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# An Organizational Constraint-Aware Recommender System with Choice Architecture-Based User Utility Estimation and Adaptive Organizational Strategies Considering Fuzzy Inference

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***Abstract*** *–Recommender systems (RSs) have emerged as indispensable mechanisms for alleviating information overload and facilitating decision-making processes. However, despite significant advances, traditional RSs often overlook the cognitive processes underlying human choice. Additionally, they frequently fail to consider the strategic interests of multiple stakeholders. This study proposes an adaptive approach that seamlessly integrates human decision behaviors, cognitive biases, and organizational strategies to optimize recommendation delivery. By leveraging insights from choice architecture and behavioral science, the proposed RS dynamically adjusts its recommendations to serve the overall interests of multiple stakeholders. The proposed model also simultaneously exploits the results of other RSs, expert knowledge, and contextual information. The recommendation strategies, as intended by organizational experts, are modeled using a fuzzy inference system (FIS). This facilitates the recommender system's ability to align the interests of both stakeholders—the organization and the customer—by integrating essential contextual data and domain-specific expertise to optimize efficiency. This approach enables RSs to effectively balance individual user needs with organizational priorities. This paper evaluates the approach through a simulation-based study using KPI-driven comparisons. Results show substantial improvements in organizational capacity utilization, with over-utilization decreasing from approximately 85% under the traditional RS to 19% under the proposed RS. The simulation-based validation process suggests that the proposed model can enhance organizational performance while accounting for both short- and long-term customer benefits. The results indicate that this adaptive model significantly improves overall benefits.*

***Keywords***– *Recommender system; Choice architecture; Contextual information; Cognitive biases; Multi-stakeholders.*

## I. INTRODUCTION

Recommender systems (RSs) are pivotal in mitigating information overload for consumers and enhancing their overall satisfaction by streamlining the decision-making process (Xu et al., 2023). Over the past decade, the use of RSs has experienced unprecedented growth, demonstrating proven efficacy across diverse domains such as energy management, travel planning, healthcare, financial services, and e-learning. Notably, their integral role in organizations such as Amazon and Netflix underscores their importance: roughly 30% of Amazon’s page views and 80% of Netflix's

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content consumption are driven by recommendations generated by RSs (Deldjoo et al., 2021).

One of the main reasons for the widespread acceptance of RSs by both consumers and organizations is their essential role in facilitating decision-making processes, ultimately leading to higher satisfaction by mitigating issues such as information overload and other barriers. Although RSs have reached a high level of maturity and proven effective across a variety of applications, significant gaps remain in addressing actual needs. Moreover, certain intrinsic risks and challenges threaten the seamless implementation of RSs within real-world settings.

The perspective adopted by RSs toward human decision-making processes plays a crucial role in explaining why, despite significant advancements in algorithm development, achieving optimal performance remains a considerable journey. Consequently, understanding human decision-making processes and identifying methods to support these cognitive procedures represent a clear pathway for advancing recommender system (RS) development (Ricci et al., 2021). The critical first step in designing RSs is modeling stakeholders' perspectives, analyzing their decision-making processes, and subsequently developing the algorithm based on these behavioral insights. For instance, a fundamental question must be asked: can merely suggesting items that are similar to a user's previous choices serve as an effective and comprehensive solution? To find solutions to such questions, it is vital to thoroughly examine the underlying human decision-making mechanisms.

Examining human decision-making without considering the context can lead to an incomplete understanding of reality. The decision-making environment constitutes a vital element that significantly influences human preferences and, ultimately, their choices. As a result, extensive research has focused on choice architecture, the study of how the presentation of options affects decision-making. Researchers have shown considerable interest in applying choice architecture principles to RSs, which focus on how options are presented to users. Within the realm of RSs, choice architecture primarily pertains to how options are presented to users, such as the quantity of choices offered, the ordering of lists, or the informational framing. In essence, the way recommendations are presented, beyond just the content, can significantly influence customer decisions.

Customers are key stakeholders in the RS ecosystem, and the organization itself is equally important and must be considered in the recommendation process. In this context, stakeholders refer to any group or individual capable of influencing the delivery of recommendations to users or being affected by these recommendations. RSs must accurately account for and support the preferences of all key stakeholders. Although the importance of addressing diverse stakeholder needs is widely acknowledged, research in RS has predominantly focused on customers. This often results in the neglect of other stakeholders' preferences. Engaging all stakeholders, including organizations, is crucial because neglecting their preferences over time can lead to decreased system efficiency and lower user satisfaction. Therefore, actively involving all relevant parties can strengthen overall collaboration, improve system performance, and ultimately enhance customer satisfaction in the long term.

This study focuses on the importance of considering both the organization and the customer as key stakeholders, with their shared interests serving as the basis for recommendations. Additionally, by integrating choice architecture principles and leveraging cognitive biases, the study models how presentation format influences customer preferences and encourages the selection of options that maximize overall benefit. This paper emphasizes human decision-making processes, recognizing that humans tend to make choices based on comparative evaluations, similar to the decoy effect, where all utilities are computed in relative and comparative terms. In other words, inspired by the natural decision-making tendencies of humans—grounded in the relative evaluation of alternatives and shaped by cognitive biases—the proposed RS highlights options with greater overall benefit and utilizes the comparative structure of human cognition through intelligent data presentation. This approach helps transform choices aligned with shared interests into outcomes that feel natural and intuitive.

Organizations have varying degrees of flexibility in meeting customer expectations depending on the specific circumstances they encounter. In certain scenarios, an exclusive focus on customer benefits may adversely affect organizational objectives, whereas in other cases, such limitations may not exist. Therefore, it is essential for RSs to incorporate two key principles when generating recommendations:

- ☑ Consider the organizational strategies as a guiding framework.
- ☑ Prioritize customer needs when the organization has sufficient capacity or flexibility; in other words, allow customer needs to supersede organizational interests where feasible.

This combination of flexibility and transparency helps establish a reasonable balance between the interests of various stakeholders. Furthermore, leveraging expert insights into organizational strategies enhances the algorithm's capabilities beyond relying solely on historical data, such as customer profiles or purchase transactions, enabling the RS to perform more effectively by combining historical data with expert knowledge. In light of these considerations, the primary contributions of this study can be summarized as follows:

- ☑ The nudge effect is inherently integrated into the computational logic of the customer-perceived utility, rather than being applied as a post-processing filter, considering the influence of recommendation delivery on the perceived utility across all stakeholders.
- ☑ The proposed method can be easily combined with other RSs and use their results.
- ☑ Recommendations are generated considering two primary stakeholders, namely, customers and the organization, based on their overall benefit.
- ☑ The proposed method integrates the organization's strategies into the recommendation process, leveraging both historical data and expert insights. This approach enhances the flexibility of the RS in adapting to diverse situations.

Having established the theoretical framework, the remainder of this paper is organized as follows: Section II reviews relevant literature; Section III describes the methodology. Section IV presents simulation experiments for method validation, while Section V provides the conclusion and future work.

## II. LITERATURE REVIEW

The proposed RS is developed based on the principles of choice architecture. It is capable of simultaneously considering the interests of two primary stakeholders, customers and the organization, and incorporating their influences into the recommendation process. This model delivers its recommendations by considering certain cognitive biases that influence human decision-making. This section reviews recent studies in the following three related areas:

- ☑ The application of choice architecture and nudge in RSs
- ☑ Multi-stakeholder RSs
- ☑ Supply chain constraints and their role within RSs

At the end of this section, methodological limitations in prior studies are presented to identify the methodological shortcomings of existing research and highlight the resulting research gaps in the RS field.

### *A. The Application of Choice Architecture and Nudge in RSs*

Choice architecture refers to the design of decision-making environments that intentionally structure options to influence human behavior. It involves the deliberate integration of nudges into the decision-making process to highlight better options for users. Any modification to the user's decision environment that gently encourages specific behaviors is considered a nudge. In other words, a nudge denotes any component of choice architecture that predictably modifies behavior, without prohibiting options or substantially altering economic incentives (Caraban et al., 2019). This concept was first introduced by Thaler & Sunstein (2008) within the field of behavioral economics.

Nudge theory draws on dual-process theory, a psychological framework that describes how the human mind makes decisions. This psychological framework explores how individuals process information and arrive at choices. Humans utilize two systems for decision-making: System 1 (intuitive) and System 2 (analytical). System 1 operates unconsciously, employing heuristic shortcuts to facilitate rapid decisions with minimal cognitive load. Its quick processing makes it particularly susceptible to subtle changes. In contrast, System 2 operates consciously, in a controlled and analytical manner, requiring significant cognitive resources. Nudge methodologies primarily focus on System 1, aiming to influence decision-making and behavior effectively through targeted interventions (Dolan et al., 2012; Bammert et al., 2020).

Recently, nudge-based methodologies and their application in modeling RSs have garnered increasing attention from researchers. In this context, Starke and Willemsen (2024) investigated whether displaying appealing images alongside recipes and re-ranking search results based on health considerations could support healthy food choices. Their analysis showed that users preferred healthier recipes when these were paired with attractive images or ranked higher in search results. This approach promoted less popular recipes without negatively impacting user satisfaction. The study by Bothos et al. (2015) examines how choice architecture can influence the effectiveness of RSs, particularly in promoting environmentally friendly travel options. The aim of this RS is to guide users to environmentally friendly routes and transportation options that produce less CO2. Unlike many previous studies on RSs that prioritize accuracy, this research focuses on using RSs to encourage users towards environmentally friendly choices. Jesse and Jannach (2021) reviewed 87 choice architecture methods and identified only 18 that have been applied in RSs, thereby highlighting a gap in the field. According to this study, only 18 of them have been used in RSs, and 69 methods remain unused. Karlsen & Andersen (2019) presented a conceptual model for combining users' current situation and decision-making conditions, such as location, weather, road conditions, and destination, to design a smart nudge. According to the definition provided in this study, a smart nudge is a type of digital nudge in which recommendations are adjusted to the user's current situation, such as location and weather conditions. In the study by Nielek et al. (2025), the challenge of inefficient user exploration in Multi-List Recommender Interfaces (MLRIs) is addressed through a digital nudge. Guided by foraging theory, a visual cue was designed to prompt users to switch from depleted carousels. This intervention was found to significantly enhance exploration efficiency and item discovery for both younger and older adults.

### *B. Multi-Stakeholder RSs*

In the context of RSs, providing filtered information to users is not usually considered the only goal. Instead, other stakeholders may have other goals. Stakeholders include any group or individual who can influence or be influenced by the recommendations (Abdollahpouri and Burke, 2022). Most importantly, organizations typically aim to sell specific products or promote targeted behaviors while also striving to enhance customer satisfaction (Starke and Willemsen, 2024). However, academic studies in the field of RSs have largely focused on customers and optimizing their experience. This user-centric approach limits the ability to incorporate other system goals such as fairness, balance, or profitability and ignores the concerns and priorities of other stakeholders (Sitar-Tăut and Mican, 2020).

Although systems addressing multiple stakeholder concerns have been part of RS research for years, the multi-stakeholder recommendation research area with implications in multiple application areas is relatively new (Abdollahpouri and Burke, 2022). Ranjbar Kermany et al. (2021) introduced a multi-stakeholder RS with a focus on fairness and personalized diversity. Beyond simply focusing on the accuracy of recommendations, this system also considers the needs of suppliers in addition to users and attempts to strike a balance between the two groups.

