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An Explainable AI Framework for Thai Dish Recommendation Using Sensory Profiling and Association Rule Mining

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Abstract

Food recommendation systems often struggle to model culturally grounded meal composition behaviors, particularly in multi-dish dining environments where sensory balance and dish complementarity influence menu selection. This study proposes an explainable AI framework that integrates association rule mining with tri-dimensional sensory profiling to analyze dish pairing behavior in restaurant transactions. Using real-world Thai restaurant data, dishes were categorized into 15 culinary groups and profiled according to dominant taste, texture, and aroma characteristics. The Apriori algorithm was then applied to identify statistically significant co-occurrence patterns and generate interpretable association rules. By classifying dish categories and tagging them with dominant taste, texture, and aroma profiles, we apply the Apriori algorithm to generate interpretable association rules. These rules are further enriched through tri-dimensional sensory analysis to reveal cultural and sensory rationales behind dish pairings. The results demonstrate consistent patterns of contrast and harmony in texture, taste, and aroma, reflecting deeply embedded culinary logic. We formalize these insights into a rule-based recommendation system that models authentic Thai meal compositions. The framework not only advances computational food pairing research but also offers practical implications for menu design, inventory planning, and personalized food recommendation systems in culturally rich dining environments.

Keywords: Explainable Artificial Intelligence; Apriori Algorithm; Association Rule Mining; Sensory Profiling; Taste-Texture-Aroma Interaction; Computational Gastronomy

1. Introduction

Artificial intelligence (AI)-driven recommendation systems have become increasingly important in digital commerce and service industries, particularly in domains where consumers are confronted with a large number of choices. In the food and restaurant sector, recommendation systems are widely used to assist diners in navigating extensive menus, reducing decision fatigue, and improving personalized dining experiences (Ifada et al., 2020). Conventional food recommendation systems commonly rely on collaborative filtering, content-based filtering, or latent factor models derived from historical user interactions and preference similarity. Although these approaches can improve recommendation accuracy, many function as black-box systems with limited interpretability and weak cultural contextualization, making it difficult to explain why certain food combinations are recommended.

In computational gastronomy, traditional food pairing approaches have largely focused on ingredient-level compatibility through the food pairing hypothesis, which proposes that ingredients sharing volatile flavor compounds are more likely to form successful combinations (Amorim et al., 2017). Such approaches have been extensively applied in molecular gastronomy, recipe generation, and Western-style food pairing systems. However, these models are often developed within culinary contexts characterized by sequential or course-based meal structures and may inadequately capture the multisensory and communal nature of non-Western cuisines.

Recent developments in explainable AI (XAI) and knowledge-based recommendation systems have highlighted the importance of transparent decision-making processes, particularly in domains involving human preference, culture, and sensory perception. Unlike opaque recommendation models, explainable systems provide interpretable reasoning that allows users

and practitioners to understand the logic behind recommendations. This is especially relevant in food recommendation contexts, where dining decisions are strongly influenced by cultural expectations, sensory balance, and shared eating practices rather than solely by individual item preferences.

Thai cuisine presents a particularly complex and culturally rich environment for studying explainable food recommendation systems. Thai meals are traditionally composed through the simultaneous consumption of multiple dishes, each contributing distinct sensory roles in terms of taste, texture, aroma, and preparation style. Holm et al. (2012) demonstrated that eating patterns and food behaviors are strongly shaped by cultural context, while Reddy and van Dam (2020) further emphasized that food preferences are deeply embedded in identity formation and social structures. In Thai dining culture, meals are intentionally constructed around principles of contrast and complementarity. A spicy salad may be paired with a mild curry, a crispy fried dish balanced with a sour soup, or a rich meat preparation offset by fresh herbs and acidic components. These combinations reflect not only flavor compatibility but also culturally embedded sensory logic.

The multisensory nature of Thai cuisine presents important challenges for conventional recommendation systems. Thai dishes often combine salty, sour, spicy, sweet, bitter, and umami tastes alongside diverse textures and complex aromatic profiles. Moreover, dish selection behavior is influenced by communal meal composition, where diners select combinations of dishes intended to create balance across the entire table rather than maximizing the appeal of a single item. Despite these complexities, existing AI-based food recommendation systems rarely incorporate sensory interactions, preparation-based structures, or cultural meal logic into their recommendation processes.

This study addresses this gap by proposing an explainable AI framework for Thai dish recommendation that integrates sensory profiling with association rule mining. The proposed framework combines two complementary layers of knowledge representation. First, dishes are profiled according to dominant sensory attributes, including taste, texture, and aroma. Second, dishes are categorized based on preparation methods and culinary functions, such as curry, fried, grilled, or spicy salad. Using real-world restaurant transaction data, the Apriori algorithm is employed to identify frequent co-occurrence patterns among dishes and generate interpretable association rules that reflect recurring meal composition behaviors.

