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PAPER

Relationship between Perceived Value and Purchase Intention in Manufacturing Enterprises' Mobile Interaction Platforms

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ABSTRACT

Mobile interaction platforms of manufacturing enterprises have become core channels for digital marketing and customer value co-creation. Understanding how these platforms influence customers' purchase intention (PI) is of critical importance for advancing digital transformation. Traditional research has primarily relied on questionnaire-based static validation of the relationship between perceived value and PI, which has limited capacity to reveal the dynamic formation of value perception and often neglects authentic, fine-grained behavioral data of users. In this study, sequential pattern mining was innovatively introduced into the domain of consumer behavior research to dynamically identify and quantify the pathways of value perception on mobile platforms. A value perception measurement method, ValuePath-K, integrating sequence length, was developed, together with an efficient mining algorithm, ValuePathMiner-Final, to extract key behavioral patterns driving purchase decisions from user interaction sequences. Through these methods, the dynamic mechanisms linking the dimensions of perceived value and PI were uncovered. The findings provide not only a new paradigm for advancing the perceived value–PI theory in the context of industrial digitalization but also quantifiable decision support for the optimization of platform design, precision marketing, and customer relationship management in manufacturing enterprises.

KEYWORDS

perceived value, purchase intention (PI), mobile interaction platform, sequential pattern mining, manufacturing enterprises

1 INTRODUCTION

As Industry 4.0 and digital transformation continue to evolve, manufacturing enterprises are increasingly shifting their competitive priorities—from emphasizing product functionality to focusing on customer-centric value co-creation and service-oriented innovation [1–5]. Against this backdrop, mobile interaction

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platforms [6–9] have become essential vehicles for connecting with customers, delivering services, and demonstrating value. However, unlike the consumer Internet domain [10], purchasing decisions in the manufacturing sector [11] are characterized by high involvement, extended decision cycles, and strong rationality, rendering conventional e-commerce theories developed for fast-moving consumer goods [12, 13] only partially applicable. A critical unresolved question arises: through which mechanisms do the mobile platforms of manufacturing enterprises shape customers' perceived value, and how do these multidimensional perceptions progressively deepen to ultimately catalyze explicit purchase intention (PI)?

Existing research has largely relied on questionnaire surveys [14, 15] and structural equation modeling [16, 17] to statically validate hypothesized relationships among variables. Although such approaches have confirmed the positive effect of value on intention, they remain essentially "snapshot" analyses with notable limitations. First, they fail to capture the dynamic formation of perceived value, leaving the complete journey—from initial exposure, information gathering, and evaluation to the final decision—unrevealed. Second, retrospective questionnaires [18] are susceptible to subjective biases and cannot accurately quantify users' authentic, fine-grained behavioral sequences on the platforms. Finally, traditional methods lack the capability to automatically and efficiently identify the most representative "golden pathways" from vast behavioral datasets, thereby constraining the practical applicability of research conclusions.

To address the aforementioned limitations, an exploratory study integrating consumer behavior theory with advanced data mining techniques was undertaken. The main objectives are as follows: First, a theoretical model of perceived value and PI within manufacturing enterprises' mobile interaction platforms was constructed; second, sequential pattern mining was innovatively introduced. By means of the improved ValuePath-K value perception measurement method and the efficient ValuePathMiner-Final algorithm, users' back-end behavioral data were deeply mined with the aim of objectively and dynamically identifying the critical value perception pathways that drive PI from authentic behavioral sequences such as "login → case browsing → manual download → customer service consultation → order placement."

This study carries significant theoretical and practical implications. Theoretically, the abstract concept of perceived value is transformed into observable and quantifiable behavioral sequences, thereby greatly extending the depth and explanatory power of this construct in the context of industrial digital marketing. Practically, a data-driven decision-making tool is provided for enterprises, enabling the precise identification of critical value-delivery touchpoints, the optimization of mobile platform functionality and customer guidance processes, and the enhancement of both customer conversion rates and loyalty. In this way, a sustainable competitive advantage can be established amid the ongoing wave of digital transformation.

2 MINING USER VALUE PERCEPTION PATHWAYS FOR THE UNDERSTANDING OF PI SEQUENCES

To accurately extract long sequence patterns that are information-rich and capable of fully reflecting the deepening process of value perception from the massive interaction data generated on manufacturing enterprises' mobile platforms, a systematic implementation framework was designed in this study. First, in terms of measurement, an improved value perception method, ValuePath-K, integrating sequence length, was proposed on the basis of traditional indicators. To efficiently compute this metric, a specialized, improved vertical data format structure, VDF-ValuePath, was developed. Furthermore, to address the problem of combinatorial explosion in sequential patterns, a compact upper bound of ValuePath-K was derived, upon which powerful pruning strategies were designed. By integrating the metric, structure, and pruning strategies with a baseline mining algorithm, an efficient and precise enhanced algorithm—ValuePathMiner-Final—was ultimately established. The algorithm outputs the *Top-K* sequences, each representing a distinctive and complete user value perception journey. These sequences constitute the "golden pathways" that provide clear and non-redundant data-driven insights into the underlying mechanisms shaping purchase intention.