Traditional RSs often prioritize popular items, which can lead to an imbalance that multi-stakeholder systems aim to address. This imbalance can lead to supplier dissatisfaction. As a result, giving less popular providers a chance is considered fairer, a practice followed in the research of Ranjbar Kermany et al. (2021). In their research, a fairness-aware multi-stakeholder RS is introduced that uses a multi-objective evolutionary algorithm to balance provider coverage, long-tail inclusion, personalized diversity, and recommendation accuracy. The study by Shrivastava et al.

(2022) addresses multi-stakeholder RSs by proposing dedicated utility functions for four key stakeholders: users, producers, cast, and the system itself, moving beyond traditional single-stakeholder approaches. To balance conflicting stakeholder objectives, the authors employ evolutionary optimization (NSGA-II), enabling a trade-off recommendation solution that enhances utility gains while maintaining personalization.

### *C. Supply Chain Constraints and Their Role Within RSs*

The researchers' findings demonstrate that product recommendations without considering supply chain constraints increase supply chain costs. This can lead to recommendations that may result in delays or increased costs, which are undesirable for both customers and the supply chain. The recommendation of products with relatively high lead times or shipping costs is an example of this. This situation increases the complexity of supply chain processes.

In the study by Dadouchi & Agard (2021), delivery constraints are incorporated into product recommendations in RSs. This study proposes an approach to shift demand toward products that can be delivered using the existing delivery network within a specified time frame, without incurring additional resources, while ensuring a minimum acceptable profit in the e-commerce domain. The approach presented by Dadouchi & Agard (2021) is not a new theory, but rather a new conceptual framework that connects RSs to the supply chain and product inventory management. In the study by Zhang et al. (2021), product availability constraints are incorporated into the recommendation process. The primary challenge faced by the online grocery store analyzed was the presence of products with high profit margins but low sales velocity, resulting in excess supply relative to demand. Conversely, some products experienced limited availability. To address this, the company aimed to identify suitable customers and offer them unused products directly, rather than providing discount coupons to the entire customer base. Customer identification for nudging was performed using the support vector machine (SVM) method. A novel aspect of this research is the consideration of Type I errors as a criterion for selecting target customers for nudging. The core idea is that Type I errors in the dataset are not inherently problematic—they may include customers who did not purchase the original product due to unawareness of its availability. The study by Li et al. (2023) presents a novel knowledge graph-based recommendation method for cold chain logistics, addressing critical limitations in existing context-aware RSs. This work bridges the gap between semantic reasoning and logistics optimization, offering a scalable solution for intelligent cold chain management. A misalignment in research on fashion RSs is systematically identified in the study by Pereira et al. (2022). Their review concludes that while significant focus is placed on enhancing the customer buying experience within the retail domain, the potential of customer models to support decision-making in other critical supply chain areas—such as design, production, and distribution—remains largely untapped. The study by Hu (2025) addresses a critical gap in supply chain resilience (SCRes) literature by proposing a novel blockchain-based intelligent recommender system (BLC-IRS) framework. Their research finds that although digital technologies are widely explored for proactive SCRes, there is a significant lack of development of reactive digital tools specifically designed to respond to disruptions. Specifically, the application of RSs as a decision-support mechanism that can facilitate agile resource reallocation by quickly identifying alternative resources during supply chain disruptions is neglected. To bridge this gap, a two-tiered framework is designed. First, an intelligent recommender system (IRS) baseline was developed to rapidly identify and recommend both internal and external supplementary resources (e.g., inventory, capacity) to a disrupted entity. Second, recognizing the vulnerabilities of a centralized information system, they integrated blockchain technology to decentralize the information-sharing scheme. This integration enhances data reliability and security, crucial for generating trustworthy recommendations during a crisis. The study by Bandyopadhyay et al. (2021) focuses on enhancing product recommendations in the apparel e-commerce sector through unsupervised machine learning techniques, with particular emphasis on improving customer segmentation and supply chain management. The core methodology involves the application of Principal Component Analysis (PCA) for dimensionality reduction, followed by K-means clustering to accurately segment customers based on their purchasing behavior, specifically capturing associations among brand, product, and price range. The research further introduced a product segmentation model based on Stock Keeping Units (SKUs), derived from sales volume and revenue data. This model is intended to assist retailers in optimizing inventory management and marketing strategies, thereby fostering a sustainable, profitable, and scalable e-commerce business model that accounts for environmental, social, and economic considerations.

The proposed model represents an advanced RS that incorporates closed-loop feedback mechanisms to enhance the customer experience while optimizing business management and logistics. According to the authors, this integration contributes to the overall sustainability of the business. Nevertheless, the RS model functions, at best, as an early warning mechanism, remaining largely confined to the roles of analyst and reporter. The intelligence generated by the system is not intrinsically embedded in the recommendation-delivery process to enable direct corrective action at the customer level. Instead, the execution of such remedial actions remains the responsibility of managerial personnel, who rely on the generated reports to implement the necessary corrective measures. Within the evolving domain of Circular Supply Chain Management (CSCM), a significant challenge lies in identifying viable industrial symbiosis partnerships, owing to the vast and complex datasets associated with industrial waste streams and sector-specific activities. To address this challenge, the study by Capelleveen et al. (2021) introduces an innovative interactive visual RS, representing a substantial advancement in the domain of decision-support tools for circular supply chain management (CSCM). Their work tackles a critical research gap stemming from the absence of transparent decision-support mechanisms, which has historically impeded the efficient identification of circular business opportunities. Departing from conventional "black-box" RSs, the proposed model integrates algorithmic filtering with interactive visualization capabilities, thereby establishing a hybrid framework that enhances user control and transparency throughout the decision-making process. The system enables the exploration of potential industrial symbiosis matches through hierarchical visualizations of standardized waste (EWC) and industry (NACE) taxonomies. Collectively, this research illustrates how visual-interactive RSs can contribute to more sustainable supply chains and facilitate the practical implementation of circular economy principles.

### *D. Methodological Limitations in Prior Studies*

Nudge Implementation: The integration of nudges and RSs is considered a promising research area for the RSs community, and this potential has not yet been fully exploited (Lex et al., 2021). However, research has so far focused more on the effects of nudges than on their underlying mechanisms. Specifically, while there is much discussion and research on the whys and wherefores of nudges, there is little on the hows of nudges (i.e., the precise mechanisms used to nudge and change behavior) (Lindenberg & Papies, 2019; Caraban et al., 2019).

Different types of nudge mechanisms and their implementations generate distinct psychological outcomes that influence user satisfaction. Evidence from current research suggests that social nudges—such as those based on conformity or popularity—can sometimes trigger negative user responses, as individuals may perceive these interventions as overt attempts to manipulate their choices (Alves et al., 2024). Some users who become aware of such persuasive cues may experience a sense of reduced autonomy, which can undermine their willingness to engage with the system. In contrast, personalized and adaptive nudges that align with users' contexts and preferences mitigate these adverse reactions. When users can clearly detect systematic efforts to shape their decisions, trust tends to erode; therefore, systems that either conceal nudging strategies seamlessly or communicate personalization transparently tend to achieve higher user satisfaction and engagement. Consequently, a key focus in developing nudging strategies within RSs is designing mechanisms that preserve user autonomy and trust while guiding decisions toward desirable outcomes. Recent studies have emphasized the integration of psychological and sociological insights into technical design, focusing on developing sophisticated personalization frameworks for adaptive and trust-sensitive nudging in RSs.

Supply Chain Constraints and Multi-Stakeholder: Current literature regards RSs as promising yet still nascent tools for enhancing supply chain performance. This perspective stands in contrast to the findings of several recent studies, which indicate that the application of RSs to improve supply chain performance has either been overlooked or characterized as relatively limited in prior work, as exemplified by Hu & Ghadimi (2024) and Coscrato & Bridge (2024). A central challenge across this line of inquiry is how to integrate supply chain priorities with user preferences in a way that also advances equity, thereby enabling more balanced and just outcomes within the supply chain. This challenge becomes even more complex when the objectives of different stakeholders conflict with one another.

Consequently, methods must be developed to establish a fair equilibrium among stakeholders, taking into account specific factors such as environmental conditions and organizational strategies.

## III. THE PROPOSED METHOD

As discussed in the previous section, the proposed method incorporates recommendations generated by a traditional RS as one of its primary inputs. In addition, the organization periodically ranks its products based on their desirability, with this ranking serving as another input to the recommendation algorithm. Another critical input is the set of recommendation strategies, which are essential for balancing the organization's interests with those of the customer. For example, the recommendation strategies allow the organization to prioritize accepting customer orders over its own preferences when operational capacity is underutilized. Conversely, if the inventory of a particular product exceeds demand, the organization must focus on selling those items, thereby reducing its flexibility to meet specific customer needs. These recommendation strategies, periodically configured by experts, are integrated into the algorithm to ensure it effectively balances organizational and customer needs. Fig. 1 illustrates the main steps of the proposed method, which are explained in detail below. Additionally, Table I presents a comprehensive summary of the key parameters, variables, and notations used throughout the proposed recommender system framework.

**Table I. Summary of parameters and variables in the proposed RS**

| Parameters | Description | Context | Source |
|---|---|---|---|
| N | Total number of candidate products | Step 1 | External data input |
| $V^{*O}$ | Organizational score vector | Step 1 | External data input |
| $v_{\mathrm{i}}^{*O}$ | Organizational score for product $p_i$ | Step 1 | Automatically computed |
| $v_{\mathrm{i}}^{*O}$ | Normalized organizational score for product $p_i$ | Step 1 | Automatically computed |
| $R_{p_i}^{(O)}$ | Rank of product $p_i$ from the organizational perspective | Step 1 | Automatically computed |
| $R_i^{-(O)}$ | Product associated with the i-th organizational priority level | Step 1 | Automatically computed |
| $S^h$ | Score vector of $h$-th customer | Step 2 | External data input |
| $s_{\mathrm{i}}^h$ | Score of product $p_i$ for $h$-th customer | Step 2 | External data input |
| $s_{\mathrm{i}}^{*h}$ | Normalized score of product $p_i$for $h$-th customer | Step 2 | Automatically computed |
| $G^h$ | Organizational reward of $h$-th customer endorsement | Step 3 | Manually defined |
| $M_1^h$,$M_2^h$ | Maximum organizational penalties due to non-endorsement by customer $h$ | Step 3 | Manually defined |
| $R_{p_i}^{(h)}$ | Rank of product $p_i$ from the customer $h$ perspective | Step 2 | Automatically computed |
| $R_i^{-(h)}$ | Product associated with the $i$-th customer $h$ priority level | Step 2 | Automatically computed |
| $m_{ij}^h$ | Organization relative utility reduction when product $p_i$ is recommended by RS and product $p_j$ is selected by the $h$-th customer | Step 3:Eq.(4) | Automatically computed |
| $\rho_{ij}^{h(O)}$ | Organizational expected relative utility when product $p_i$ is recommended by RS and product $p_j$ is selected by the $h$-th customer | Step 3:Eq.(3) | Automatically computed |
| $B^h$ | Enhancing $h$-th customer relative utility through choice alignment with recommendation | Step 4 | Manually defined |
| $E^h$ | Maximum penalty for the $h$-th customer due to non-compliance with recommendation | Step 4:Eq.(6) | Manually defined |
| $e_{ij}^h$ | Customer relative utility reduction when product $p_i$ is recommended by RS and product $p_j$ is selected by the $h$-th customer | Step 4:Eq.(6) | Automatically computed |

