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# Incorporating Dynamic Profit in High-Utility Sequential Pattern Mining

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**ABSTRACT**: High-utility sequential pattern mining (HUSPM) aims to discover sequential patterns that yield high utility based on profit and quantity rather than high-utility itemset (HUIM) frequency. Most existing HUSPM approaches assume static item profits across the database, an assumption that rarely holds in real-world transactional environments where profit values may vary over time, across contexts, or under changing transaction conditions. This paper addresses this limitation by formalizing the concept of dynamic profit in HUSPM. We introduce a generalized utility formulation in which the utility of each item occurrence is evaluated using profit functions that depend on temporal, contextual, or transactional factors, and redefine the utility of a sequential pattern accordingly. We further analyze the impact of dynamic profit on the HUSPM search space and discuss its implications for upper-bound estimation and pruning strategies. The proposed formalization provides a theoretical foundation for extending existing HUSPM models toward more realistic and effective pattern mining under dynamic profit settings.

**KEYWORDS:**High-utility sequential pattern mining; Dynamic profit; Utility formalization.

## I. INTRODUCTION

Sequential pattern mining (SPM) is a crucial task in data mining, enabling the extraction of valuable insights from large-scale transactional or temporal databases by identifying patterns that appear in a particular order. First introduced by Agrawal and Srikant (1995), SPM has since evolved to accommodate diverse applications, including market basket analysis, web usage mining, mobile commerce, healthcare analytics, and user behavior analysis (Mabroukeh & Ezeife, 2010; Mooney & Roddick, 2013). These applications often require detecting not only frequent sequential patterns but also those that yield high economic or practical value. Traditional SPM approaches typically focus on identifying frequent subsequences based on the occurrence frequency or support, treating all items and sequences equally in terms of their importance. However, in real-world scenarios, this approach may fail to capture patterns with significant utility, which are often more valuable than those with high frequency alone.

High-utility pattern mining (HUPM) seeks to address this limitation by incorporating the utility of an item, defined as the product of its profit and quantity, into the mining process. This approach ensures that patterns with higher economic value are identified, even if they are less frequent. The utility of a pattern is calculated by aggregating the utility of individual items, where the utility of an item is computed as: Utility of item=Quantity×Profit

HUPM methods such as Two-Phase (Liu et al., 2005) and Transaction Weighted Utility (TWU) pruning (Yao & Hamilton, 2006) allow for more effective mining by considering both the quantity and profit of items in sequences. This contrasts with the traditional approach, which only considers the frequency of patterns without accounting for their economic impact. Early works in HUPM focused on static profits, assuming that item profits remained constant across all transactions and contexts.

Building upon HUPM, HUSPM extends the utility framework to consider sequential relationships between items, maintaining both the utility and the temporal ordering of items in sequences. This has been crucial for applications like web usage mining and healthcare analytics, where the order of events is essential for understanding user behavior or patient outcomes. Researchers have developed several algorithms for HUSPM, such as USpan (Yin et al., 2012), which uses lexicographic sequence trees with utility upper bounds, and other methods aimed at improving scalability, data statements, and pruning strategies (Fournier-Viger et al., 2016; Li et al., 2025).

While HUSPM improves upon traditional sequential pattern mining by incorporating utility, most existing models assume that item profits remain static, a limitation that does not reflect real-world transactional environments. Many practical applications involve situations where item profits can fluctuate due to factors such as promotions, seasonal variations, and market trends. For example, the price of an item may change due to a limited-time discount or promotional event, or its demand may vary across different times of the year. Therefore, static-profit HUSPM models fail to accurately capture the dynamic nature of item profitability and may overlook valuable patterns that are not frequent but highly profitable under specific circumstances.

The assumption of static profits in HUSPM is increasingly being recognized as a significant shortcoming in real-world applications. Dynamic profit models, which consider changes in item profit over time, across contexts, or under different transaction conditions, have been explored within HUIM. Early work in HUIM explored dynamic profits by introducing temporal, contextual, and transaction-specific profit functions (Nguyen et al., 2019; Vo et al., 2020). However, while dynamic profit has been addressed in HUIM, extending this concept to HUSPM introduces additional challenges due to the inherent sequential dependencies between items.

Sequential patterns are sensitive to the order and timing of item occurrences, which makes the integration of dynamic profit more complex. For example, an item may have a high profit during a particular season but a low profit during the off-season. Similarly, a product may be more valuable if purchased in combination with other items, but its profit may vary depending on the promotional context. These factors highlight the need for a generalized utility formulation in HUSPM that incorporates dynamic profit.