2.1 Value perception in mobile interaction sequences

In the mining of sequential patterns related to PI, attention is not only directed to whether a purchase is ultimately completed but, more critically, to the progressive deepening of perceived value that culminates in PI. This process is manifested as a series of continuous platform interaction behaviors, referred to as "value perception pathways." The length of such a pathway—the number of key behavioral events contained in the interaction sequence—should not be regarded as a mere numerical count. Rather, it serves as a direct reflection of the depth and breadth of value exchange between the user and the platform. For example, a short pathway such as "login → order placement" may indicate that the decision was driven by pre-existing brand recognition or explicit demand, where perceived value is instantaneous and superficial. In contrast, a longer pathway such as "login → browsing of industry white papers → use of product configurator → comparison of technical parameters → consultation with online customer service → download of quotation → order placement" delineates a comprehensive value perception journey, from initial interest and knowledge formation to evaluation, validation, and ultimately, trust. The latter pathway provides substantially deeper insights into how value is created and perceived, offering knowledge of greater significance for the optimization of customer journeys and the empowerment of precision marketing strategies. Therefore, sequence length was adopted in this study as a critical proxy indicator for assessing the completeness and depth of the value perception process.

To effectively identify long sequence patterns that are information-rich and capable of fully reflecting the deepening process of value perception from large volumes of user interaction data, an improved value perception measurement method—ValuePath-K—was designed. This method was constructed by innovatively integrating the pathway length factor into traditional interest-based measures. Let the length of an interaction sequence T be denoted as $\Sigma_i |A_i|$, and the maximum sequence length among all sequences be represented by $MAX\Sigma_i |A_i|$. The support of sequence T is denoted as $SUP(T)$, and its expected support as $ES(T)$. The core formula of ValuePath-K can therefore be expressed as:

$$ValuePath_K(T) = leverage_K(T) = \frac{\sum_i |A_i|}{MAX\sum_i |A_i|} \times (SUP(T) - ES(T)) \quad (1)$$

Since $1 \leq \Sigma_i \left|A_i\right| \leq MAX\Sigma_i \left|A_i\right|$, it follows that $0 < \Sigma_i \left|A_i\right| / MAX\Sigma_i \left|A_i\right| \leq 1$. For a given interaction sequence set, $\left|MAX\Sigma_i \left|A_i\right|\right.$ is fixed, meaning that the regulatory factor in the length coefficient $\left|\Sigma_i \left|A_i\right| / MAX\Sigma_i \left|A_i\right|\right.$ is primarily determined by the length of sequence T, denoted as $\Sigma_i \left|A_i\right.$. Consequently, even when the statistical significance of a long sequence is slightly lower than that of a short sequence, its larger length coefficient substantially elevates its final ValuePath-K value. Through this mechanism, the ranking weight of long sequences that capture complete user journeys is intentionally enhanced. This ensures that the analysis is not biased toward short "shortcut" sequences, which, though frequent, reflect only fleeting value perception processes. Instead, the method emphasizes long value perception pathways that embody deeper interactions and require more deliberate cultivation.

2.2 Improved vertical data format structure

Efficient processing of large-scale mobile interaction sequence data constitutes the primary challenge in mining user value perception pathways. Sequential pattern mining algorithms generally adopt either a horizontal or vertical data format. In the horizontal format, user sessions or visits are stored as the recording unit, capturing the complete mobile interaction behavior flow of each user, such as SID-1: [login, case browsing, manual download, customer service consultation, order placement]. However, when the prevalence of a specific interaction pattern is to be calculated, the horizontal format requires repeated scans across all user interaction sequences, resulting in low computational efficiency. By contrast, the vertical format indexes each independent behavior event and records the lists of positions where it appears across different user interaction sequences. This structure enables the support and occurrence positions of any behavior combination to be rapidly computed through simple list intersection operations, eliminating the need for full-database scans. Such efficiency makes it particularly well suited for the deep mining of large-scale behavior repositories. Figure 1 illustrates the vertical data format structure of the interaction behavior sequence database.