**Continue Table I. Summary of parameters and variables in the proposed RS**

| Parameters | Description | Context | Source |
|---|---|---|---|
| $\pi_{ij}^{h}$ | Expected relative utility for the $h$-th customer when product $p_i$ is recommended by RS and product $p_j$ is selected by the $h$-th customer | Step 4:Eq.(5) | Automatically computed |
| $Y^h$ | Payoff matrix of organization and $h$-th customer | Step 5 | Automatically computed |
| $X = \{x_i\}_{i=1}^{x}$ | Input data related to the $h$-th customer | Step 6 | External data input |
| $Z = \{z_i\}_{i=1}^{z}$ | Organizational input data | Step 6 | External data input |
| $T = \{t_i\}_{i=1}^{t}$ | Environmental input data | Step 6 | External data input |
| $R^r$ | The $r$-th fuzzy rule (or recommendation strategy) | Step 6:Eq.(7) | External data input |
| $w^r$ | Emphasis on organizational priorities under activated rule $R^r$ | Step 6:Eq.(7) | External data input |
| $\kappa^r$ | Firing strength of the fuzzy rule $R^r$ | Step 6 | Automatically computed |
| $\alpha^O$ | Weight of organizational priority | Step 6 | Automatically computed |
| $\alpha^h$ | Weight of customer priority | Step 6 | Automatically computed |
| $\Phi^h$ | Overall benefit matrix of organization and $h$-th customer | Step 7 | Automatically computed |
| $\Gamma^h$ | Regret matrix associated with h-th customer | Step 7:Eq.(10) | Automatically computed |
| $\Gamma_i^h$ | Average regret for recommending $p_i$ to $h$-th customer | Step 7:Eq.(11) | Automatically computed |

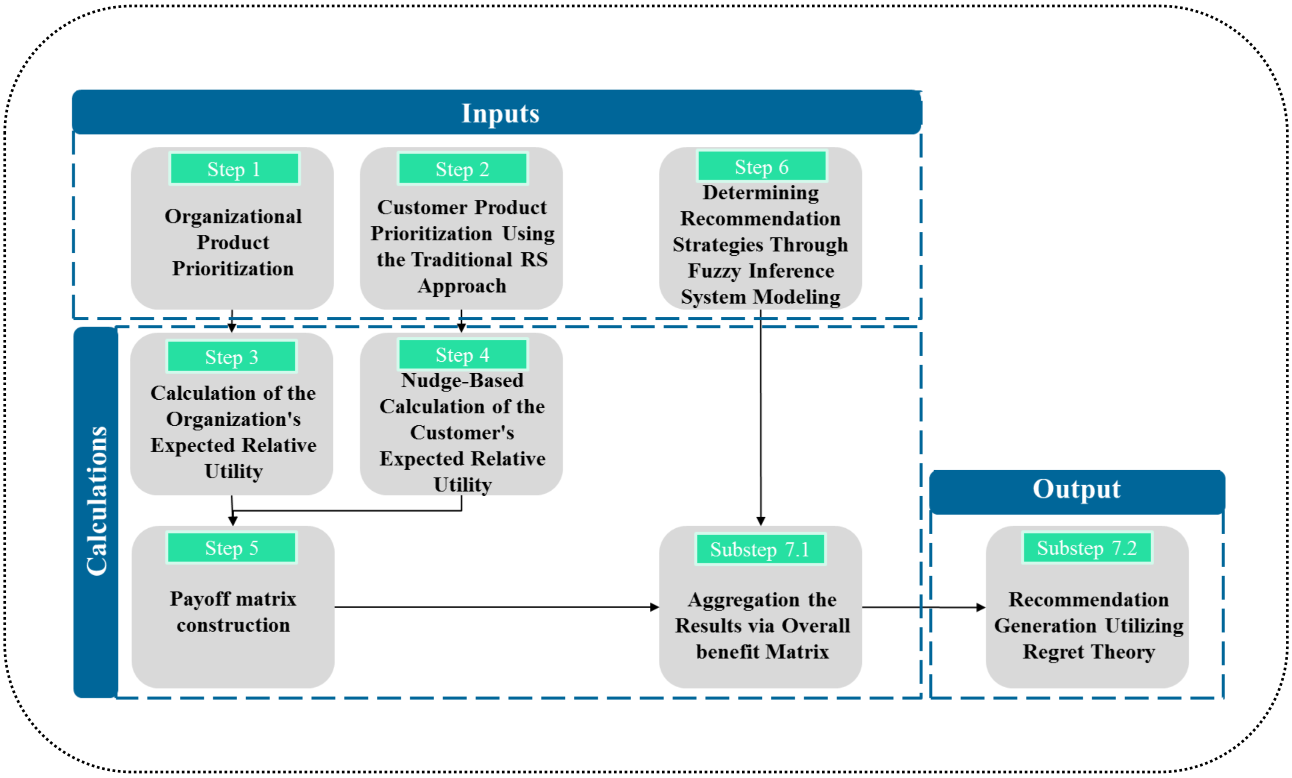



**Fig. 1. The main steps of the proposed method. A flowchart illustrating the overall structure of the proposed method, highlighting its input, computational and final recommendation steps. The diagram demonstrates how inputs, as the required resources for executing the computational steps, are systematically processed to generate final recommendations.**

**Step 1:** Organizational Product Prioritization

This step begins with a set of candidate products, denoted as $C = \{p_1, p_2, \ldots, p_N\}$, where N= |C| denotes the total number of available products. Each product in $C$ is evaluated and ranked based on its anticipated benefits and alignment with organizational objectives, resulting in a score vector $\boldsymbol{V^O} = [v_1^O, v_2^O, \ldots, v_N^O]$, where $v_i^O \geq 0$ uniquely corresponds to product $p_i \in C$ and these scores are supplied by the organization rather than generated by the algorithm. Based on $\boldsymbol{V^O}$, products are ranked in descending order of scores. As the priority of a product increases, $v_i^O$ rises. Let $R_{p_i}^{(O)}$ denote the rank of product $p_i$ from the organizational perspective, and $R_i^{-(O)}$denote the product assigned to rank *i*. A lower value of $R_{p_i}^{(O)}$ corresponds to a higher priority (i.e., $R_{p_i}^{(O)} = 1$ indicates the top organizational priority). It can also be mentioned that some products may share the same rank simultaneously. Normalization is essential to enable direct comparability between organizational and customer scores, which often reside on disparate scales. For this reason, the organizational score vector $\boldsymbol{V^O}$ is normalized to a standardized interval [0,1] using min-max normalization, as defined in Eq. (1):

$$\boldsymbol{V^{*O}} = [v_1^{*O}, v_2^{*O}, \ldots, v_N^{*O}] = \left[\frac{v_1^O - \min\limits_k\{v_k^O\}}{\max\limits_k\{v_k^O\} - \min\limits_k\{v_k^O\}}, \frac{v_2^O - \min\limits_k\{v_k^O\}}{\max\limits_k\{v_k^O\} - \min\limits_k\{v_k^O\}}, \ldots, \frac{v_N^O - \min\limits_k\{v_k^O\}}{\max\limits_k\{v_k^O\} - \min\limits_k\{v_k^O\}}\right] \tag{1}$$

where $v_i^{*O} \in [0,1]$ represents the normalized score of the product $p_i$, with higher values indicating greater organizational preference. This normalization ensures that the scores are comparable to customer preference scores. Notably, this transformation maintains the original ranking structure while enabling direct comparison between products with different baseline score magnitudes.

Each organization may adopt its own procedure for scoring products. Scoring criteria might include indicators such as inventory levels, profit margins, quality, ease of procurement, and production complexity, each of which provides insight into different aspects of product evaluation.

**Step 2:** Customer Product Prioritization Using the Traditional RS Approach

This step leverages outputs from a traditional RS to prioritize products for individual customers. For each candidate product $p_i \in C$ the RS computes a recommendation score $s_i^h \in R^+$ quantifying its alignment with the *h*-th customer's preferences. Higher scores indicate stronger recommendation priority. These scores form a score vector $\boldsymbol{S^h} = [s_1^h, s_2^h, \ldots, s_N^h]$ where $s_i^h$ corresponds uniquely to product $p_i \in C$. Based on $\boldsymbol{S^h}$ values, products are ranked in descending order. Let $R_{p_i}^{(h)}$ denotes the rank of product $p_i$ from the perspective of the *h*-th customer and $R_i^{-(h)}$ denotes the product assigned to rank *i* for the *h*-th customer. The customer score vector $\boldsymbol{S^h}$ is normalized to a standardized interval [0,1] using min-max normalization, as defined in Eq. (2):

$$\boldsymbol{S^{*h}} = [s_1^{*h}, s_2^{*h}, \ldots, s_N^{*h}] = \left[\frac{s_1^h - \min\limits_k\{s_k^h\}}{\max\limits_k\{s_k^h\} - \min\limits_k\{s_k^h\}}, \frac{s_2^h - \min\limits_k\{s_k^h\}}{\max\limits_k\{s_k^h\} - \min\limits_k\{s_k^h\}}, \ldots, \frac{s_N^h - \min\limits_k\{s_k^h\}}{\max\limits_k\{s_k^h\} - \min\limits_k\{s_k^h\}}\right] \tag{2}$$

where $s_i^{*h} \in [0,1]$ represents the normalized score of product $p_i$, with higher values indicating greater preference for the *h*-th customer.

Example 1 (Score-based prioritization):

Consider candidate products $C = \{p_1, p_2, p_3\}$ with recommendation scores $\boldsymbol{S^h}$ =[0.8,0.3,0.3] for the *h*-th customer. Here, $p_1$ achieves the highest score (0.8) and is assigned rank 1 ($R_{p_1}^{(h)} = 1$). Products $p_2$ and $p_3$ receive identical scores of 0.3, resulting in a tied rank assignment at rank 2 ($R_{p_2}^{(h)} = R_{p_3}^{(h)} = 2$). Consequently: $R_1^{-(h)} = p_1; R_2^{-(h)} = \{p_2, p_3\}$.

**Step 3:** Calculation of the Organization's Expected Relative Utility

This step quantifies the Expected Relative Utility (ERU) of each recommendation for the organization. The relative utility depends on both the organization's priorities (i.e., results of Step1) and the customer's choice. Together, these factors determine the overall benefit. For this purpose, an incentive parameter, $G^h$ and a penalty parameters, $M_1^h$ and $M_2^h$, are considered. The parameter values are inherently dependent on individual customers and exhibit variability across different client segments. This heterogeneity stems from differing perceptions of each customer's strategic significance to the organization. For instance, the organization may deliberately allocate greater incentives or penalties to customers deemed of higher strategic importance.

