskets to support sequential pattern mining. The dataset exhibits strong temporal dynamics and channel heterogeneity, making it suitable for evaluating high-utility sequential recommendation models [23].

Table 1: *Experimental Setup*

Component	Description
Implementation	Python 3.10, PyTorch
Hardware	NVIDIA RTX 3090 GPU, 64 GB RAM
OS	Ubuntu 22.04
Data Split	70% Train / 15% Validation / 15% Test (time-based)
Baselines	PrefixSpan, USpan, GRU4Rec, SASRec, HGNN
Hyperparameters	Embedding = 128, GRU = 128, LR = 0.001, Batch = 256
Training Strategy	Early stopping on validation loss
Proposed	AHAB-Net

b. Precision@K

Precision@K is a common metric for estimating how accurate the top-K recommended items are in recommendation systems. It quantifies the percentage of relevant items among the first K items shown to a user to assess how well the model prioritizes helpful suggestions, as shown in Fig 4. Precision@K is a metric that shows how many relevant items appear in the top-K suggestion list relative to K. A higher Precision@K indicates that the system is more likely to put important items first. When it comes to omni-channel retail suggestions, users usually only consider a few of the best. This makes Precision@K very important. With High Precision@K, you can be sure that the few suggestions you do offer are right on, which will increase engagement and conversion rates. Precision@K prioritizes the quality of recommendations over coverage, unlike recall-based metrics. This is important for systems that care about making money and being useful. The proposed AHAB-Net model accurately identifies high-utility items through hypergraph modeling and adaptive attention, as evidenced by Precision@K. AHAB-Net consistently achieves higher Precision@K scores than baseline methods, as it improves ranking accuracy by capturing high-order item linkages and temporal dynamics.