Although the traditional vertical data format demonstrates efficiency in frequency computation, its design does not sufficiently account for sequence depth, a critical dimension in value perception pathways. Since the core computation of the ValuePath-K metric relies on pathway length, targeted optimization of the traditional vertical format was undertaken. An enhanced structure, VDF-ValuePath, was proposed. This structure retains the "sequence flow" and "position" attributes but introduces an additional attribute, "path length," for each sequence pattern. During initialization, the length of each elementary behavior event is assigned the value of 1. When longer sequences are generated through pattern extension, their path length is calculated in real time as the sum of their parent sequence lengths. This improvement ensures that the physical length of a sequence becomes a readily available static attribute within the data structure, rather than a dynamically computed value that must be recalculated each time it is required.

Pattern:a		
Sequence flow	Position	Length
1	2	1
2	2,3	

Pattern:b		
Sequence flow	Position	Length
1	1	1
2	3	
3	2	
4	2,4	

Pattern:*c*		
Sequence flow	Position	Length
1	1.3.4	1
2	1.2	
4	1.3	

Pattern:d		
Sequence flow	Position	Length
1	1	1
2	3	
3	1	
4	4	

Pattern:e		
Sequence flow	Position	Length
1	2	1
2	4	
3	2,3	
4	3	

Fig. 1. Vertical data format structure of the interaction behavior sequence database

2.3 ValuePathMiner algorithm for value pathway mining

The proposed ValuePathMiner algorithm takes as input the user mobile interaction sequence database *D* and the desired number of pathways *k*. Using the ValuePath-K metric as the core evaluation indicator for quantifying the depth of value perception, the algorithm outputs the set of *Top-k* most representative value perception pathways from database *D*. The objective of its design is to efficiently and precisely identify behavioral sequences that do not occur by chance but instead reflect the complete process through which users' perceived value evolves from initial emergence to maturity. A representative example of such a pathway is "login → browsing of industry white papers → use of product configurator → customer service consultation → order placement." The ValuePathMiner algorithm employs a hybrid search strategy that combines breadth-first initialization with depth-first extension. An efficient bootstrapping process is first applied to rapidly establish an initial *Top-k* set, thereby improving pruning efficiency during subsequent searches. This is followed by recursive pattern expansion, which explores longer user interaction pathways embodying deeper value perception, while dynamically updating the final output.

Figure 2 illustrates the design framework of the ValuePathMiner algorithm. The algorithm begins with a series of initialization operations. First, the result queue *top_K* is cleared, and a variable *min_ValuePath* is set to dynamically record the minimum value perception score among the current *Top-K* results. The sequence database is then scanned to construct the improved vertical data format structure (VDF-ValuePath) for all elementary mobile interaction events, which are subsequently ordered by descending support and stored in queue *w*. The critical bootstrapping step is then executed. In this step, a broad and rapid search is conducted over all possible two-event behavior combinations in the database. Their ValuePath-K values are calculated, and the results are used to pre-populate the initial *top-K* set. This strategy enables the early establishment of a relatively high *min_ValuePath* threshold, enabling earlier and more decisive pruning of path branches with low potential for value perception in subsequent, deeper pattern extensions. As a result, the search space is substantially reduced and overall mining efficiency is improved.