The parameter $G^h$ acts as a reward when the $h$-th customer's choice aligns with the organization's recommendation. If the $h$-th customer accepts the recommendation, the $G^h$ score is added as a reward to the organization's utility. On the other hand, the penalty parameters indicate that greater disagreement between the customer and the organization reduces the organization's benefit. In other words, as the distance between the organization's recommendation and the user's choice increases, the penalty increases. The main reason for implementing this penalty is to ensure that the organization's ERU calculation for recommendations incorporates factors beyond organizational preferences. Exclusive reliance on internal preferences would inevitably lead to customer dissatisfaction and consequent market share erosion. The penalty parameter $M$ serves as a moderating factor that simultaneously incorporates both short-term benefits (i.e., preferences identified in Step1) and long-term considerations (customer satisfaction) into the organization's relative utility function. As depicted in Eq. (3), $\rho_{ij}^{h(o)}$ denotes the ERU for the organization when recommending the product $p_i$, given that the $h$-th customer selects the product $p_j$.

$$\rho_{ij}^{h(O)} = \begin{cases} v_{\mathrm{i}}^{*O} + G^h & i = j \\ v_j^{*O} - m_{ij}^h & i \neq j \end{cases} \tag{3}$$

where $m_{ij}^h$ quantifies the reduction in ERU caused by the discordance between the recommended product $p_i$ and the product $p_j$ selected by the $h$-th customer, reflecting its impact on organizational ERU, as defined by Eq. (4).

$$m_{ij}^h = \begin{cases} M_1^h \left(R_{p_i}^{(O)} - R_{p_j}^{(O)}\right) \Big/ N-1 & i \neq j \; and \; R_{p_i}^{(O)} > R_{p_j}^{(O)} \\ 0 & i = j \\ M_2^h \left(R_{p_j}^{(O)} - R_{p_i}^{(O)}\right) \Big/ N-1 & i \neq j \; and \; R_{p_i}^{(O)} < R_{p_j}^{(O)} \end{cases} \tag{4}$$

Based on Eq. (4), two parameters, $M_1^h$ and $M_2^h$, are introduced as metrics for evaluating the costs associated with misdiagnosis in RS. These errors occur in two distinct scenarios.

☑ Lost Opportunity Cost:

The RS recommends product $p_i$, while the customer selects $p_j$, where $R_{p_i}^{(O)} > R_{p_j}^{(O)}$. In this case, $M_1^h$ represents the maximum score deducted from the organization's ERU due to lost opportunities caused by the $h$-th customer.

☑ Conflict of Interest Cost:

The RS recommends product $p_i$, and the customer selects $p_j$, where $R_{p_i}^{(O)} < R_{p_j}^{(O)}$; here, $M_2^h$ signifies the maximum ERU reduction due to conflict of the h-th customer's choice with the organization's interests.

**Step 4:** Nudge-Based Calculation of the Customer's Expected Relative Utility

The purpose of this step is to assess the customer's ERU for each choice under different conditions. This utility extends beyond the individual preferences obtained in Step 2 and also depends on recommendations from the organization.

At this step, the customer's ERU is modulated not only by the user's intrinsic preferences (obtained in Step 2) but also by the configuration of the decision-making environment. A key innovation of our approach lies in the a priori integration of choice architecture effects into the ERU estimation, prior to final recommendation generation. For instance, an item with a baseline utility score of 8 may be strategically elevated within the system, resulting in a perceived ERU exceeding its initial value (e.g., 8.5). Conversely, another item with an identical baseline score might be deprioritized, leading to a diminished ERU (e.g., 7.5). Crucially, the nudge is not applied as a post-processing filter; rather, its effects are embedded in the ERU's computational logic. Prior to presenting the calculations, two concepts—social proof and confirmation bias—are introduced to explain why organizational recommendations influence customer ERU.

☑ Social Proof

This phenomenon describes the tendency of individuals to rely on the opinions and actions of others when making decisions. People often adjust their behavior based on others' behavior, particularly in unfamiliar or uncertain situations. Consequently, individuals perceive the behavior and decisions of others as evidence supporting the correctness of their own choices (Venema et al., 2020; Park and McCallister, 2023).

☑ Confirmation Bias (or Myside Bias)

This cognitive bias leads individuals to unconsciously accept information that affirms their pre-existing beliefs or assumptions while disregarding or devaluing conflicting information (Peters, 2022; Modgil et al., 2024).

Based on these phenomena, it can be argued that when an RS's suggestion aligns with the customer's choice, the customer's utility derived from that decision increases. Conversely, when the recommendation diverges from the customer's actual choice, increased uncertainty about the decision occurs, resulting in a decrease in choice satisfaction. Accordingly, the magnitude of utility enhancement—when the $h$-th customer's choice is corroborated by the recommendation of the organization—is represented by the parameter $B^h$. Additionally, $e_{ij}^h$ denotes the penalty experienced by the $h$-th customer when selecting product $p_j$, given that the RS chose product $p_i$. As defined in Eq. (5), $\pi_{ij}^h$ represents the ERU for the h-th customer when product $p_i$ is recommended and the customer selects product $p_j$.

$$\pi_{ij}^h = \begin{cases} s_i^{*h} + B^h & i = j \\ s_j^{*h} - e_{ij}^h & i \neq j \end{cases} \tag{5}$$

where $e_{ij}^h$ quantifies the cost of discordance between the recommended product $p_i$ and the product $p_j$ selected by the $h$-th customer, reflecting its impact on the customer's ERU, as defined by Eq. (6).

$$e_{ij}^h = {E^h \left| R_{p_i}^{(h)} - R_{p_j}^{(h)} \right|} \Big/ {N - 1} \qquad \forall i \neq j; h \tag{6}$$

where parameter $E^h$ represents the maximum possible reduction in the $h$-th customer's ERU; this occurs when the rank of the selected product with respect to the proposed product reaches its highest value (i.e., N−1 ), leading to a reduction in ERU by exactly $E^h$.

**Step 5:** Construction of the Payoff Matrix

In this step, the results of the calculations performed in Steps 1 to 4 are summarized in a payoff matrix $Y^h = [y_{ij}^h]_{n\times n}$. Each element $y_{ij}^h = \left(\rho_{ij}^{h(O)}, \pi_{ij}^h\right)$ is an ordered pair representing the ERU obtained by the organization and the $h$-th customer when the organization recommends product $p_i$ and the customer selects product $p_j$. More explicitly, $Y^h$ is defined as:

$$Y^h = \begin{bmatrix} \left(\rho_{11}^{h(O)}, \pi_{11}^h\right) & \left(\rho_{12}^{h(O)}, \pi_{12}^h\right) & \cdots & \left(\rho_{1n}^{h(O)}, \pi_{1n}^h\right) \\ \left(\rho_{21}^{h(O)}, \pi_{21}^h\right) & \left(\rho_{22}^{h(O)}, \pi_{22}^h\right) & & \left(\rho_{2n}^{h(O)}, \pi_{2n}^h\right) \\ & \vdots & \ddots & \vdots \\ \left(\rho_{n1}^{h(O)}, \pi_{n1}^h\right) & \left(\rho_{n2}^{h(O)}, \pi_{n2}^h\right) & \cdots & \left(\rho_{nn}^{h(O)}, \pi_{nn}^h\right) \end{bmatrix}_{n\times n}$$

In Table II, it is assumed that $P_i = R_i^{-(O)}$; that is, for simplicity, the products are labeled according to their organizational priority ranking.

**Table II. Payoff calculations for all combinations of recommendations and the h-th customer's choice**

| | | **Customer** Choice | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | $P_1$ | $P_2$ | $P_3$ | $P_4$ | . | . | $P_N$ |
| **Organization Recommendation** | $P_1$ | $\begin{pmatrix} (v_1^{*O} + G^h) \\ (s_1^{*h} + B^h) \end{pmatrix}$ | $\begin{pmatrix} \left(v_2^{*O} - \frac{M_2^h}{N-1}\right) \\ \left(s_2^{*h} - \frac{\Delta R_{21}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} \left(v_3^{*O} - \frac{2M_2^h}{N-1}\right) \\ \left(s_3^{*h} - \frac{\Delta R_{31}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} \left(v_4^{*O} - \frac{3M_2^h}{N-1}\right) \\ \left(s_4^{*h} - \frac{\Delta R_{41}^h}{N-1}\right) \end{pmatrix}$ | | | $\begin{pmatrix} (v_N^{*O} - M_2^h) \\ \left(s_N^{*h} - \frac{\Delta R_{N1}^h}{N-1}\right) \end{pmatrix}$ |
| | $P_2$ | $\begin{pmatrix} \left(v_1^{*O} - \frac{M_1^h}{N-1}\right) \\ \left(s_1^{*h} - \frac{\Delta R_{12}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} (v_2^{*O} + G^h) \\ (s_2^{*h} + B^h) \end{pmatrix}$ | $\begin{pmatrix} \left(v_3^{*O} - \frac{M_2^h}{N-1}\right) \\ \left(s_3^{*h} - \frac{\Delta R_{32}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} \left(v_4^{*O} - \frac{2M_2^h}{N-1}\right) \\ \left(s_4^{*h} - \frac{\Delta R_{42}^h}{N-1}\right) \end{pmatrix}$ | | | $\begin{pmatrix} \left(v_N^{*O} - \frac{(N-2)M_2^h}{N-1}\right) \\ \left(s_N^{*h} - \frac{\Delta R_{N2}^h}{N-1}\right) \end{pmatrix}$ |
| | $P_3$ | $\begin{pmatrix} \left(v_1^{*O} - \frac{2M_1^h}{N-1}\right) \\ \left(s_1^{*h} - \frac{\Delta R_{13}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} \left(v_2^{*O} - \frac{M_1^h}{N-1}\right) \\ \left(s_2^{*h} - \frac{\Delta R_{23}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} (v_3^{*O} + G^h) \\ (s_3^{*h} + B^h) \end{pmatrix}$ | $\begin{pmatrix} \left(v_4^{*O} - \frac{M_2^h}{N-1}\right) \\ \left(s_4^{*h} - \frac{\Delta R_{43}^h}{N-1}\right) \end{pmatrix}$ | | | $\begin{pmatrix} \left(v_N^{*O} - \frac{(N-3)M_2^h}{N-1}\right) \\ \left(s_N^{*h} - \frac{\Delta R_{N3}^h}{N-1}\right) \end{pmatrix}$ |
| | $P_4$ | $\begin{pmatrix} \left(v_1^{*O} - \frac{3M_1^h}{N-1}\right) \\ \left(s_1^{*h} - \frac{\Delta R_{14}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} \left(v_2^{*O} - \frac{2M_1^h}{N-1}\right) \\ \left(s_2^{*h} - \frac{\Delta R_{24}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} \left(v_3^{*O} - \frac{M_1^h}{N-1}\right) \\ \left(s_3^{*h} - \frac{\Delta R_{34}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} (v_4^{*O} + G^h) \\ (s_4^{*h} + B^h) \end{pmatrix}$ | | | $\begin{pmatrix} \left(v_N^{*O} - \frac{(N-4)M_2^h}{N-1}\right) \\ \left(s_N^{*h} - \frac{\Delta R_{N4}^h}{N-1}\right) \end{pmatrix}$ |
| | . | | | | | | | |
| | . | | | | | | | |
| | $P_N$ | $\begin{pmatrix} (v_1^{*O} - M_1^h) \\ \left(s_1^{*h} - \frac{\Delta R_{1N}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} \left(v_2^{*O} - \frac{(N-2)M_1^h}{N-1}\right) \\ \left(s_2^{*h} - \frac{\Delta R_{2N}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} \left(v_3^{*O} - \frac{(N-3)M_1^h}{N-1}\right) \\ \left(s_3^{*h} - \frac{\Delta R_{3N}^h}{N-1}\right) \end{pmatrix}$ | $\begin{pmatrix} \left(v_4^{*O} - \frac{(N-4)M_1^h}{N-1}\right) \\ \left(s_4^{*h} - \frac{\Delta R_{4N}^h}{N-1}\right) \end{pmatrix}$ | | | $\begin{pmatrix} (v_N^{*O} + G^h) \\ (s_N^{*h} + B^h) \end{pmatrix}$ |

**Step 6:** Determining Recommendation Strategies Through Fuzzy Inference System Modeling

The key question at this step relates to how to appropriately weigh organizational ERU relative to customer ERU. Addressing this question requires a solid understanding of the organization's context and the strategies it uses to navigate it. By analyzing these two fundamental concepts—the operational environment and the corresponding strategic response, referred to here as "*recommendation strategies*"—we can determine the appropriate importance to assign to each stakeholder's ERU: that of the organization and the customer.