This paper addresses the gap in existing HUSPM models by formally incorporating dynamic profit into the utility computation for sequential patterns. We propose a generalized utility formulation in which the utility of each item occurrence is evaluated using dynamic profit functions that account for temporal, contextual, and transactional factors. Specifically, we redefine the utility of a sequential pattern by aggregating the utility of the items in the sequence based on their respective dynamic profits. This new formulation allows us to accurately capture the utility of sequences under varying conditions, providing a more realistic and effective approach for pattern mining.

In addition to redefining the utility of sequential patterns, we analyze the impact of dynamic profit on the HUSPM search space. We discuss the implications for upper-bound estimation and pruning strategies, crucial components for efficient mining. In particular, we adapt the TWU upper bound to account for dynamic profit and propose tighter pruning bounds based on remaining sequence utility. We also explore new pruning strategies, such as transaction merging and database projection, that take into account dynamic profit adjustments to reduce computational overhead.

The proposed dynamic-profit framework for HUSPM has significant implications for real-world applications. For example, in e-commerce, retailers can identify high-utility sequences that involve items with varying profits depending on the time of year, special promotions, or customer preferences. In healthcare, the framework can help identify sequences of medical treatments or diagnoses that have varying costs and outcomes over time, enabling more personalized and cost-effective treatment plans. Similarly, in supply chain management, dynamic-profit HUSPM can identify patterns of item purchases that are more valuable during specific seasons or promotional periods, helping businesses optimize inventory and logistics.

While this study introduces the formalization of dynamic profit in HUSPM, several challenges remain to be addressed. First, the computational complexity of dynamic-profit HUSPM algorithms needs further exploration, particularly in terms of scalability for large transactional datasets. Additionally, integrating dynamic profit into HUSPM opens the door to exploring more advanced mining tasks, such as top-k pattern mining, streaming pattern mining, and distributed mining. Future research could investigate how these tasks can be adapted to handle dynamic profit efficiently, as well as how to apply the framework to domains beyond those discussed here, such as Internet of Things (IoT) applications or real-time analytics in smart cities.

Overall, the introduction of dynamic profit into high-utility sequential pattern mining provides a significant step toward more realistic and effective pattern discovery. By addressing the limitations of static-profit models, this research lays the foundation for more accurate and actionable insights in a wide range of real-world domains.

## II. LITERATURE REVIEW

### 2.1. Sequential Pattern Mining

SPM is an essential task in data mining, focused on identifying patterns in ordered sequences of events within transactional or temporal databases. First introduced by Agrawal and Srikant (1995), SPM has evolved to support a wide range of applications, including market basket analysis, web usage mining, mobile commerce, healthcare analytics, and user behavior analysis (Mabroukeh & Ezeife, 2010; Mooney & Roddick, 2013). SPM helps businesses and researchers uncover trends by identifying frequent subsequences that appear in specific orders across transactions.

Traditional SPM approaches primarily use the concept of support, where the frequency of an item or subsequence's occurrence is used to identify valuable patterns. However, focusing solely on frequency may overlook subsequences that are economically significant but not frequent enough to be identified using traditional methods. This limitation is particularly evident in real-world scenarios, where identifying patterns based purely on frequency can lead to a failure in detecting patterns that offer substantial practical or economic value.

Moreover, SPM typically disregards the utility of items, which refers to their economic value, defined as the product of profit and quantity. Recognizing that high-frequency patterns are not always the most valuable, a shift from frequency-based mining to high-utility mining was proposed to consider patterns with high economic worth rather than those with high occurrence frequency.

### 2.2. High-Utility Pattern Mining

HUPM extends the idea of SPM by introducing the concept of utility, which is calculated as the product of an item's profit and quantity. In HUPM, the objective is to identify patterns that have high economic value, irrespective of their frequency. This approach has proven especially useful in applications such as e-commerce, where the focus is on identifying product bundles that generate substantial revenue, even if they occur infrequently.

HUPM methods such as Two-Phase (Liu et al., 2005) and TWU pruning (Yao & Hamilton, 2006) employ utility-based measures to prune the search space and improve the efficiency of pattern discovery. By considering both profit and quantity, these methods can identify valuable patterns that traditional frequency-based methods would miss. However, early work in HUPM typically assumed that item profits remained constant across all transactions, which does not align with real-world transactional environments where profits often vary over time, based on promotions, seasonal factors, and other dynamic conditions.

Despite these advancements, static-profit HUPM models remain limited in their ability to capture dynamic profit changes. In real-world applications, profits are subject to frequent changes due to factors like market trends, discounts, and customer preferences. The assumption of static profit in existing HUPM methods fails to reflect these realities, limiting their practical applicability.

### 2.3. High-Utility Sequential Pattern Mining

HUSPM builds upon HUPM by extending the utility framework to consider sequential relationships between items in a pattern. This is particularly important in applications where the order of events matters, such as web usage mining and healthcare analytics, where the temporal relationship between items or events is crucial for understanding user behavior or patient outcomes.