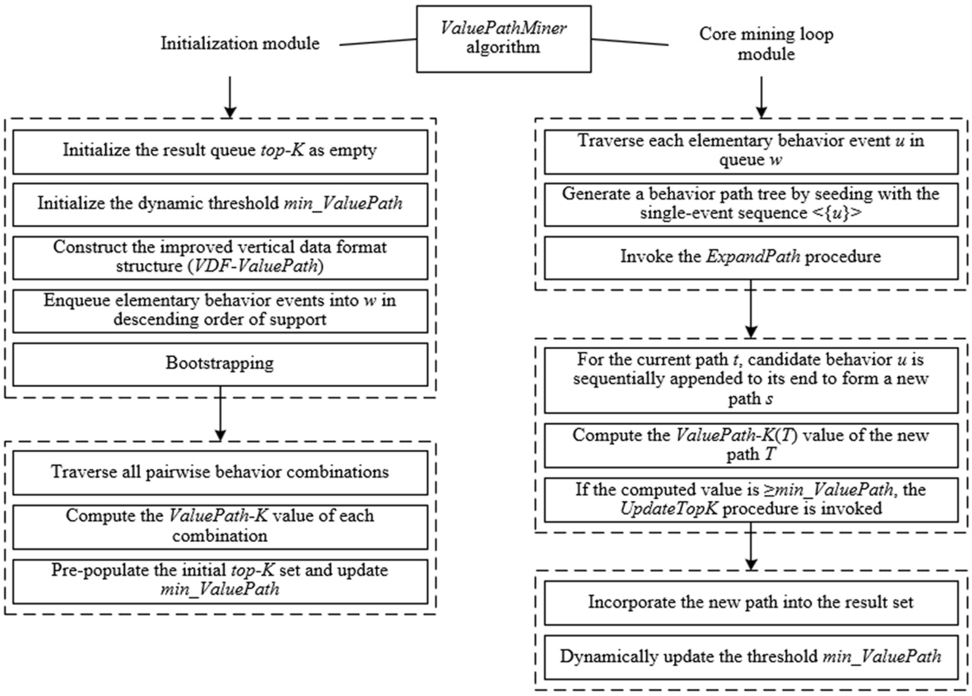


Fig. 2. Design framework of the ValuePathMiner algorithm

Following initialization, the algorithm enters the core mining loop. Each elementary behavior event *u* in queue *w* is traversed, and the single-event sequence <{*u*}> is designated as the seed of a behavior path tree. The ExpandPath procedure is then invoked to recursively extend the path in a depth-first manner. The procedure serves as the core of the algorithm. For a given current path *s* and its list of candidate extensions, each candidate behavior *u* is sequentially appended to the end of path *t* to form a new, longer potential value perception pathway *s*. For each new path *s*, its ValuePath-K(s) value is immediately computed. If the value exceeds the current threshold *min_ValuePath*, the path is recognized as both sufficiently long and of significant value perception depth. The UpdateTopK procedure is then invoked to incorporate the new path into the final result set, and the threshold is updated. This mechanism ensures that the final *Top-K* output consistently represents the most valuable user interaction journeys discovered.

2.4 Pruning strategies

In the study of mining user value perception pathways for understanding PI sequences, the challenges posed by the massive scale of mobile interaction sequence data and the combinatorial explosion of candidate patterns were addressed through the design and implementation of a set of collaborative pruning strategies. These strategies are not applied selectively but operate in coordination, jointly forming the algorithmic core for efficiently and accurately discovering the most representative value perception pathways. Their collaborative workflow and respective functions are detailed below.

First, a hybrid search strategy is employed as the foundation and starting point of the entire pruning process. This strategy is not a mere technical choice but serves the strategic objective of rapidly establishing a high threshold. The algorithm begins with a breadth-first bootstrapping search, which quickly computes the ValuePath-K values of all elementary two-event sequences. This operation, conducted at minimal computational cost, pre-populates the result queue with *K* of the most valuable initial sequences, thereby dynamically elevating the global pruning threshold *min_ValuePath* from its initial value of zero to a substantially higher level. The threshold, once raised, acts as a stringent "gatekeeper" for all subsequent deeper mining, imposing a rigorous screening standard. The objective is to eliminate as many low-potential search directions as possible during the early stage of mining, thereby clearing the ground for more efficient deep exploration.

Subsequently, during the mining of sequences longer than two events, branch-pruning strategies based on the upper bound of value perception are applied as the "gatekeeper" at each extension node. Whenever a new candidate path *s* is generated through sequential extension, its theoretical upper bound of value perception $UB(t) = \Sigma_i \left|A_i\right| + 1 / MAX\Sigma_i \left|A_i\right| \times SUP(t)$ is immediately calculated.

$$ValuePath_K(s) = \frac{j_s}{MAX\sum_i |A_i|} \times (SUP(s) - ES(s)) \tag{2}$$

$$\because\ ES(s) \geq 0 \tag{3}$$

$$\therefore ValuePath_K(s) \leq \frac{j_s}{MAX\sum_i |A_i|} \times SUP(s) \tag{4}$$

Since $ValuePath_K(s)$ satisfies the above conditions and because sequence *t* is extended to sequence *s* through the *t*-extension illustrated in Figure 3, it follows that:

$$ValuePath_K(s) \leq \frac{j_t + 1}{MAX\sum_i |A_i|} \times SUP(s) \tag{5}$$

Given the anti-monotonic property of support, the following relationship holds:

$$SUP(s) \leq SUP(t) \tag{6}$$

Therefore,

$$ValuePath_K(s) \leq \frac{j_s}{MAX\sum_i |A_i|} \times SUP(s) \leq \frac{j_t + 1}{MAX\sum_i |A_i|} \times SUP(t) \tag{7}$$

Pattern:a		
Sequence flow	Position	Length
1	1	1
2	2,3	

Pattern:b		
Sequence flow	Position	Length
1	1	1
2	3	
3	4	
4	1	

Pattern:a,b		
SID	Position	Length
1	2	2
3	3	

Fig. 3. Illustration of *t*-extension based on the improved vertical data format structure