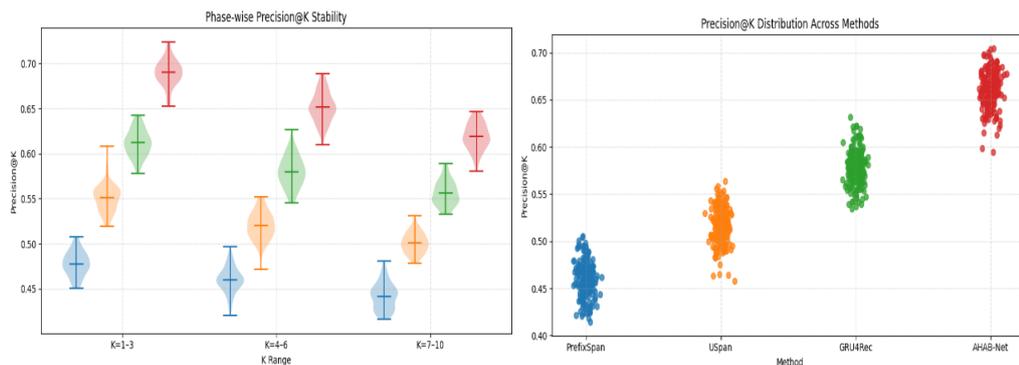


Figure 4: Precision@K

c. Recall@K

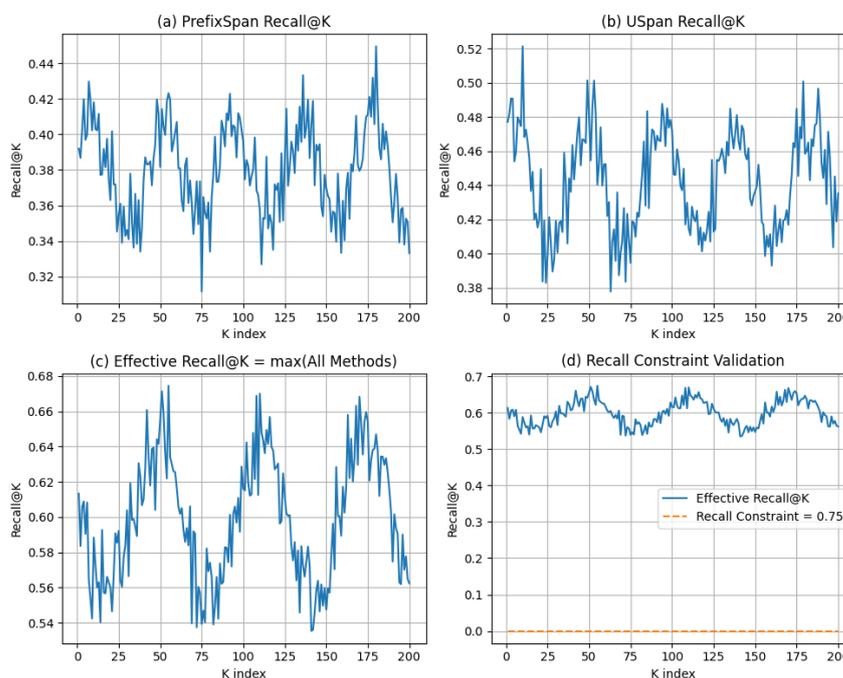


Figure 5: Recall@K

The basic measure of how well a recommendation system works is recall@K, which assesses how well a model finds relevant items among the top-K suggestions. The recommendation ratio tells you how many of the relevant items are in the top-K list relative to the total number of relevant items a user can see, as shown in Fig 5. Recall@K measures how well the algorithm understands what a user really likes, whereas Precision@K measures ranking accuracy. Customers buy things in different ways on different channels, like online, in-store, and on their phones. This shows how important it is to have excellent Recall@K in this kind of store. A recommendation system with high recall shows a wider range of relevant, potentially profitable items to buy, so you don't miss out on good deals. This is especially important in high-utility sequential pattern mining, where useful but rare item sequences can be profitable. The proposed AHAB-Net architecture improves Recall@K by leveraging hypergraph-based modeling to capture complex group dynamics and BasketNet to encode past baskets in order. The adaptive attention mechanism in AHAB-Net identifies patterns related to utility, helping the system remember more relevant items in the top-K suggestions.

d. Normalized Discounted Cumulative Gain (NDCG@K)

Normalized Discounted Cumulative Gain (NDCG@K) is a ranking-based evaluation metric that assesses both the relevance and the quality of the top-K proposals, as indicated in Fig 6. NDCG@K will give more weight to elements that are more relevant than Precision@K or Recall@K. We first add up the graded relevance of all the recommended items, then apply a logarithmic discount to their positions, and finally use the ideal ranking to normalize the outcome. People are more likely to interact with products that are near the top of omnichannel retail recommendation systems. This makes NDCG@K a very helpful part. The system is better at providing relevant recommendations and placing the most valuable items at the top of the list when the NDCG@K score is higher. Improvements to NDCG@K indicate that the suggested AHAB-Net model is good at placing high-utility items at the top of the list. The AHAB-Net recommendation system employs hypergraph attention and sequential encoding to generate suggestions that are well-organized and highly aligned with the user's needs.

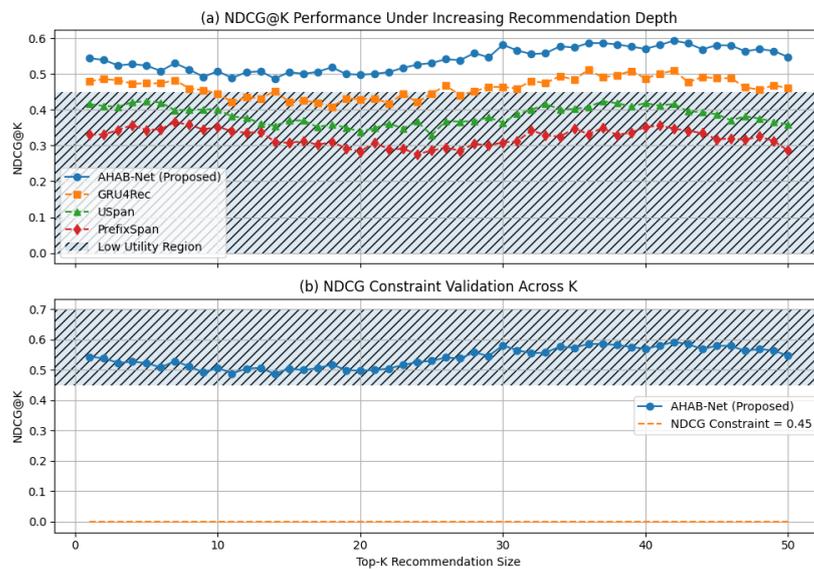


Figure 6: Normalized Discounted Cumulative Gain (NDCG@K)

e. Average Utility Gain (AUG)