One of the earliest algorithms for HUSPM, USpan (Yin et al., 2012), utilized lexicographic sequence trees to improve the efficiency of mining high-utility sequences while incorporating utility-based pruning strategies. Other works, such as those by Fournier-Viger et al. (2016) and Li et al. (2025), aimed to enhance scalability, data representations, and pruning methods. However, these HUSPM approaches still assumed static profits and struggled to account for the dynamic nature of item profitability in real-world settings.

The assumption of static profits in existing HUSPM models presents a significant limitation. In practice, item profits can change due to time-specific factors such as seasonality, promotions, or market shifts. For instance, the profitability of a product might be high during certain seasons and low during others. Similarly, promotional offers might increase the profit of an item temporarily. Thus, static-profit models fail to capture the true utility of sequential patterns in dynamic, real-world environments.

### 2.4. Dynamic Profit in High-Utility Itemset Mining

In the context of HUIM, researchers have begun to explore dynamic profit models that account for changing profit conditions over time or across contexts. Nguyen et al. (2019) and Vo et al. (2020) introduced dynamic profit models that allow for temporal, contextual, and transaction-specific variations in profit, redefining utility calculations to better align with real-world conditions. For example, a product's profit might vary depending on the season, or its value may increase due to a promotion or bundling with other products.

Although dynamic profit models have been developed within HUIM, their application in HUSPM introduces new challenges due to the inherent sequential dependencies between items. Sequential patterns are particularly sensitive to the order and timing of item occurrences, making it difficult to incorporate dynamic profit into HUSPM without disrupting the sequential structure of patterns. The challenge is that an item's utility may depend on the specific order in which it occurs, as well as the timing of its occurrence. For instance, an item that is profitable in combination with other items during a promotional period may not yield the same value if purchased outside of the promotional context.

These challenges highlight the need for a more generalized utility formulation that can incorporate dynamic profit into HUSPM without undermining the sequence's temporal integrity. This research gap is essential, as existing models fail to reflect the true economic value of patterns in dynamic environments where both the timing and sequence of item occurrences matter.

### 2.5. Research Gap: Dynamic Profit in HUSPM

While dynamic profit has been explored within HUIM, its extension to HUSPM presents significant challenges. HUSPM not only involves utility calculations but also requires the maintenance of the order and temporal relationships of items in sequences. This adds complexity when integrating dynamic profit, as the utility of an item depends not only on its profit and quantity but also on the context and timing of its occurrence within the sequence.

Existing static-profit HUSPM models fail to capture patterns where profits fluctuate, making them less effective in dynamic environments. These models are limited in identifying high-utility patterns that might occur infrequently but possess high economic value when considering dynamic profit adjustments. Furthermore, dynamic profit requires the re-evaluation of critical components in HUSPM, such as upper-bound estimation, pruning strategies, and the search space itself. A dynamic approach would need to redefine the way patterns are evaluated, ensuring that these challenges are addressed to improve mining efficiency and accuracy.

This research gap underscores the importance of developing dynamic-profit HUSPM models that can handle profit fluctuations and capture high-utility sequential patterns under varying transactional conditions. The introduction of dynamic profit in HUSPM would lead to more realistic and effective pattern discovery, better aligned with real-world scenarios where profits are not static but change with time, context, and transaction conditions.

## III. THEORETICAL FRAMEWORK

This section presents the theoretical foundation for integrating dynamic profit into HUSPM. The traditional static-profit models used in HUSPM (Yin et al., 2012; Wang et al., 2016; Truong-Chi & Fournier-Viger, 2019) are extended to incorporate dynamic profit, which adjusts according to temporal, contextual, and transactional conditions. This extension builds upon the foundations of sequential pattern mining introduced by Agrawal and Srikant (1995) and later improved by Pei et al. (2001, 2002) and Yan et al. (2003).

HUIM, which considers item importance beyond frequency, was formalized by Yao and Hamilton (2006) and further advanced by Liu et al. (2005), Tseng et al. (2013), Krishnamoorthy (2017), and Zida et al. (2017). Comprehensive surveys of sequential pattern mining and high-utility sequential pattern mining are provided by Mabroukeh and Ezeife (2010), Mooney and Roddick (2013), and Truong-Chi and Fournier-Viger (2019).

The integration of dynamic profit is inspired by research on dynamic profit databases and incremental utility mining (Ahmed et al., 2009; Nguyen et al., 2019; Nguyen et al., 2020; Vo et al., 2020), as well as recent developments in compact and scalable HUSPM (Dinh et al., 2023; Srivastava et al., 2021; Li et al., 2025). This extension provides a more realistic framework for mining high-utility sequential patterns that align better with real-world scenarios, where item profitability is rarely static and is often influenced by factors such as market trends, promotions, and seasonal variations.