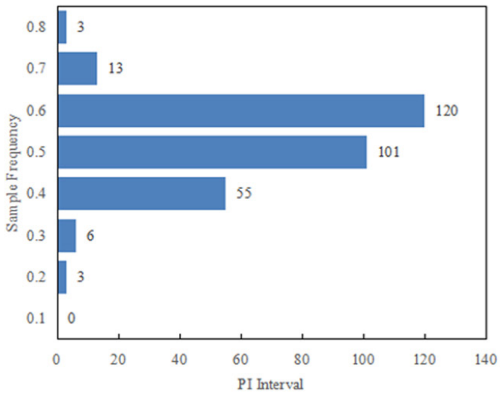
From the above formulation, it can be concluded that the upper bound *UB*(*t*) constitutes a rigorous mathematical estimate representing the maximum possible ValuePath-K value attainable by any path with *s* as its prefix. At this stage, the algorithm compares $UB(t)$ with the real-time high threshold *min_ValuePath* established through the hybrid search strategy. If $UB(t) <$ *min_ValuePath*, it indicates that even with additional computational effort, no subsequent extension of t could yield a path superior to the current *Top-K* results. In such cases, further exploration of this branch is decisively terminated, thereby achieving precise local pruning.

3 RESULTS AND DISCUSSION

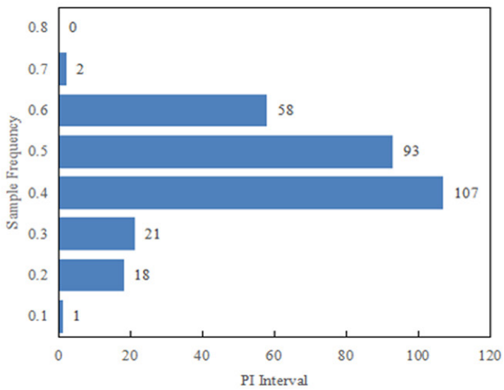
To validate the adaptability and effectiveness of the ValuePathMiner-Final algorithm in mining different types of user interaction sequences on manufacturing enterprises' mobile platforms, experiments were conducted using datasets that cover multiple scenarios. As shown in Table 1, the datasets encompass product consultation, document acquisition, purchase conversion, mixed interaction, and simulated testing contexts. The total number of sequences ranges from 5,000 to 15,000, the number of behavior event types varies between 10 and 20, the average sequence length ranges from 9.6 to 16.3, and the maximum sequence length falls between 25 and 45. With the exception of Manu-Demo, which represents a simulated scenario, all datasets are derived from real business data. These datasets provide representative samples in terms of scale, behavioral complexity, and scenario authenticity, thereby offering robust empirical support for mining deep value perception pathways such as "login → case browsing → manual download → customer service consultation → order placement."

Table 1. Characteristics of user behavior sequence datasets from the mobile platforms of manufacturing enterprises

Dataset Name	Manu-Consult	Manu-Doc	Manu-Buy	Manu-Mix	Manu-Demo
Total number of sequences	10,000	8,000	12,000	15,000	5,000
Number of behavior event types	15	12	18	20	10
Total occurrences of behavior events	120,531	98,342	156,890	189,234	58,210
Average sequence length	12.8	11.5	14.2	16.3	9.6
Maximum sequence length	35	30	40	45	25
Data scenario	Real	Real	Real	Real	Simulated
Behavior sequence type	Product consultation	Document acquisition	Purchase conversion	Mixed interaction	Mixed behavior (test)