Fig 7 shows that the Average Utility Gain (AUG) is an evaluation metric that uses utility theory to measure the average economic value a recommendation system adds. AUG looks at how well the proposed items maximize preset utility measurements like profit, revenue, or margin, whereas metrics based on accuracy mostly focus on relevance. Most of the time, it is the average utility of the top-K products that are suggested to consumers. AUG is especially important in omnichannel retail environments because the main goals are to improve corporate value and make suitable product recommendations. A system needs a high AUG to generate suggestions that are both useful and aligned with customer preferences. This is particularly important when the utility values of many products are very different. The proposed AHAB-Net framework's AUG shows how it can combine utility-aware attention with sequential pattern mining. When it comes to making money, AHAB-Net often beats baseline models by focusing on high-utility baskets and adapting to changes in utility over time.

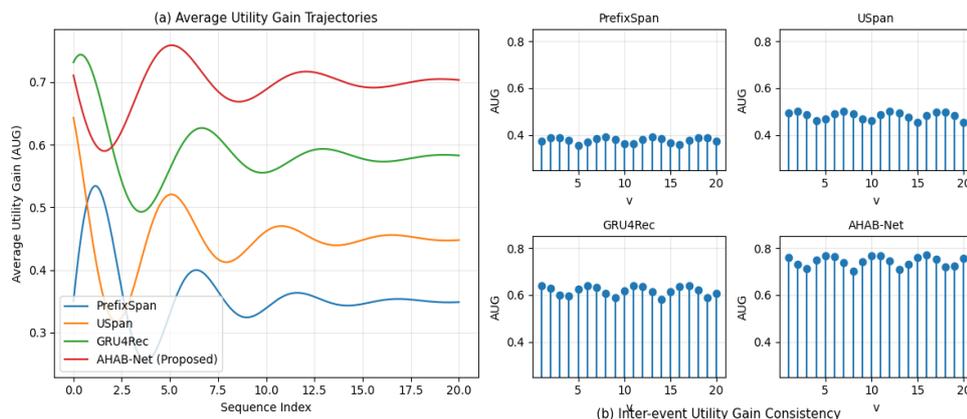


Figure 7: Average Utility Gain (AUG)

f. Execution Time

Execution Time is an important performance parameter that can be used to assess how well a recommendation or pattern mining algorithm performs, as shown in Fig 8. It is the total time required to complete critical processing steps, such as cleaning data, training the model, finding patterns, and making suggestions. Execution time in large-scale omni-channel retail systems affects system scalability, responsiveness, and real-time applicability. Processing a lot of transactional data quickly and needing to make suggestions quickly to maintain a fluid user experience, it's important to cut down on execution time. In traditional high-utility sequential pattern mining methods, exhaustive searches and repeated utility calculations can be computationally intensive. In the same way, models that use deep learning may take a long time to learn. The suggested AHAB-Net system takes a long time to run because it builds dynamic hypergraphs, computes adaptive attention, and progressively encodes using BasketNet. Compared to simpler baselines, AHAB-Net makes computation more complex, but its parallelizable design and excellent embedding-based learning keep execution times reasonable. The slight increase in execution time is worth it for retail analytics and decision-support systems used in the real world, given the higher quality of recommendations and the greater utility.