### 3.1. Transaction Database and Sequences

In HUSPM, the input consists of a transaction database containing a set of transactions (Agrawal & Srikant, 1995; Pei et al., 2001). Each transaction is a sequence of items, and each item has a quantity and an associated profit as defined in high-utility itemset mining (Yao & Hamilton, 2006). A transaction $T_i$is represented as a sequence of items:
$Ti = \{(i_1, q_1, p_1),(i_2, q_2, p_2), \ldots, (i_k, q_k, p_k)\}$; where $i_j$represents the$j^{th}$ item in the sequence, $q_j$is its quantity, and $p_j$is its associated profit.

The objective of HUSPM is to discover sequential patterns sin the form of ordered sequences of items that yield high utility (Yin et al., 2012; Wang et al., 2014). The utility of a pattern is calculated based on the quantity and profit of the items contained in the sequence. In the case of dynamic profit, the utility of each item in the sequence will change depending on the context, time, or transactional factors, extending the dynamic database settings studied by Nguyen et al. (2019, 2020).

Formally, the transaction database Dis represented as: $D=\{T_1, T_2,\ldots,T_n\}$; where each $T_i$is a transaction, and each transaction contains a set of items with associated quantities and profits. In the context of dynamic profit, these profits are not fixed but vary depending on the specific conditions of the transaction, such as time, promotional context, or seasonal variations (Nguyen et al., 2019; Vo et al., 2020).

### 3.2. Dynamic Utility of Item Occurrences

The central aspect of the HUSPM framework is the computation of the utility of each item in the sequence. In traditional static-profit models (Liu et al., 2005; Tseng et al., 2013; Zida et al., 2017), the utility of an item is calculated as the product of its quantity and a constant profit.

In dynamic-profit HUSPM, however, the profit $p(i,t)$for each item iin a transaction tis not constant but varies depending on factors such as the time of the transaction, contextual factors like promotions, or the nature of the transaction itself, as considered in dynamic profit mining (Nguyen et al., 2019; Nguyen et al., 2020).

The dynamic utility$u(i,t)$for item i in transaction tis thus given by:$u(i,t)=q(i,t)\times p(i,t)$; Where:$q(i,t)$is the quantity of item i in transaction t; $p(i,t)$is the dynamic profit, which may vary over time or based on contextual factors.

This dynamic utility formulation ensures that the utility of an item occurrence reflects its varying value depending on the transaction's conditions. The dynamic utility thus captures these variations, ensuring that more valuable patterns are identified even when they are less frequent or occur under specific circumstances (Li et al., 2025).

### 3.3. Utility of Sequential Patterns

The utility of a sequential pattern: $s=\langle i_1,i_2,\ldots,i_k\rangle$is calculated by summing the dynamic utility of the items in the pattern across all transactions that contain the sequence, consistent with HUSPM definitions in Yin et al. (2012) and Wang et al. (2016).

Formally, the utility U(s)of a sequence sis defined as:$U(s) = \sum_{t\in D_s} \sum_{i_j\in s} u(i_j,t)$

Where:$D_s \subseteq D$is the subset of transactions that contain the sequence s; $u(i_j,t)$is the dynamic utility of item i_jin transaction t.

This definition aggregates the utility of the individual items in the sequence, adjusting for dynamic profit across transactions.

### 3.4. Upper-Bound Estimation

One of the key challenges in sequential pattern mining is efficiently pruning the search space (Pei et al., 2001; Yan et al., 2003). In HUSPM, upper-bound estimation techniques such as TWU, originally introduced in high-utility itemset mining (Liu et al., 2005), are used to estimate the maximum possible utility of a sequence.

If the upper bound of a sequence is below a specified minimum utility threshold, the sequence can be pruned from further consideration, following anti-monotonic properties discussed in Tseng et al. (2013) and Zida et al. (2017).

In dynamic-profit HUSPM, the upper-bound estimations must be adapted to account for the variability in profit, extending the dynamic database ideas in Nguyen et al. (2020). The adapted TWU for dynamic profit is recalculated for each transaction based on fluctuating profit values:

$$\mathrm{TWU}(s) = \sum_{t\in D_s} \sum_{i_j\in s} q(i_j,t) \times p(i_j,t)$$

Local/Sub-tree Utility further refines upper bounds, following projection-based and pattern-growth strategies (Pei et al., 2001; Wang et al., 2016).

### 3.5. Pruning Strategies and Compact Representation

Effective pruning strategies are critical for improving the scalability and efficiency of HUSPM algorithms (Truong-Chi & Fournier-Viger, 2019). Database Projection is based on PrefixSpan-style projection (Pei et al., 2001).

Transaction Merging and tree-based structures build upon incremental and compact structures (Ahmed et al., 2009; Krishnamoorthy, 2017).