(a) *SLPA*



(b) *Sequence+SVM*

Fig. 4. *(Continued)*

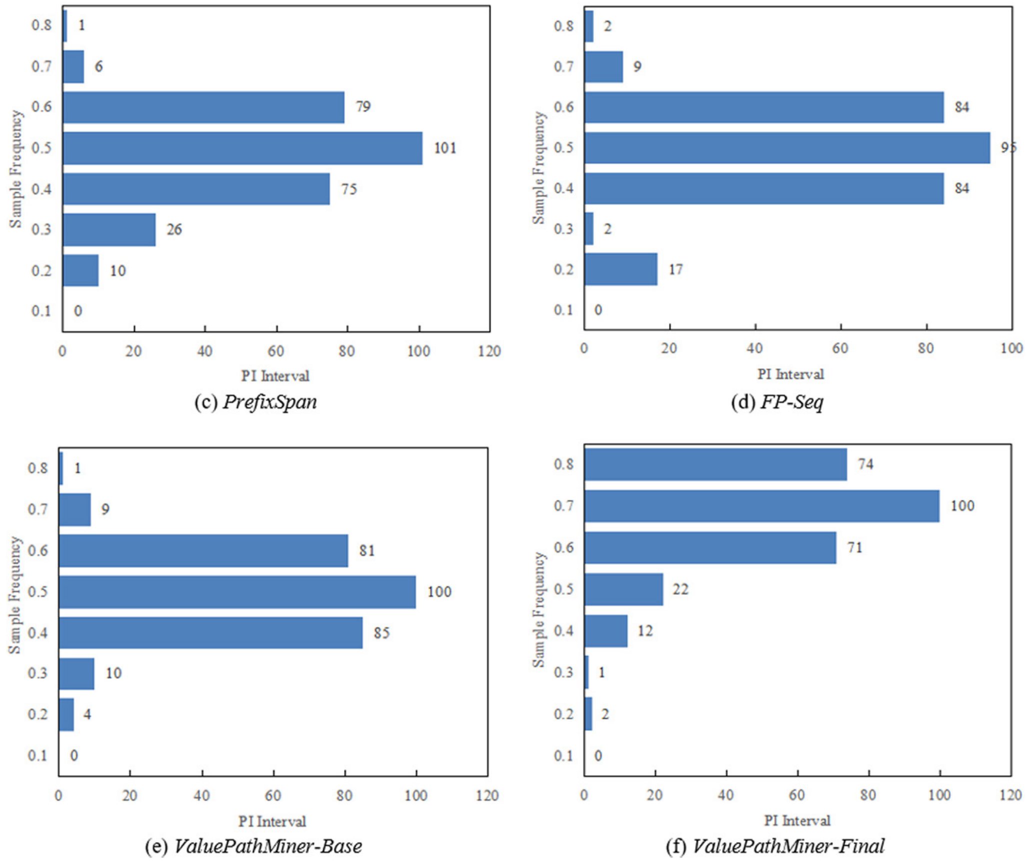


Fig. 4. Distribution of PI prediction accuracy across different sequential methods

To validate the predictive performance of different sequential mining methods in estimating PI on manufacturing enterprise mobile platforms and to determine which method can more precisely identify value perception pathways that drive PI, experiments were conducted on the distribution of PI prediction accuracy across different methods. As illustrated in Figure 4, significant distributional differences are observed in the sample frequencies across PI intervals among the various algorithms. Traditional sequential methods such as Speaker-Listener Label Propagation Algorithm (SLPA), Sequence Feature Extraction and Support Vector Machine Classification (Sequence+SVM), Prefix-Projected Sequential Pattern Mining (PrefixSpan), and Frequent Pattern-based Sequential Classification (FP-Seq) achieve some accumulation of samples in the high-PI interval, yet a non-negligible proportion of samples remain in the low-PI interval. In contrast, within the proposed ValuePathMiner series of algorithms, ValuePathMiner-Base exhibits a noticeably more concentrated distribution in the high-PI interval. The improved ValuePathMiner-Final further optimizes this distributional pattern, with samples highly concentrated in the high-PI interval and very few appearing in the low-PI interval. Overall, the distribution demonstrates a clear trend characterized by a large proportion in the high-PI interval and a minimal proportion in the low-PI interval. These results confirm that significant hierarchical differences exist among sequential methods with respect to PI prediction. Traditional methods can identify some behavior sequences associated with PI; however, the persistence of samples in the low-PI interval indicates that prediction remains biased and fails to accurately capture the critical pathways that drive purchase decisions. ValuePathMiner-Base already demonstrates superior predictive precision compared with traditional approaches, while ValuePathMiner-Final, through its enhanced ValuePath-K metric and redundancy filtering strategy, achieves further improvements. By refining the mining precision of high-value perception pathways, it markedly increases the concentration of samples in the high-PI interval while sharply reducing their proportion in the low-PI interval.

To further validate the capability of different sequential mining algorithms in extracting value perception pathways on manufacturing enterprise mobile platforms and to determine which algorithm most accurately identifies complete behavior sequences that drive PI, comparative experiments were conducted on the Top-5 pathways derived from real product consultation and purchase conversion datasets. As shown in Table 2, clear differences were observed across algorithms. In the Manu-Consult dataset, the pathways mined by ValuePathMiner-Final were both more complete and associated with higher ValuePath-K scores. For example, the pathway "login → browse industry cases → download product manual → consult online service → submit request" achieved a ValuePath-K of 0.92. In contrast, the pathways identified by ValuePathMiner-Base ("login → browse industry cases → consult online service → submit request") covered the core interactions but lacked deeper behaviors such as manual downloads, yielding a lower score of 0.81. Traditional algorithms produced even shorter pathways: PrefixSpan achieved 0.75 and FP-Seq 0.72. In the Manu-Buy dataset, ValuePathMiner-Final extracted pathways that captured the full chain from demand recognition to transaction negotiation. The sequence "login → browse product details → add to inquiry list → request quotation → confirm order" achieved a ValuePath-K of 0.95, while "login → review past transaction cases → schedule sales meeting → negotiate contract → place order" scored 0.91. By comparison, the ValuePathMiner-Base pathways ("login → browse product details → request quotation → confirm order") lacked the inquiry list stage and achieved 0.83. In contrast, the pathways generated by PrefixSpan and FP-Seq were either missing key steps or failed to extend to deeper conversion behaviors such as "contract negotiation," resulting in value perception scores of only 0.78 and 0.74, respectively.