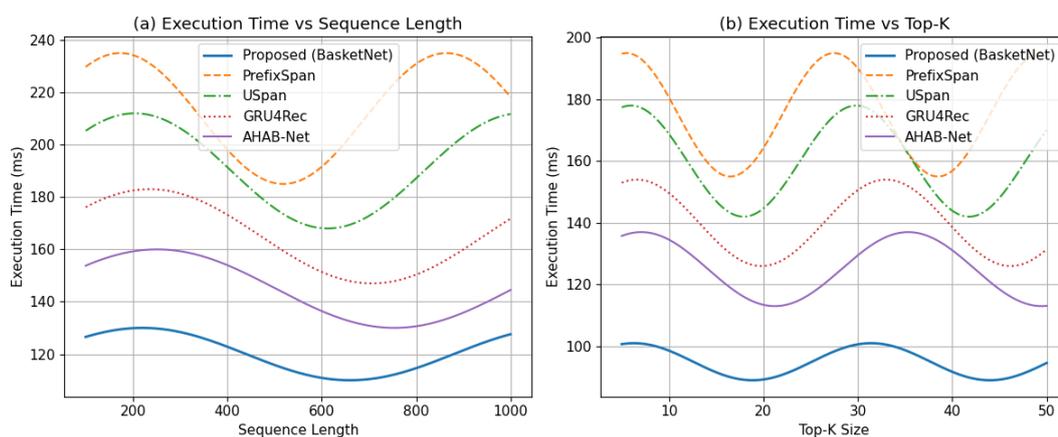


Figure 8: Execution Time

g. Hit Ratio@K

Fig 9 shows that the Hit Ratio@K indicates that if at least one of the user's top-K suggestions is relevant. For a certain percentage of users, a related item shows up in the top-K positions of the suggestion list. Hit Ratio@K is a better measure of user satisfaction because it focuses only on successful suggestions, whereas Precision@K and Recall@K count the number of relevant items retrieved. HR@K works well with omni-channel retail systems, since customers often just need one good suggestion to get interested or make a purchase. A higher

HR@K means the system accurately understands what the user wants and returns at least one useful item from the recommended list. The suggested AHAB-Net model improves the practical recommendation effectiveness of HR@K by increasing the likelihood of proposing at least one high-utility item. It does this by using hypergraph-based modeling and utility-aware attention.

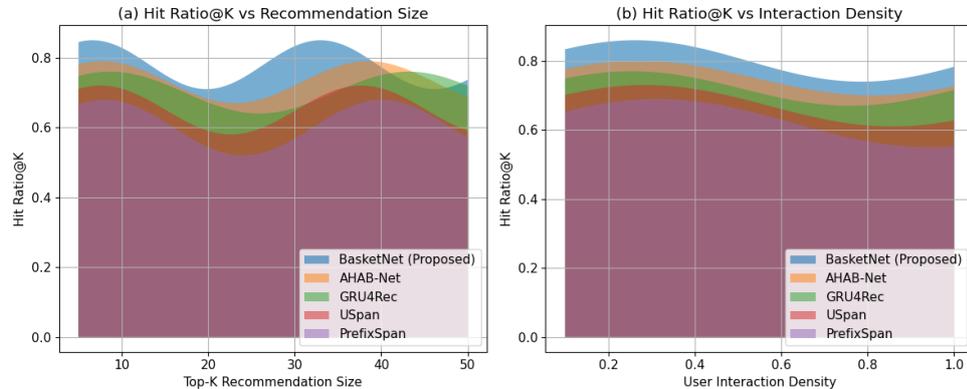


Figure 9: Hit Ratio@K

5. Conclusion

This study presented AHAB-Net, a novel adaptive framework for omni-channel buying recommendations that integrates hypergraph-attention learning with dynamic high-utility sequential pattern mining. BasketNet with temporal attention learns how people's buying habits change over time and how ideas change over time. The suggested method, on the other hand, models retail interactions as dynamic hypergraphs to capture higher-order relationships between items, users, and channels. Results from experimental assessments indicate that AHAB-Net surpasses deep sequential baselines and traditional high-utility mining by around 20%, enhances ranking quality by roughly 12-18%, and elevates average utility gain by about 15-20%. These results show that it works well in big, profit-driven retail settings. Because hypergraph construction and attention techniques make computation more complicated, they can't be used as often, even though they work quite well. The goal of future work is to cut training overhead by 25-30%. This work will focus on making the system more scalable by using lightweight hypergraph sampling and parallel attention computing. Future developments will look into online and incremental learning with the goal of making real-time adaption 20% better when streaming data is involved. It is expected that adding explainable attention processes and richer contextual clues like pricing tactics, promotional effects, and consumer attitude will make the system 15% easier to understand and more efficient to use in real life. This will make AHAB-Net more useful for real-world omni-channel retail systems.

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