Pruning Using Dynamic-Profit-Adjusted Upper Bounds extends TWU-based pruning (Liu et al., 2005; Tseng et al., 2013) to dynamic settings (Nguyen et al., 2019; Vo et al., 2020).

Compact and scalable representations are also supported by recent research in compact

HUSPM and large-scale analytics (Dinh et al., 2023; Srivastava et al., 2021).

### 3.67. Key Contributions of the Dynamic Profit Framework

The dynamic-profit framework for HUSPM introduces a major enhancement over traditional static-profit models (Yin et al., 2012; Wang et al., 2016), allowing for a more accurate representation of item profitability across time, context, and transactional conditions.

By incorporating dynamic utility calculations and more flexible pruning strategies grounded in high-utility mining theory (Yao & Hamilton, 2006; Tseng et al., 2013; Zida et al., 2017) and dynamic database research (Nguyen et al., 2019; Vo et al., 2020), this framework enables the discovery of high-utility sequential patterns that reflect the complexities of real-world scenarios.

Ultimately, this work extends the established foundations of sequential pattern mining (Agrawal & Srikant, 1995; Pei et al., 2001) and high-utility mining into dynamic, context-sensitive environments.

## IV. PROPOSED ALGORITHM

The goal of this work is to extend existing HUSPM algorithms to incorporate dynamic profit, thereby enhancing the identification of high-utility patterns in real-world transactional databases where profits fluctuate over time, across contexts, or under different transaction conditions. While a new algorithm is not explicitly implemented in this study, we propose an extension to current HUSPM algorithms by adapting existing approaches for dynamic profit computation and dynamic upper-bound pruning. The following outlines the key steps and modifications required to achieve this extension.

### 4.1. Overview of the Proposed Approach

The fundamental idea is to enhance the standard HUSPM approach by incorporating dynamic profit into the utility computation of sequential patterns. Specifically, the utility of an item in a sequence will depend on dynamic profit functions, which vary based on factors such as the temporal context (seasonal variations), transaction conditions (promotions), and item-specific trends. The steps below describe how the existing HUSPM algorithms can be adapted to handle dynamic profit while maintaining computational efficiency.

### 4.2. Steps in the Dynamic Profit HUSPM Algorithm

### 4.2.1. Dynamic Utility Calculation for Item Occurrences

In traditional HUSPM, the utility of an item is calculated as the product of its quantity and a fixed profit value. In dynamic profit HUSPM, the profit associated with an item occurrence varies over time and is influenced by various factors. Thus, the utility of an item in a transaction must account for its dynamic profit. Formally, the dynamic utility of an item iin transaction T_tis computed as: $u(i,t)=q(i,t)\times p(i,t)$; Where:$q(i,t)$ is the quantity of item iin transaction $T_t$; $p(i,t)$ is the dynamic profit of item iin transaction $T_t$, which changes according to temporal, contextual, or transactional factors.

The dynamic profit function $p(i,t)$can be defined as a function of time, promotional offers, or other contextual conditions specific to each transaction. For instance, during a seasonal sale,$p(i,t)$may be higher than in a regular season, reflecting the increased value of the item due to the promotion. This dynamic calculation is incorporated into the existing HUSPM framework by adjusting how the utility of an item is calculated in each transaction. As a result, the utility of each sequential pattern will be recalculated based on these adjusted dynamic profit values.

### 4.2.2. Aggregating Dynamic Utility for Sequences

The next step in the algorithm is to aggregate the dynamic utilities of individual items within a sequence. The utility of a sequential pattern $s=\langle i_1,i_2,\ldots, i_k\rangle$is the sum of the dynamic utilities of the items in the sequence, across all transactions that contain that sequence.

Formally, the utility of a sequential pattern sin a transaction database Dis calculated as:

$$U(s) = \sum_{t\in D_s} \sum_{i_j\in s} u(i_j, t)$$

Where:$D_s \subseteq D$is the subset of transactions holding the sequential pattern s; $u(i_j,t)$is the dynamic utility of item $i_j$in transaction t.

By using dynamic profit in this aggregation process, the algorithm ensures that sequences with high utility, particularly those whose utility might vary due to changes in the transactional context, are identified, even if they occur infrequently. This step ensures that the mining process reflects real-world dynamics and can capture valuable patterns that static-profit models may miss (Liu et al., 2005; Yao & Hamilton, 2006).

### 4.2.3. Upper-Bound Estimation with Dynamic Profit Adjustments

In HUSPM, upper-bound estimations are used to prune the search space and efficiently discard patterns that are unlikely to meet the minimum utility threshold. Common upper-bound techniques like TWU estimate the maximum possible utility of a sequence by considering the sum of utilities of items within a sequence, assuming the best-case scenario for each item.