Table 2. Top-5 value perception pathways identified by different algorithms on real behavior datasets from manufacturing enterprise mobile platforms

(a) Manu-Consult (Product Consultation Dataset)			
Algorithm No.	**Algorithm Name**	**Top-5 Value Perception Pathways (Behavior Sequences)**	**Value Perception Score (*ValuePath-K*)**
1	*ValuePathMiner-Final*	Login → browse industry cases → download product manual → consult online service → submit request	0.92
2	*ValuePathMiner-Final*	Login → view product parameters → compare configuration schemes → consult online service → request demo	0.89
3	*ValuePathMiner-Base*	Login → browse industry cases → consult online service → submit request	0.81
4	*PrefixSpan*	Login → download product manual → consult online service	0.75
5	*FP-Seq*	Login → browse industry cases → download product manual	0.72

(Continued)

Table 2. Top-5 value perception pathways identified by different algorithms on real behavior datasets from manufacturing enterprise mobile platforms *(Continued)*

(b) Manu-Buy (Purchase Conversion Dataset)			
Algorithm No.	**Algorithm Name**	**Top-5 Value Perception Pathways (Behavior Sequences)**	**Value Perception Score (*ValuePath-K*)**
1	*ValuePathMiner-Final*	Login → browse product details → add to inquiry list → request quotation → confirm order	0.95
2	*ValuePathMiner-Final*	Login → review past transaction cases → schedule sales meeting → negotiate contract → place order	0.91
3	*ValuePathMiner-Base*	Login → browse product details → request quotation → confirm order	0.83
4	*PrefixSpan*	Login → add to inquiry list → request quotation → confirm order	0.78
5	*FP-Seq*	Login → browse product details → add to inquiry list → confirm order	0.74

The experimental results confirm that significant performance differences exist among sequential mining algorithms in identifying value perception pathways on manufacturing enterprise mobile platforms. Traditional sequence algorithms tend to extract shorter behavior sequences, failing to cover the complete chain of "browsing → deep interaction → transaction negotiation," which results in lower ValuePath-K values. ValuePathMiner-Base is capable of mining longer sequences and exhibits improved performance, but it remains limited in its ability to capture the "complete value journey." By contrast, ValuePathMiner-Final, through its refined ValuePath-K metric and efficient mining strategy, accurately identifies comprehensive sequences such as "login → multi-dimensional deep interaction → transaction conversion." These sequences reflect the entire progression of value perception from initiation to maturity. Across both datasets, the Top-5 pathways derived by ValuePathMiner-Final consistently achieved significantly higher ValuePath-K values than those of other algorithms, demonstrating its superior suitability for identifying critical value perception pathways that drive PI from real behavior sequences. This outcome provides precise, sequence-level insights into the mechanisms underlying PI formation on manufacturing enterprise mobile platforms.

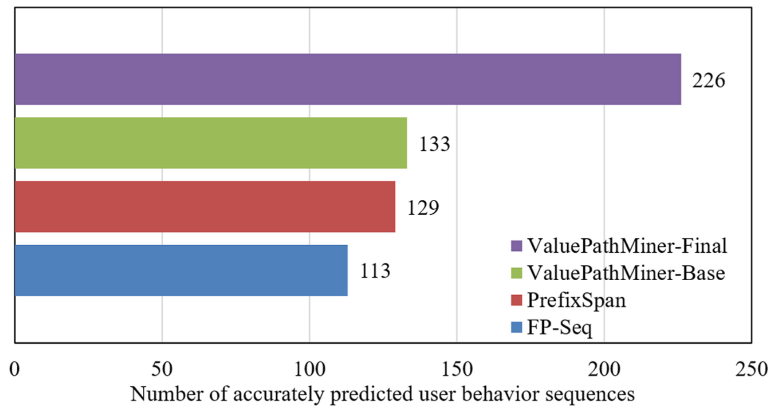


Fig. 5. Comparison of the number of accurately predicted sequences identified by different algorithms in value perception pathway mining