The proposed recommender system captures these recommendation strategies by modeling expert and managerial knowledge through a fuzzy inference system (FIS). Experts and managers within the organization must establish recommendation strategies to determine how the system should adapt its recommendations to varying circumstances. By formalizing their knowledge within an FIS framework, the system gains the ability to dynamically select the most suitable strategy at any given moment, aligned with current organizational conditions. All recommendation strategies are designed to answer the fundamental question of how much attention should be given to organizational priorities versus customer priorities, contingent on specific situational factors. This methodology ensures that the RS remains flexible, context-aware, and aligned with the organization's strategic objectives. Just as accurate and comprehensive data are essential for improving recommender system performance, the unbiased and rigorous design of recommendation strategies by the organization's experts is critical to ensuring optimal system performance.

As a widely adopted fuzzy inference framework, the Zero-order Takagi–Sugeno–Kang FIS (TSK FIS) provides an effective means to model uncertain and qualitative knowledge using interpretable IF-THEN rules (Mao et al., 2025). Unlike Mamdani systems that rely on fuzzy sets in the consequent part, TSK FIS employs constant values (in the zero-order case) or linear functions (in the first- or higher-order cases) to produce crisp numerical outputs. This feature ensures both human-like reasoning through linguistic terms in the antecedent part and computational efficiency in the consequent part, making it particularly suitable for applications requiring precise quantitative output. In this study, a zero-order TSK FIS is employed to estimate the relative importance coefficient assigned to organizational ERU, denoted as $\alpha^{O} \in [0,1]$. Consequently, the corresponding weight of the $h$-th customer ERU is directly obtained as $\alpha^{h} = 1 - \alpha^{O}$.

The coefficients $\alpha^{O}$ and $\alpha^{h}$ dictate the relative emphasis placed on organizational priorities versus customer priorities in each context. In essence, the FIS that models recommendation strategies assesses the relative importance of prioritizing organizational goals versus customer needs in each specific context. Obviously, the execution of real-time recommendations necessitates data inputs essential for operationalizing the recommendation strategies.

Let $= \{x_i\}_{i=1}^{x}$ , $\boldsymbol{Z} = \{z_i\}_{i=1}^{z}$, *and* $\boldsymbol{T} = \{t_i\}_{i=1}^{t}$ denote the sets of input variables representing customer**,** organizational, and environmental input variables, respectively. Each variable is fuzzified into linguistic terms. For each customer input $x_i \in \boldsymbol{X}$ , a fuzzy set $A_{id}$ is defined with $d = 1,2,\dots,d_i$, where $d_i$ is the number of linguistic labels (e.g., *Low*, *Medium*, *High* ) for $x_i$. $\mu_{A_{id}}(x_i): X_i \to [0,1]$ is the membership function that quantifies the degree to which $x_i$ belongs to the fuzzy set $A_{id}$. For organizational input $z_i \in \boldsymbol{Z}$, fuzzy sets $B_{il}$ are defined for $l = 1,2,\dots,l_i$ where $l_i$ is the number of linguistic labels for $z_i$. $\mu_{B_{il}}(z_i): Z_i \to [0,1]$ is the membership function that quantifies the degree to which $z_i$ belongs to the fuzzy set $B_{il}$. For environmental input $t_i \in \boldsymbol{T}$ fuzzy sets $F_{ik}$ are defined with $k = 1,2,\dots,k_i$ , where $k_i$ is the number of linguistic labels of $t_i$. $\mu_{F_{ik}}(t_i): T_i \to [0,1]$ is the membership function that quantifies the degree to which $t_i$ belongs to the fuzzy set $F_{ik}$.

Each recommendation strategy is represented by a fuzzy rule as follows:

$$R^r\text{:IF } x_1 \text{ is } A_{1d} \text{ AND} \dots \text{AND } x_n \text{ is } A_{nd} \text{ AND } z_1 \text{ is } B_{1l} \text{ AND} \dots \text{AND } z_n \text{ is } B_{nl} \text{ AND } t_1 \text{ is } F_{1k} \text{ AND} \dots \text{AND } t_n \text{ is } F_{nk} \text{ THEN } \alpha^{O}=w^r, \quad (7)$$

where the crisp weight $w^r$, which ranges between 0 and 1, represents the level of emphasis placed on organizational priorities relative to customer preferences when the fuzzy rule $R^r$ is activated.

Let $G_r \subseteq \{X, F, Z\}$ denote the subset of variables included in the rule $R^r$. The firing strength of the fuzzy rule $R^r$ is denoted as $\kappa^r$ and is computed based on Eq. (8) via the product T-norm**.**

$$\kappa^r = \prod_{g \in G_r} \mu(g) \quad (8)$$

where $\mu(g)$ denotes the membership degree of variable g in its activated fuzzy set.

Finally, the weight of $\alpha^{O}$ is determined based on whether any fuzzy rules have been activated. Let $\Omega = \{R^r \mid \kappa^r > 0\}$

denote the set of activated fuzzy rules and $\omega = |\Omega|$ represent the number of activated rules. Using Eq. (9), the weight of $\alpha^O$ is calculated through a weighted average of activated rule consequents:

$$\alpha^O = \begin{cases} \sum_{r=1}^{\omega} \kappa^r w^r \Big/ \sum_{r=1}^{\omega} \kappa^r, & \omega > 0 \\ \alpha^O_{\text{default}}, & \omega = 0 \end{cases} \tag{9}$$

**Step 7:** Determining the Recommendation

In this step, two key processes are executed: (1) updating the payoff matrix based on the recommendation strategies derived in Step 6, and (2) generating final recommendations utilizing the adopted payoff matrix.

**Substep 7.1.** Aggregation of Results Using the Overall Benefit Matrix

The overall benefit matrix for the $h$-th customer and the organization is denoted by $\Phi^h = [\phi^h_{ij}]_{n\times n}$, where $\phi^h_{ij}$ represents the aggregate benefit to both stakeholders from recommending product $p_i$ to the $h$-th customer and the customer's subsequent selection of product $p_j$. $\Phi^h$ is defined as:

$$\Phi^h = \begin{bmatrix} \alpha^O \rho_{11}^{h(O)} + \alpha^h \pi_{11}^h & \alpha^O \rho_{12}^{h(O)} + \alpha^h \pi_{12}^h & \cdots & \alpha^O \rho_{1n}^{h(O)} + \alpha^h \pi_{1n}^h \\ \alpha^O \rho_{21}^{h(O)} + \alpha^h \pi_{21}^h & \alpha^O \rho_{22}^{h(O)} + \alpha^h \pi_{22}^h & & \alpha^O \rho_{2n}^{h(O)} + \alpha^h \pi_{2n}^h \\ \vdots & & \ddots & \vdots \\ \alpha^O \rho_{n1}^{h(O)} + \alpha^h \pi_{n1}^h & \alpha^O \rho_{n2}^{h(O)} + \alpha^h \pi_{n2}^h & \cdots & \alpha^O \rho_{nn}^{h(O)} + \alpha^h \pi_{nn}^h \end{bmatrix}_{n\times n}$$

**Substep 7.2.** Recommendation Generation Based on Regret Theory

The recommendation generation approach aligns with regret theory, beyond focusing solely on the minimax method, which obviously operates on the basis of worst-case scenarios, it pays attention to all possible scenarios. This approach, moving away from excessive conservatism, bases the evaluation on the average regret of a recommendation for different Scenarios (i.e., different customer choices). Furthermore, given the inherently interactive nature of RSs and their direct engagement with humans, transparency emerges as a critical requirement. To address this, in the recommendation generation approach, an attempt has been made to provide final recommendations by providing an understandable and simple aggregation approach (for the organization and the customer). This approach differs from stochastic methods, such as random regret minimization (RRM), by avoiding reliance on historical data or parameter estimation like maximum likelihood estimation (MLE). It operates purely on the structure of the overall benefit matrix, ensuring computational efficiency and transparency in Scenarios where probabilistic models are infeasible or overly complex. Let $\Gamma^h = [\gamma^h_{ij}]_{n\times n}$ be the regret matrix associated with the $h$-th customer, where $\gamma^h_{ij}$ is defined as the relative regret of choosing product $p_j$ when product $p_i$ is recommended by the RS. In particular, this can be expressed as Eq. (10):

$$\gamma^h_{ij} = \max_j \phi^h_{ij} - \phi^h_{ij} \tag{10}$$

The average regret for recommending a product $p_i$ to the $h$-th customer is then calculated as Eq. (11):

$$\Gamma^h_i = \sum_{j=1}^{n} \gamma^h_{ij} \Big/ n \tag{11}$$

Using these values, one can identify the top-N products with the minimal average regret.

## IV. SIMULATION EXPERIMENTS FOR METHOD VALIDATION

The purpose of this section is to demonstrate the performance of the proposed method and its advantages over traditional RSs via a simulated process approach. Suppose an organization operates under a mass customization production paradigm. The primary objective of the organization is to deploy an RS that integrates concurrent optimization of customer preferences and organizational constraints, thereby dynamically balancing demand fluctuations within a mass customization environment. There are ten potential products referred to as candidate products, available to its customers (i.e., N=10). Each order incurs an inherent lead time, as products are manufactured and assembled dynamically in response to demand rather than produced in advance. To rigorously assess the RS's performance, a simulated process was designed. In the proposed simulation process, a dynamic RS comprising 10 distinct products was implemented. During each iteration, every product was assigned a unique random score $s_i^h \sim uniform(50,200)$, representing the $h$-th customer's preferences generated by a traditional RS. It is crucial to note that our simulation did not model the internal mechanics of any specific, pre-existing traditional RS. Instead, this paper used randomly generated scores as a proxy for the outputs of systems that estimate and rank user preferences. By randomly assigning scores to each customer, this paper effectively simulates the core behavior of these systems, focusing solely on predicting customer affinity while ignoring organizational constraints. These scores were interpreted as the system's estimated preference priorities, where higher values indicated stronger predicted affinity. To ensure distinctness among product evaluations, a rejection sampling procedure was employed, guaranteeing $s_i^h \neq s_j^h$ for all $i \neq j$ within each $\boldsymbol{S^h}$ vector. This scoring mechanism was designed to simulate heterogeneous customer populations, where the assigned values $s_i^h$ reflected the inherent diversity of preferences across individuals. No artificial constraints were imposed on the traditional RS's output distributions, preserving the organic variation in predicted preferences. For each simulation iteration, a cohort of 90 synthetic customers ($h = 1, \dots, 90$) was generated.