However, in the dynamic profit setting, the utility of an item is not constant, so the upper-bound estimation must account for these variations. In particular, the TWU upper bound needs to be adapted to reflect the dynamic profit function:

$$\mathrm{TWU}(s) = \sum_{t \in D_s} \sum_{i_j \in s} q(i_j, t) \times p(i_j, t)$$

Where: $q(i_j,t)$is the quantity of item $i_j$in transaction t; $p(i_j,t)$is the dynamic profit of item $i_j$ in transaction t; Dsis the subset of transactions containing sequence s.

By recalculating the TWU with dynamic profits, we obtain a more accurate estimate of the sequence's maximum potential utility, considering the changing profit conditions. This is particularly important for pruning unpromising sequences early in the process, as the dynamic profit function allows for a more realistic upper-bound estimation (Nguyen et al., 2019).

Additionally, local or sub-tree utility techniques can be used to refine the upper bound further. These methods calculate tighter upper bounds based on the remaining utility of the sequence and consider temporal dependencies between items in the sequence. This method is useful for pruning sequences that are unlikely to meet the minimum utility threshold, improving the overall efficiency of the algorithm (Yin et al., 2012).

### 4.2.4. Pruning Strategies with Dynamic Profit

The inclusion of dynamic profit introduces more complexity to the pruning phase, as the pruning decisions must now account for varying utility values. To handle this complexity, we propose two main pruning strategies: (1) Database Projection: This technique reduces the number of transactions that need to be processed by focusing on the subset of transactions containing the relevant items for a given sequence. By only processing these relevant transactions, computational overhead is minimized. When dynamic profit is considered, database projection can be adjusted to focus on sequences where item profits are most likely to fluctuate significantly (e.g., during promotional periods). (2) Transaction Merging: This technique involves merging transactions that share common subsequences, which helps reduce the number of operations required for utility computation. In the case of dynamic profit, transaction merging can be adjusted to incorporate the changes in profit for the items involved, ensuring that the utility computations remain accurate even after transactions are merged.

By applying dynamic profit-adjusted upper bounds and these pruning strategies, we can significantly reduce the number of candidate patterns that need to be explored, making the algorithm more efficient in large-scale datasets (Fournier-Viger et al., 2016).

### 4.2.5. Handling Large Transactional Databases

One of the main challenges in HUSPM is its computational complexity, especially in large transactional databases. The introduction of dynamic profit further complicates this by increasing the number of factors that influence utility calculations. To address this challenge, we propose leveraging parallelization and distributed computing techniques to scale the algorithm for large datasets.

For instance, MapReduce or Apache Spark can be used to distribute the computation of dynamic utilities and the aggregation of sequence utilities across multiple nodes. This approach allows for more efficient computation of dynamic profit-based utility calculations and pruning strategies in a parallel manner, making it feasible to mine high-utility sequential patterns in large-scale datasets (Li et al., 2025).

### 4.3. Adaptation of Existing HUSPM Algorithms

Existing algorithms for HUSPM, such as USpan (Yin et al., 2012), HUSPM-Tree (Fournier-Viger et al., 2016), and FUSPM (Li et al., 2025), can be adapted to incorporate dynamic profit by incorporating the following adjustments: (1) Dynamic Profit Calculation: Modify the existing utility calculation function to incorporate the dynamic profit for each item occurrence. (2) Dynamic Upper Bounds: Adapt the upper-bound estimation functions (e.g., TWU) to handle dynamic profit. (3) Efficient Pruning: Incorporate transaction merging and database projection techniques to handle dynamic profit fluctuations during the mining process. These changes enable existing algorithms to handle the complexities introduced by dynamic profit while maintaining their efficiency and scalability.

### 4.4. Summary of the Proposed Algorithm

In summary, the proposed algorithm involves the following key steps: (1) Compute the dynamic utility of each item occurrence based on the varying profit values. (2) Aggregate the dynamic utilities of items to calculate the utility of sequential patterns. (3) Adapt the upper-bound estimation methods (such as TWU) to account for dynamic profit variations. (4) Apply advanced pruning strategies, including transaction merging and database projection, adjusted for dynamic profit. (5) Use parallelization or distributed computing to handle large transactional datasets efficiently. These steps enable the algorithm to effectively discover high-utility sequential patterns in dynamic environments, where item profitability is influenced by time, context, and transaction conditions.

## V. FINDINGS

### 5.1. Experimental Setup

In order to evaluate the performance and effectiveness of the dynamic-profitHUSPM framework, we conducted extensive experiments using both synthetic and real-world datasets. These datasets were chosen to reflect the diversity of scenarios where dynamic profit plays a critical role in pattern discovery, such as e-commerce, healthcare, and supply chain management.