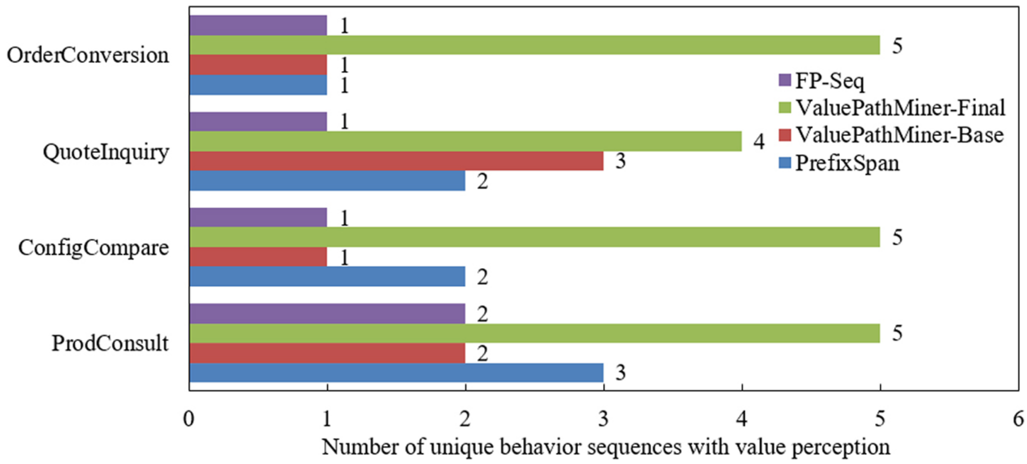


Fig. 6. Comparison of the number of unique value perception behavior sequences mined by different algorithms in manufacturing enterprises

To verify the precision and unique sequence discovery capability of different sequential mining algorithms in extracting user value perception paths on manufacturing enterprise mobile platforms, comparative experiments were conducted on the number of accurately predicted sequences and the number of unique value perception sequences. As shown in Figure 5, which compares the number of accurately predicted user behavior sequences across algorithms, ValuePathMiner-Final achieved 226 accurately predicted sequences, far exceeding the results of ValuePathMiner-Base (133), PrefixSpan (129), and FP-Seq (113). In Figure 6, which illustrates the number of unique value perception behavior sequences mined under typical manufacturing scenarios such as order conversion, configuration comparison, and product consultation, ValuePathMiner-Final identified nearly five unique sequences with significant value perception, a result substantially higher than that obtained by FP-Seq, ValuePathMiner-Base, and PrefixSpan.

These results demonstrate that traditional sequential mining algorithms, lacking targeted measures for "value perception depth," fail to capture the deeper behavioral chains that drive PI on mobile platforms. Consequently, their performance is limited both in the number of accurately predicted sequences and in the discovery of unique value perception sequences. While ValuePathMiner-Base shows improvement by incorporating the value perception metric, a performance gap remains in both precision and adaptability across scenarios. By contrast, ValuePathMiner-Final, through its refined ValuePath-K metric and efficient mining logic, not only substantially increases the number of accurately predicted user behavior sequences but also more precisely uncovers unique sequences such as "login → case browsing → manual download → service consultation → order placement" in several business scenarios such as order conversion and configuration comparison. These sequences clearly reflect the progression of user value perception from emergence to maturity. The results highlight that ValuePathMiner-Final exhibits superior precision and scenario generalizability in identifying the critical pathways that drive PI.

4 CONCLUSION

This study explored the association mechanism between perceived value and PI among users of manufacturing enterprise mobile platforms. The core research progression can be summarized in three stages: theoretical modeling, methodological innovation, and empirical validation. First, a theoretical framework linking perceived value and PI in mobile manufacturing contexts was constructed based on consumer behavior theory, with "deep behavioral interactions" identified as the key bridge connecting value perception to conversion decisions. Second, to address the limitations of traditional sequential mining algorithms—namely, the inability to quantify "value perception depth" and the tendency to generate redundant short sequences—an innovative ValuePath-K metric and the ValuePathMiner-Final algorithm were proposed. Finally, empirical experiments were conducted on real business datasets from manufacturing enterprises. The results demonstrated that, compared with traditional algorithms such as PrefixSpan and FP-Seq, as well as the baseline ValuePathMiner-Base, ValuePathMiner-Final identified more complete value perception pathways, achieved significantly higher ValuePath-K scores, and yielded superior performance in both the number of accurately predicted sequences and the discovery of unique value perception sequences. Although theoretical and methodological advances were achieved, certain limitations remain. The empirical validation relied on data from a single manufacturing sector, and user attribute data were not incorporated, restricting the ability to analyze value perception differences across user subgroups. Future research should therefore broaden the data scope by extending the application to multiple Business-to-Business (B2B) industries and integrating user attribute data, thereby enabling differentiated analyses of value perception pathways among distinct user segments.

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