Subsequently, a capacity-responsive approach was formulated to generate the organizational priority vector $\boldsymbol{V^O}$, which dynamically realigns scoring priorities with production capacity constraints. The person-hour requirements for each product are formally encoded in the production feature vector $\mathrm{F} = [\mathrm{f}_1 = 90, \mathrm{f}_2 = 40, \mathrm{f}_3 = 35, \mathrm{f}_4 = 60, \mathrm{f}_5 = 100, \mathrm{f}_6 = 15, \mathrm{f}_7 = 30, \mathrm{f}_8 = 14, \mathrm{f}_9 = 50, \mathrm{f}_{10} = 42]$, where $\mathrm{f}_i$ denotes the person-hours required to produce one unit of product i for i=1,2,…,10. Within this approach, during periods characterized by low customer order volume and substantial surplus production capacity (i.e., simulation step ≤ 40), elevated priority scores were allocated to products exhibiting higher resource demands, such as $P_5$ ($f_5$=100 person-hours). Conversely, as cumulative monthly production neared the nominal capacity threshold of 4000 person-hours, a deterministic switching mechanism was activated, systematically reallocating precedence to resource-efficient products—exemplified by $P_6$ ($f_6$=15 person-hours). Within this approach, organizational priority scores $v_i^O$ are generated through the capacity-aware allocation algorithm (see Table III), where $i \in \{1,2,...,10\}$. This dynamic allocation mechanism adjusts the scoring ranges based on the current simulation step, favoring high-resource products during periods of surplus capacity (step ≤ 40) and shifting toward resource-efficient alternatives as capacity limits are approached.

**Table III. Capacity-Aware dynamic prioritization mechanism for organizational preferences**

| Candidate products | Simulation step ≤ 40 | Simulation step > 40 |
|---|---|---|
| $P_1$ | $v_1^O \sim uniform(150,190)$ | $v_1^O \sim uniform(50,90)$ |
| $P_2$ | $v_2^O \sim uniform(90,150)$ | $v_2^O \sim uniform(70,110)$ |
| $P_3$ | $v_3^O \sim uniform(70,110)$ | $v_3^O \sim uniform(90,150)$ |
| $P_4$ | $v_4^O \sim uniform(100,180)$ | $v_4^O \sim uniform(60,100)$ |
| $P_5$ | $v_5^O \sim uniform(170,200)$ | $v_5^O \sim uniform(50,80)$ |
| $P_6$ | $v_6^O \sim uniform(50,90)$ | $v_6^O \sim uniform(150,190)$ |
| $P_7$ | $v_7^O \sim uniform(60,100)$ | $v_7^O \sim uniform(100,180)$ |
| $P_8$ | $v_8^O \sim uniform(50,80)$ | $v_8^O \sim uniform(170,200)$ |
| $P_9$ | $v_9^O \sim uniform(90,170)$ | $v_9^O \sim uniform(90,150)$ |
| $P_{10}$ | $v_{10}^O \sim uniform(90,150)$ | $v_{10}^O \sim uniform(90,170)$ |

In this simulation, we assume the organization begins each iteration with a capacity of zero, meaning no products are present in the production line at the start of the simulation. The process is repeated 90 times in each iteration, corresponding to 90 different customers, each placing an order, within a single run, to simulate a typical monthly demand cycle. After completing this set, the capacity is reset to zero for the subsequent iteration, effectively simulating a restart of operations. This approach emphasizes that the simulation operates as a discrete-interval (or window-based) process rather than a continuous dynamic system.

Specifically, the simulation continues until the organization's total capacity usage reaches 4000 person-hours, which represents the maximum operational capacity for a month. The input demand in each iteration is modeled to align approximately with this capacity, since the entry of about 90 customers aligns with the monthly organizational capacity of 4000 person-hours. This assumes that each batch of 90 customers can be handled in one discrete period, which aligns with the organization's capacity constraints.

Furthermore, to model the stability of organizational priorities over time, we introduce a variable called the step size, which determines the duration for which product priority scores remain constant. Once the product priority scores are calculated for a given iteration using the mechanism outlined in Table III, these scores are kept unchanged for the next step size of customer entries—in this case, 10. In other words, for each block of 10 customer arrivals, the organizational product priorities derived from the algorithm remain fixed. After these 10 customers have been processed, the algorithm recalculates the priority scores to reflect any updated organizational preferences, and this new set of priorities remains in effect for the next 10 customers, and so forth. This approach ensures that the priority scores remain consistent for a defined number of customer entries, allowing for effective analysis of the impact of organizational preferences on production decisions.

**Table IV. Comprehensive overview of FIS input variables**

| Variable | Description | Unit | Range of change | Linguistic variables |
|---|---|---|---|---|
| Z1:productionUsedCapacity | The capacity utilization of the organization's production lines resulting from customer orders | person-hours | [0 4000] | {Low(L),RelativelyLow(RL),Moderate (M),RelativelyHigh(RH),High(H)} |
| X1:CustomerHistory | Customer lifetime duration | year | [0 20] | |
| X2:CustomerExpectedLeadTime | Maximum waiting time for product delivery | Day | [1 100] | |
| T1:FutureOrderPrediction | Forecast of next month's orders based on historical averages | Number of orders | [0 300] | Moderate(M), {Low (L), High (H)} |

The recommendation strategies were modeled using a FIS, developed based on four key variables detailed in Table IV and Fig. 2. Experts formulated 52 fuzzy rules using these variables to represent the recommendation strategies within the FIS framework. Each rule is associated with an $\alpha^{O}$, indicating its influence, which is presented alongside the rules in Table V. In the fuzzy rules, the symbol '¬' is used to signify negation. The symbol '_' is used to indicate values that do not correspond to any linguistic variable in a rule, signifying that the rule is insensitive to that variable and takes all possible values.

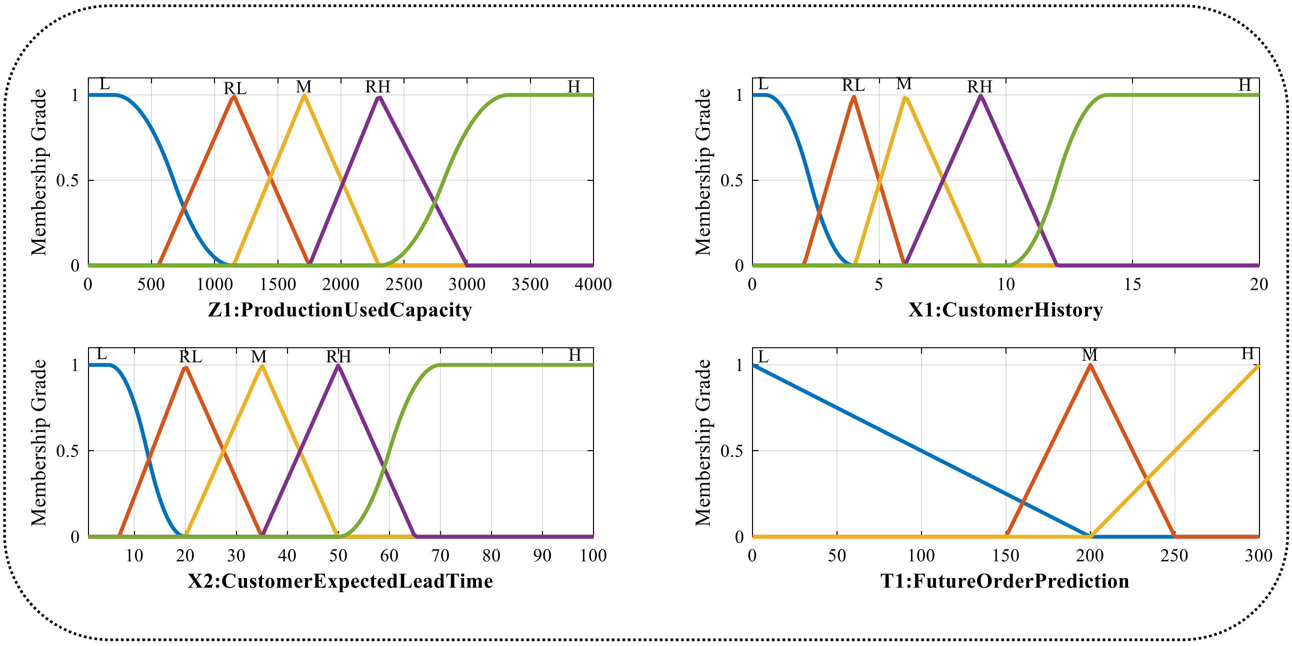



**Fig. 2. Architecture of the FIS along with the corresponding input membership functions. The figure illustrates the FIS framework, demonstrating the membership functions for the four input variables. Each membership function is defined over the full domain of its respective variable and has been determined based on expert domain knowledge and experience.**

**Table V. Recommendation strategies**

| ID | Z1:production UsedCapacity | X1:Customer History | X2:Customer ExpectedLeadTime | T1:FutureOrder Prediction | $\alpha^0$ |
|---|---|---|---|---|---|
| 1 | L | _ | ¬L | _ | 0.2 |
| 2 | H | ¬H | RL | L | 0.8 |
| 3 | H | ¬H | M | L | 0.6 |
| 4 | H | ¬H | RH | L | 0.4 |
| 5 | H | ¬H | H | _ | 0.2 |
| 6 | L | L | L | {L, M} | 0.2 |
| 7 | L | L | L | H | 0.2 |
| 8 | L | L | RL | {L, M} | 0.2 |
| 9 | L | L | RL | H | 0.4 |
| 10 | L | L | M | _ | 0.2 |
| 11 | L | L | RH | _ | 0.2 |
| 12 | L | L | H | _ | 0.2 |
| 13 | L | RL | L | ¬M | 0.2 |
| 14 | L | RL | RL | _ | 0.2 |
| 15 | L | RL | M | _ | 0.2 |

**Continue Table V. Recommendation strategies**

| ID | Z1:production UsedCapacity | X1:Customer History | X2:Customer ExpectedLeadTime | T1:FutureOrder Prediction | $\alpha^O$ |
|---|---|---|---|---|---|
| 16 | L | RL | RH | _ | 0.2 |
| 17 | L | RL | H | _ | 0.2 |
| 18 | L | M | H | _ | 0.2 |
| 19 | L | RH | H | _ | 0.2 |
| 20 | L | H | H | _ | 0.2 |
| 21 | L | H | _ | _ | 0.2 |
| 22 | RL | H | _ | _ | 0.2 |
| 23 | M | H | _ | _ | 0.4 |
| 24 | RH | H | _ | _ | 0.4 |
| 25 | H | H | _ | _ | 0.6 |
| 26 | H | ¬H | _ | _ | 0.8 |
| 27 | RH | H | L | H | 0.6 |
| 28 | RH | H | RL | H | 0.6 |
| 29 | RH | H | M | H | 0.6 |
| 30 | RH | H | RH | H | 0.4 |
| 31 | RH | H | H | H | 0.2 |
| 32 | M | M | M | M | 0.4 |
| 33 | L | _ | _ | {L, M} | 0.2 |
| 34 | L | _ | _ | H | 0.4 |
| 35 | {RL, M, RH} | _ | _ | L | 0.2 |
| 36 | H | _ | _ | L | 0.4 |
| 37 | H | ¬H | _ | H | 0.4 |
| 38 | H | H | _ | H | 0.6 |
| 39 | ¬{L,M} | H | H | ¬M | 0.2 |
| 40 | ¬{L,M} | _ | H | H | 0.4 |
| 41 | H | L | {L, RL} | H | 1 |
| 42 | H | L | {M, RH} | H | 0.8 |
| 43 | H | L | H | H | 0.6 |
| 44 | H | RL | H | H | 0.6 |
| 45 | H | M | H | H | 0.6 |

**Continue Table V. Recommendation strategies**

| ID | Z1:production UsedCapacity | X1:Customer History | X2:Customer ExpectedLeadTime | T1:FutureOrder Prediction | $\alpha^{O}$ |
|---|---|---|---|---|---|
| 46 | H | RH | H | H | 0.4 |
| 47 | H | H | H | H | 0.2 |
| 48 | M | L | L | H | 0.4 |
| 49 | H | L | L | H | 0.8 |
| 50 | RL | L | L | H | 0.4 |
| 51 | H | ¬H | L | H | 1 |
| 52 | RH | L | L | H | 0.6 |

Next, the model's parameters need to be assigned specific values. While these parameters are inherently customer-dependent, for simplicity, we assume that they are constant across all customers. The values assigned are as follows: $G^{h} = 0.2, M_1^{h} = M_2^{h} = 0.1, B^{h} = 0.2, E^{h} = 0.1$. Based on these assumptions, several simulation scenarios were designed.