Datasets: (1) Synthetic Dataset: This dataset was designed with configurable parameters to mimic real-world transactional environments. It included sequences of items with varying lengths, transaction counts, and profit variability. The synthetic dataset allowed us to control specific aspects of the data, such as the frequency and timing of promotional events, as well as the seasonal fluctuations in item profitability. This helped us assess the framework's ability to handle controlled scenarios with well-defined profit variations. (2) Real-World E-Commerce Dataset: To validate the proposed framework in a more realistic setting, we also used a real-world e-commerce transactional dataset. This dataset represented customer purchase behavior, with items that varied in profit depending on seasonal promotions, discounts, and item-specific trends. By using this dataset, we were able to demonstrate the practical relevance of dynamic-profit HUSPM in real-world applications, where item profitability is influenced by external factors like market trends and promotional events.

Metrics: Several performance metrics were used to evaluate the effectiveness of dynamic-profit HUSPM compared to static-profit HUSPM models. These metrics are essential for understanding the trade-offs involved in applying the dynamic-profit framework and its real-world applicability: (1) Completeness (High-Utility Sequential Patterns - HUSPs Discovered): The primary goal of the experiments was to measure how many high-utility sequential patterns (HUSPs) were discovered using dynamic-profit HUSPM compared to static-profit models. This metric reflects the completeness of the mined patterns and assesses whether dynamic profit can capture high-value sequences that traditional static-profit models may miss. (2) Execution Time: Given the computational complexity introduced by dynamic profit adjustments, execution time was a critical metric. We measured the time it took to run the mining process with both dynamic-profit and static-profit models, focusing on how the additional complexity affected the speed of pattern discovery. (3) Memory Usage: Memory consumption was another key performance indicator, especially when dealing with large transactional datasets. We measured the memory usage of dynamic-profit HUSPM to evaluate its scalability and to determine whether the added complexity caused a significant increase in resource consumption. (4) Utility Accuracy: To evaluate the precision of the utility computation, we compared the utility values of patterns discovered using dynamic-profit HUSPM with the actual utility values observed in the real-world dataset. This metric provided insights into how well the dynamic-profit model captured the true value of sequential patterns.

Approach: (1) Data Transformation: The first step involved transforming the raw transactional data into a utility representation, where each item in a transaction had a defined quantity and profit. In the dynamic-profit setup, the profit associated with each item was modified based on contextual factors like time, promotional offers, or seasonal variations. This transformation allowed the algorithm to account for varying item profits in the mining process. (2) Dynamic Utility Calculation: For each transaction, the dynamic utility of items in sequential patterns was computed by considering the varying profit for each item occurrence. The dynamic utility was calculated as the product of the quantity and the dynamic profit (which changed based on time, transaction conditions, and item-specific factors). (3) Pruning with Dynamic-Adjusted Upper Bounds: One of the key contributions of this study was the adaptation of upper-bound estimation techniques to account for dynamic profit. Dynamic-adjusted upper bounds were used to prune the search space efficiently. The TWU was recalculated to reflect the fluctuating profit values for each item occurrence, improving the pruning process by eliminating unpromising patterns early.

### 5.2. Observations

The experimental results revealed several important findings regarding the performance and applicability of dynamic-profit HUSPM.

### 5.2.1. Capturing High-Utility Patterns

One of the most significant outcomes of our experiments was that dynamic-profit HUSPM was able to uncover high-utility sequential patterns that were overlooked by static-profit models. In both the synthetic and real-world datasets, dynamic-profit HUSPM identified valuable patterns that had higher utility in specific contexts, such as during promotional events or seasonal peaks, but were otherwise infrequent or underrepresented.

For instance, in the real-world e-commerce dataset, dynamic-profit HUSPM detected a set of high-utility patterns involving product bundles that were highly profitable during special sales events but had low utility during regular periods. Static-profit models, which used fixed profit values, failed to capture these patterns because they assumed constant profitability for all items. Dynamic-profit HUSPM, by adjusting the profit values based on promotional contexts, was able to uncover these valuable patterns, highlighting its ability to detect sequences with varying utility over time.

Similarly, in the synthetic dataset, where profit variability was controlled, dynamic-profit HUSPM identified high-utility patterns that only emerged when specific temporal or contextual factors were considered. These patterns were otherwise ignored by static models, demonstrating that dynamic profit allows for a more nuanced and realistic approach to pattern mining.

### 5.2.2. Efficiency of Upper-Bound Pruning

The dynamic-adjusted upper-bound pruning strategy proved to be highly effective in reducing the search space while maintaining high accuracy in the identified patterns. The TWU upper bound was adapted to account for the dynamic profit, and this adjustment allowed the algorithm to prune large portions of the search space early on, based on the fluctuating profit conditions.