**Table VI. Input variable distributions in simulated Scenarios**

| Scenario | Z1:productionUsedCapacity | X1:CustomerHistory | X2:CustomerExpectedLeadTime | T1:FutureOrderPrediction |
|---|---|---|---|---|
| **Scenario 1** | Dynamically updated using the customer arrival sequence and their choice | $L: X1 \sim uniform(0,2)$ | $L: X2 \sim uniform(1,20)$ | $H: T1 \sim uniform(250,300)$ |
| **Scenario 2** | | $\neg H: X1 \sim uniform(0,10)$ | $M: X2 \sim uniform(20,50)$ | $L: T1 \sim uniform(50,200)$ |
| **Scenario 3** | | $H: X1 \sim uniform(10,16)$ | $H: X2 \sim uniform(50,80)$ | $L: T1 \sim uniform(50,200)$ |

For a comprehensive analysis, three distinct simulation Scenarios were developed to represent different operational conditions within the organization. The primary differentiating factors among these scenarios are the values assigned to the variables X1, X2, and T1. The specific parameter configurations for each scenario are presented in Table VI. Additionally, Table VII links each Scenario to the corresponding recommendation strategies that guide decision-making under those conditions.

**Table VII. Mapping of Scenarios to corresponding recommendation strategies**

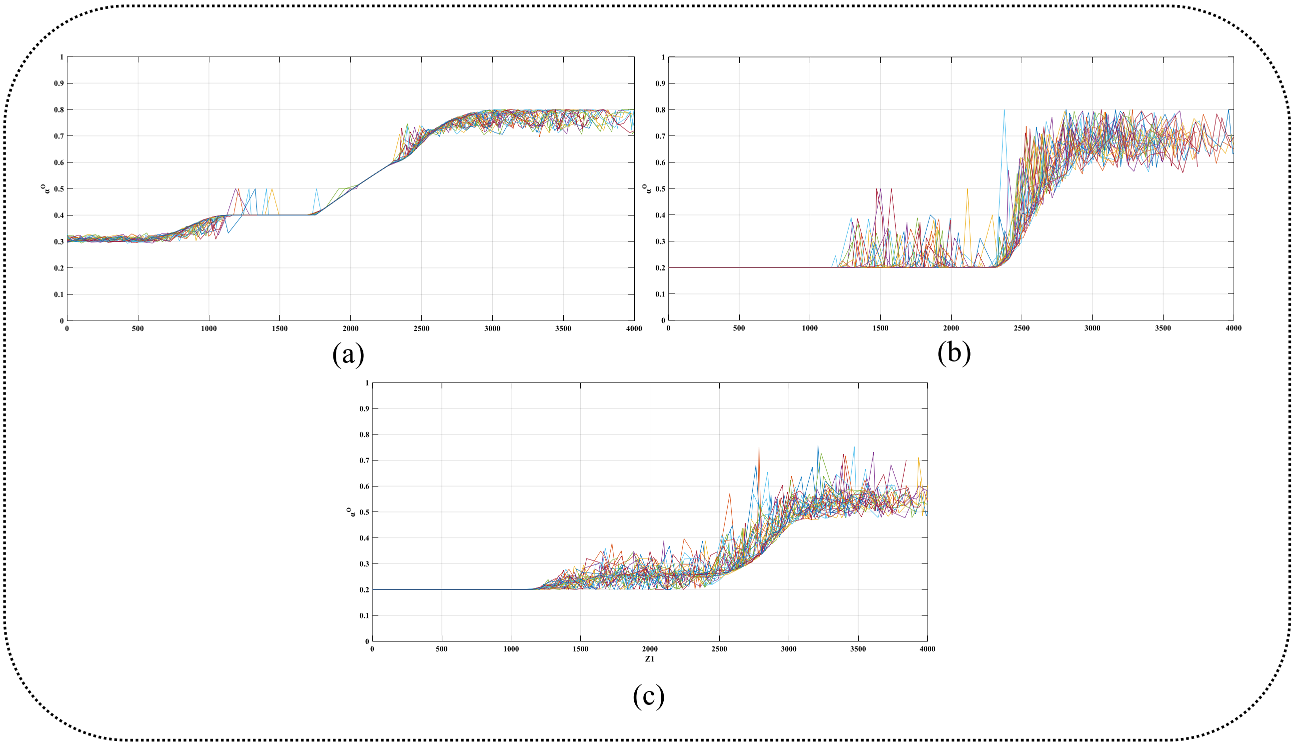
| Scenario | ID for related recommendation strategies |
|---|---|
| **Scenario 1** | 7,26,34,37,41,48,49,50,51,52 |
| **Scenario 2** | 1,3,10,15,18,19,26,33,35,36 |
| **Scenario 3** | 1,20,25,33,36,39 |

Scenario 1 models an operational environment characterized by emergent customer segments with limited prior organizational engagement. These customers typically demonstrate low historical transaction volumes and demand abbreviated order fulfillment lead times, while the organization anticipates managing high-volume future order projections. In contrast, Scenario 2 describes a setting in which customers are more engaged and have more reasonable expectations regarding delivery times. Despite this, the organization anticipates a relatively low volume of orders from customers in the upcoming period. Scenario 3 depicts a situation where customers have a very high level of historical engagement, typically representing long-standing clients. These customers do not expect early deliveries, and their expected lead time is quite long. Additionally, the organization expects the volume of orders received from customers in the next period to be low.

## *A. Analysis of the $\alpha^O$-Z1 Interdependency Across Scenarios*

This section evaluates how well the proposed RS assigns different $\alpha^O$ values across various Z1 levels in different Scenarios. We assume that customers accept the RS suggestions, aligning their choices with the recommendations. Given this assumption, we dynamically adjust the variable Z1 throughout the simulation process to reflect customer alignment with RS recommendations. Fig. 3 presents the results, illustrating the outcomes for all three scenarios, highlighting the RS's performance.

Comparing the results presented in Fig. 3, it can be seen that as the organization's unused capacity decreases, the $\alpha^O$ parameter increases in all scenarios. In scenario 1, the organization is expected to face a significant increase in demand soon, necessitating operational adjustments to manage this surge effectively. Accordingly, it is expected that the organization will place greater emphasis on its priorities as the demand approaches its capacity limits. This behavior is clearly reflected in Fig. 3(a), where a notable increase in the $\alpha^O$ occurs after demand exceeds 2500 person-hours—the largest jump among the three Scenarios, indicating its critical role in managing high demand. This is logical, given that Scenario 1 forecasts a very high demand in the subsequent period (as the variable T1 equals H), indicating that the RS should proactively prepare for such conditions. In contrast, Scenario 3 models a situation in which longstanding customers place orders with long delivery times. At the same time, the organization simultaneously predicts a sharp decline in demand in the subsequent period, necessitating a shift in the RS to prioritize customer preferences. As a result, the RS should assign greater importance to customer preferences, which is illustrated by the lower $\alpha^O$ compared to the other Scenarios (see Fig. 3(c)). Scenario 2 represents an intermediate case, where $\alpha^O$, which measures the priority level assigned to organizational objectives, is expected to be higher than in Scenario 3 but lower than in Scenario 1, as shown in Fig. 3(b). This analysis highlights how the RS dynamically adjusts priorities by recalibrating resource allocation and customer engagement strategies based on demand forecasts and customer engagement levels, ensuring more effective decision-making across different operational contexts.




(a) (b) (c)

**Fig. 3. Dynamic interaction between $\alpha^O$ and $Z_1$ across three simulation scenarios (a) scenario 1, (b) scenario 2, and (c) scenario 3. Scenario (a) depicts the most constrained condition, where the organization experiences the highest level of restrictions. Scenario (c) illustrates a minimally organizationally restricted environment. Scenario (b) represents an intermediate case, demonstrating a moderate level of organizational flexibility between the two extremes.**

### *B. Analysis of Organizational Capacity Utilization Across Scenarios*

This section evaluates the organization's capacity utilization across different scenarios using two distinct approaches: the traditional RS and the proposed RS with dynamic priority adjustment. The comparison focuses on how each approach affects total production capacity consumption over time. For each simulation iteration g, the total capacity utilized by the organization under both approaches is computed as follows:

$Z1_T^g$: Total capacity utilized in the g-th iteration using the traditional RS
$Z1_P^g$: Total capacity utilized in the g-th iteration using the proposed RS
To quantify the overall performance difference between the two approaches, we calculate the following metrics:

1. Mean deviation from organizational capacity utilization under the traditional RS:

$$MD_T = \sum_{g=1}^{50}\left(Z1_T^g - 4000\right) \Big/ 50 \tag{12}$$

2. Mean deviation from organizational capacity utilization under the proposed RS:

$$MD_P = \sum_{g=1}^{50}\left(Z1_p^g - 4000\right) \Big/ 50 \tag{13}$$

3. Over-utilization frequency under the traditional RS:

$$OUF_T = 100 * \sum_{g=1}^{50} \mathbf{1}_{\{Z1_T^g > 4000\}} \Big/ 50 \tag{14}$$

4. Over-utilization frequency under the proposed RS:

$$OUF_P = 100 * \sum_{g=1}^{50} \mathbf{1}_{\{Z1_P^g > 4000\}} \Big/ 50 \tag{15}$$

5. Over-utilization intensity under the traditional RS:

$$OUI_T = \sum_{g=1}^{50} max(0, Z1_T^g - 4000) \Big/ \sum_{g=1}^{50} \mathbf{1}_{\{Z1_T^g > 4000\}} \tag{16}$$

6. Over-utilization intensity under the proposed RS:

$$OUI_P = \sum_{g=1}^{50} max(0, Z1_P^g - 4000) \Big/ \sum_{g=1}^{50} \mathbf{1}_{\{Z1_P^g > 4000\}} \tag{17}$$

The organizational performance improves as the values of metrics $Z1_T^g$ and $Z1_p^g$ approach 4000 person-hours, which is the organization's nominal capacity. Specifically, the closer the values of $MD_T$ and $MD_P$ are to zero, the better the alignment between demand and capacity of the organization. Positive $MD_T$ and $MD_P$ values imply that the volume of orders exceeds the organizational capacity; negative values signify that the volume of orders is below the organizational capacity. The metrics $OUF_T$ and $OUF_P$ quantify the proportion of simulation iterations in which the organization exceeds its nominal capacity of 4000 person-hours. Mathematically, this is captured through the indicator function $\mathbf{1}_{\{x>m\}}$, which takes the value of 1 if, x surpasses m, and 0 otherwise. The metrics $OUF_T$ and $OUF_P$ provide insight into how often and to what extent the organization is operating beyond its nominal capacity. A lower value indicates better capacity alignment, implying that the organization can meet demand without frequently overextending its resources. Conversely, higher values suggest a tendency toward over-utilization, which may indicate strain on resources or the need for capacity expansion. The metrics $OUI_T$ and $OUI_P$, on the other hand, focus on the intensity of over-utilization, representing the mean excess capacity used in those iterations where over-utilization occurs. To quantify this, the mean of the positive deviations from the capacity threshold in over-utilizing scenarios is computed. This metric provides a more nuanced understanding by indicating how substantial the over-utilization tends to be when it occurs. Lower values here suggest that, when it occurs, overutilization is minimal, indicating efficient use of resources within capacity limits. Higher values, on the other hand, reveal significant bursts of overutilization that might compromise organizational sustainability or require costly operational adjustments. The results are presented in Table VIII.

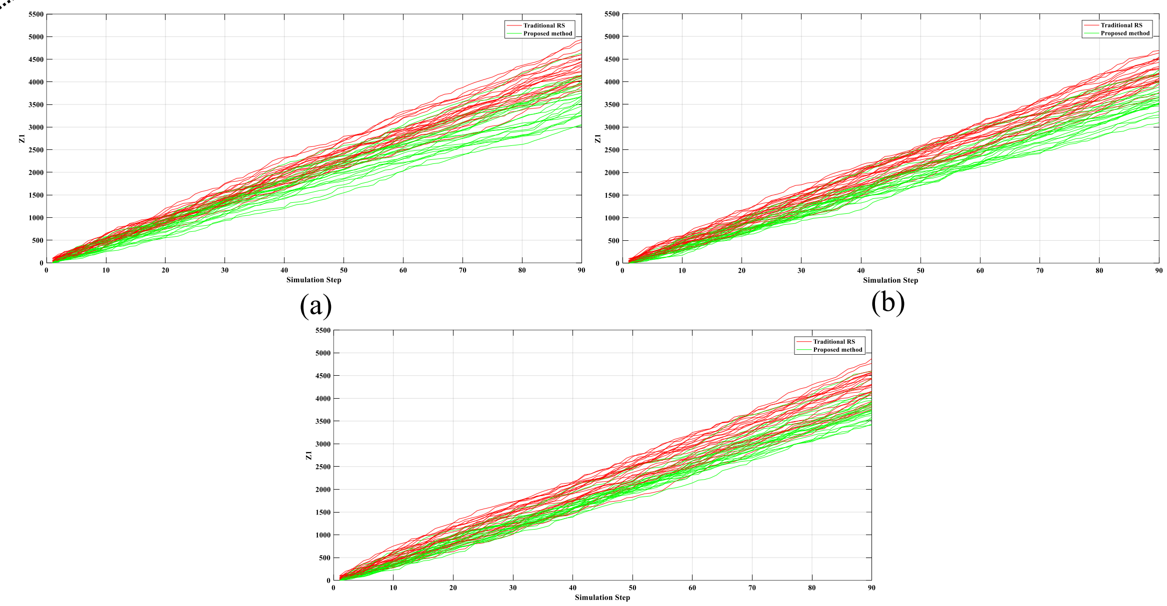
**Table VIII. Capacity utilization deviation across Scenarios**

| Scenario | $MD_T$ | $MD_P$ | $OUF_T$ | $OUF_P$ | $OUI_T$ | $OUI_P$ |
|---|---|---|---|---|---|---|
| **1** | 328 | -298 | 90% | 22% | 373 | 193 |
| **2** | 265 | -361 | 80% | 8% | 359 | 179 |
| **3** | 304 | -166 | 86% | 28% | 384 | 183 |

Several insights can be drawn from Table VIII, which details the impact of customer choice mechanisms on organizational capacity utilization. The first pertains to the impact of customer choice mechanisms on organizational capacity utilization. In all three scenarios, when customer decisions are based on the traditional RS, capacity is overutilized. This is evidenced by the positive values of $MD_T$ across each scenario. Conversely, when customer preferences align with the proposed RS, the organization can operate with greater confidence in its ability to fulfill orders within scheduled timeframes, since the values of $MD_P$ are negative in all scenarios. In the third scenario, which features fewer organizational production constraints compared to the other two, $MD_P$ attains its minimum value, indicating improved capacity utilization. This suggests that as organizational limitations decrease, the organization can better leverage its capacity to meet customer demand.

Another significant insight is the comparative frequency of over-utilization incidents under different RSs. On average, if customer choices are guided by the traditional RS, the organization encounters over-utilization in approximately 85.3% of cases. In contrast, this percentage drops to 19.3% when customer preferences are aligned with the proposed RS. Furthermore, analysis of indices $OUI_T$ and $OUI_P$ indicates that even in instances where the proposed RS contributes to over-utilization, both its frequency and magnitude are lower than those associated with the traditional RS. In scenarios of over-utilization, the proposed RS outperforms the traditional one in both the proportion of cases and the extent of capacity excess.

The trend in organizational capacity fulfillment during the simulation processes is illustrated in Fig. 4. The data presented in Table VIII confirm that the red lines (representing traditional RS) consistently show higher Z1 values than the green lines (representing proposed RS) across all three scenarios. In the first scenario, the proposed RS assigns a higher weight to organizational priorities, specifically using a larger $\alpha^O$ (see Fig. 3). As a result, the lines associated with this RS are positioned farther from the red lines representing the traditional RS. This indicates a greater divergence between the two RSs in this scenario (Fig. 4(a)). In the third scenario, which features the lowest $\alpha^O$, the disparity between the two RSs diminishes due to the reduced emphasis on organizational preferences. As depicted in Fig. 3(c), this reduction in $\alpha^O$ leads to reduced emphasis on organizational preferences, causing the behavior of the two systems to converge. In essence, situations that emphasize customer priorities over organizational constraints, such as the third scenario, yield similar operational behaviors between the proposed and traditional RSs. Nevertheless, even in these conditions, the proposed RS integrates organizational preferences into its calculations. This is evidenced by the fact that most green lines remain below the nominal capacity threshold of 4000 person-hours, illustrating that the proposed RS effectively accounts for organizational constraints while prioritizing customer satisfaction.




(a) (b) (c)

**Fig. 4. Comparative analysis of capacity utilization in traditional and proposed RSs across three simulation scenarios (a) scenario 1, (b) scenario 2, and (c) scenario 3. The figure illustrates how the proposed RS, by incorporating organizational preferences through varying levels of α^O, results in lower capacity utilization (green lines) compared to the traditional RS (red lines). The gap between the two RSs is progressively reduced from scenario 1 to scenario 3, indicating a convergence in behavior as customer priorities become more dominant. Nonetheless, the proposed RS consistently respects organizational constraints, as evidenced by its adherence to the 4000 person-hour capacity threshold.**

## V. CONCLUSION AND FUTURE WORK

Recommender systems (RSs) are essential tools for mitigating information overload and enhancing user satisfaction by streamlining decision-making. However, the traditional RS carries various well-known limitations. Despite this, little progress has been made in exploiting human decision-making processes in recommendation mechanisms. This study presents a novel recommendation approach that integrates cognitive biases and expert insights into the recommendation process. The proposed model facilitates a balanced consideration of multiple stakeholders through the implementation of a fuzzy inference system (FIS) and regret theory. Unlike traditional RSs that primarily rely on historical data, the proposed method enhances utility computation by incorporating psychological factors and organizational strategies. This results in a more flexible and context-aware RS. Furthermore, it facilitates interoperability with other RSs by utilizing their outputs. Additionally, it explicitly accounts for the overall benefits of both customers and the organization. The integration of cognitive, strategic, and stakeholder-oriented elements makes our approach a significant advancement in developing adaptive and multi-perspective RSs. The validity of the proposed model was assessed through a simulation-based approach, which was then followed by an evaluation of its performance in relation to organizational outcomes. Subsequently, several key performance indicators (KPIs) were introduced, and the performance of the proposed method was examined and compared with that of traditional RSs based on these KPIs.

The simulation results consistently show how different recommendation approaches impact the organization's capacity utilization, highlighting significant differences in organizational efficiency. Across all scenarios, when customer choices are guided by the traditional RS, the organization frequently exceeds its nominal capacity of 4000 person-hours. This is evidenced by positive values of $MD_T$ and high $OUF_T$ indices. This indicates a persistent over-utilization of resources, which can lead to potential operational strain. In contrast, when customer preferences are aligned with the proposed RS, negative $MD_P$ values demonstrate a more balanced alignment between demand and available capacity. On average, the occurrence of over-utilization declines sharply, from approximately 85% under the traditional RS to 19% under the proposed RS, highlighting the improved efficiency of the proposed mechanism. Furthermore, even in cases where over-utilization occurs, the intensity indices ($OUI_T$ and $OUI_P$) confirm that the proposed RS leads to milder and less frequent capacity excesses. Scenario-based comparison further indicates that as organizational constraints decrease (scenario 3), the proposed RS achieves the lowest $MD_P$ value, signifying optimized resource utilization with minimal deviation from the nominal capacity. Graphical trends (Fig. 4) corroborate this observation by illustrating that the proposed RS consistently maintains performance below or close to the 4000 person-hour benchmark, unlike the traditional RS, which regularly surpasses this threshold, indicating better resource management. The evidence presented in the simulation experiments section supports the idea that the proposed method has capabilities that traditional RSs do not support. The findings demonstrate the proposed RS's ability to balance customer preferences with organizational constraints, ensuring sustainable resource management under varying scenarios.

Notwithstanding the substantial improvements achieved by the proposed method, a fundamental sensitivity intrinsic to its design warrants explicit acknowledgment: the system's performance is highly contingent on the fairness and strategic balance of the expert-defined recommendation strategies embedded within the FIS, which can significantly influence the system's outcomes and effectiveness. The framework rests on the premise that the organizational strategies encoded by domain experts are equitable. If these rules are formulated in a manner that is overly restrictive and consistently prioritizes organizational interests over customer satisfaction across contexts, the long-term consequences may be detrimental. Such a bias could not only erode customer satisfaction but also precipitate customer churn, thereby undermining the organization's market position. The current model lacks an internal mechanism to audit or guarantee the fairness of these expert-prescribed strategies, which poses a risk as fairness is treated as a foundational assumption without verification. Consequently, a critical avenue for future work involves developing specific methodologies, such as fairness metrics or expert training programs, to assess and raise awareness among experts regarding the fairness implications of their prescribed strategies. This could include the integration of fairness metrics or feedback loops to steer the rule-definition process toward more balanced outcomes. In addition to focusing on fairness, several other promising research trajectories emerge. First, to further enhance the psychological realism of the model, it is advisable to identify and incorporate a broader set of cognitive biases into the utility computation mechanism. Second, the recommendation interface could be extended toward a hybrid persuasive approach. Rather than presenting a single option or a shortlist, the system could display multiple alternatives simultaneously while explicitly discouraging certain selections, thereby guiding user choice more actively. Finally, incorporating uncertainty into the proposed method could enhance the model's efficiency and robustness.

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