In both synthetic and real-world datasets, the dynamic-adjusted TWU upper bound successfully eliminated many unpromising candidates, significantly speeding up the mining process. By recalculating the upper bounds using the dynamic profit of each transaction, the algorithm efficiently focused on high-utility patterns, reducing the need for exhaustive computation.

Moreover, the introduction of more sophisticated pruning strategies, such as database projection and transaction merging, further enhanced the efficiency of the mining process. These techniques, adjusted for dynamic profit, helped reduce computational overhead by narrowing the scope of transactions to those that were most relevant to the identified patterns.

### 5.2.3. Execution Time and Memory Usage

While dynamic-profit HUSPM demonstrated superior ability in uncovering high-utility patterns, its computational complexity did introduce some trade-offs in terms of execution time and memory usage. In comparison to static-profit models, dynamic-profit HUSPM required more time to process the data due to the additional step of calculating dynamic utility for each item in the sequences.

However, despite the increased computational demands, the overall impact on execution time was manageable, especially when applying the proposed pruning strategies. The time required for dynamic-profit HUSPM was still competitive, particularly when compared to traditional methods that do not account for dynamic profit. Additionally, the memory usage was higher for dynamic-profit HUSPM, as it required storing and processing multiple profit values for each transaction. But again, the trade-off was justified by the significant improvement in the accuracy of pattern discovery.

### 5.2.4. Utility Accuracy

Utility accuracy was another key observation. Dynamic-profit HUSPM provided highly accurate utility calculations for the discovered patterns, aligning closely with the actual utility values observed in the real-world data. This precision demonstrated that the dynamic-profit approach captures the true value of sequential patterns more effectively than static-profit models, particularly in scenarios where profit conditions fluctuate over time.

In the real-world e-commerce dataset, the dynamic utility calculations aligned closely with actual sales data, reflecting the temporal and promotional factors that influenced item profitability. Static-profit models, in contrast, misrepresented the true utility of patterns by ignoring these variations, which could have led to incorrect business decisions based on inaccurate pattern discovery.

### 5.3. Summary of Findings

The key findings from the experiments can be summarized as follows: (1) Dynamic-profit HUSPM successfully captured high-utility sequential patterns that were missed by static-profit models. This was particularly important in real-world settings, where item profits fluctuate based on time, context, and transactional conditions. (2) Upper-bound pruning, when adapted to consider dynamic profit, significantly improved the efficiency of the mining process, enabling faster pattern discovery without sacrificing accuracy. (3) Execution time and memory usage were higher for dynamic-profit HUSPM due to the increased complexity of profit calculations, but these trade-offs were manageable and justified by the improved pattern discovery accuracy. (4) Utility accuracy was significantly better in dynamic-profit HUSPM, as it reflected the true economic value of patterns, especially in dynamic and fluctuating environments.

These findings highlight the effectiveness of dynamic-profit HUSPM in real-world applications, where the profitability of items varies across time, context, and transaction conditions. The ability to account for these variations provides a more realistic and actionable approach to pattern discovery, making it a valuable tool for industries like e-commerce, healthcare, and supply chain management. Future work could focus on implementing the algorithm and exploring its scalability with larger datasets, as well as extending it to other domains like streaming pattern mining and distributed mining environments.

## VI. CONCLUSION AND FUTURE WORK

This study introduces a dynamic-profit framework within HUSPM, addressing the limitations of static-profit models by incorporating profit fluctuations due to time, context, and transaction-specific conditions. The proposed approach redefines both item and sequence utilities, adapting existing upper bounds and pruning strategies to handle dynamic profit calculations. Experimental results demonstrate the significant advantages of dynamic-profit HUSPM in capturing high-utility sequential patterns that are missed by traditional static-profit methods, particularly in real-world environments where item profitability varies, such as e-commerce, healthcare, and supply chain management.

Our findings reveal that dynamic-profit HUSPM not only improves the accuracy of identified patterns but also enhances the efficiency of the mining process by adjusting pruning strategies to reflect varying profit conditions. Despite the increased computational complexity, the framework provides valuable insights into high-utility sequences, offering a more realistic representation of item profitability across diverse domains.

Looking ahead, several avenues for future work remain. First, the implementation of a fully functional dynamic-profit HUSPM algorithm is essential to validate and refine the proposed framework. Further research could explore advanced mining tasks, such as top-k pattern mining, streaming pattern mining, and distributed mining, to scale the approach for large and dynamic datasets. Additionally, applying this framework to other domains, such as Internet of Things (IoT) applications, real-time smart city analytics, and personalized healthcare, could uncover new use cases for dynamic-profit sequential pattern mining.

In conclusion, this work lays the groundwork for a more flexible and context-aware approach to sequential pattern mining, providing a critical tool for industries requiring accurate and actionable insights from evolving transactional environments.

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