Unlike ingredient-level pairing systems, this study focuses on whole-dish recommendation behavior and the sensory logic underlying multi-dish meal construction. The resulting framework functions as a knowledge-based recommendation system capable of generating culturally grounded and explainable pairing suggestions. By integrating association rule mining with sensory knowledge representation, the study contributes to the growing field of explainable AI in food recommendation systems while simultaneously advancing computational gastronomy research through the modeling of culturally embedded dining behavior.

The contributions of this study are threefold. First, it introduces a culturally grounded explainable AI framework for food recommendation based on multisensory dish representation. Second, it demonstrates how association rule mining can be enriched with sensory profiling to improve interpretability and contextual relevance in recommendation systems. Third, it provides empirical insights into Thai meal composition behavior using real-world restaurant transaction data, offering practical implications for intelligent menu design, digital ordering platforms, and culturally adaptive AI-driven dining systems.

2. Literature review

2.1 Multisensory Meal Structures and Sensory Representation in Food Systems

Food selection behavior is influenced not only by individual preferences but also by multisensory interactions occurring across entire meals. In many dining systems, dishes are consumed as combinations rather than isolated items, requiring diners to balance taste intensity, texture, aroma, temperature, and preparation style within a single eating experience (Holm et al., 2012). Such meal-level sensory balancing is especially relevant in shared dining environments where complementary and contrasting dishes are intentionally combined.

From a sensory science perspective, food perception is inherently multisensory, involving interactions among gustatory, olfactory, trigeminal, and textural stimuli. Modern sensory research has demonstrated that flavor perception emerges not from isolated sensory dimensions but from cross-modal integration occurring throughout consumption (Rahman, 2019). Consequently, meal composition behavior depends not only on ingredient compatibility but also on how dishes collectively contribute to sensory equilibrium.

Many culinary systems provide examples of such multisensory balancing principles. Meals frequently combine contrasting sensory characteristics, such as spicy and cooling elements, crispy and fluid textures, or rich and acidic flavor profiles. For example, a spicy and acidic seafood salad may be paired with a crispy fried meat dish, while a rich curry may be balanced by fresh vegetables or light soups. These combinations create sensory contrast across moisture, aroma intensity, texture, and taste, reducing sensory fatigue while enhancing meal diversity.

This multisensory logic is particularly evident in cuisines characterized by shared dining structures and simultaneous multi-dish consumption. Rather than optimizing the sensory appeal of individual dishes independently, meal composition behavior seeks balance across the entire dining experience. Soups and curries contribute moisture and aromatic depth, fried dishes introduce crispness and richness, while salads and fresh herbs provide acidity, freshness, and palate cleansing effects. Consequently, dish selection behavior reflects coordinated sensory interactions operating at the meal level rather than isolated item preference.

Such complexity presents important challenges for artificial intelligence-based recommendation systems. Many existing food recommendation models simplify food representation into ingredient lists, nutritional information, ratings, or transactional histories while neglecting sensory relationships between dishes. As a result, conventional recommendation systems may fail to capture the sensory balancing mechanisms underlying real dining behavior.

To address this limitation, recent research has emphasized the importance of sensory knowledge representation in computational gastronomy and food recommendation systems. Sensory descriptors such as taste, aroma, and texture provide interpretable semantic features capable of linking statistical consumption patterns with human sensory reasoning. These representations are especially valuable in explainable recommendation systems because they allow recommendations to be interpreted through meaningful sensory logic rather than opaque statistical similarity alone.

In this study, dishes are represented through tri-dimensional sensory profiling consisting of taste, texture, and aroma attributes. This representation enables analysis of how sensory

complementarity influences dish co-occurrence patterns within real-world restaurant transactions. By modeling dishes through interpretable sensory dimensions, the study seeks to bridge sensory science and explainable artificial intelligence within the context of food recommendation systems.

2.2 Computational Food Pairing and Association Rule Mining

Computational gastronomy has increasingly adopted artificial intelligence and data mining techniques to analyze food behavior, recipe generation, and recommendation systems. One major area of research concerns computational food pairing, where algorithms are used to identify compatible food combinations based on chemical similarity, ingredient networks, consumer behavior, or sensory relationships.

Traditional food pairing approaches are largely based on the food pairing hypothesis, which proposes that ingredients sharing volatile flavor compounds are more likely to form compatible combinations (Amorim et al., 2017). Such approaches have been widely applied in ingredient recommendation systems, molecular gastronomy, and automated recipe generation. Ingredient-level pairing models commonly rely on flavor networks, co-occurrence analysis, or molecular similarity to identify potential combinations.

However, ingredient similarity alone cannot fully explain meal composition behavior in complex dining environments. Many successful dish combinations rely on sensory contrast rather than similarity. Crispy foods may be paired with soups to balance moisture, spicy dishes may be combined with cooling or sour elements, and aromatic intensity may be offset by neutral or refreshing components. These interactions operate across multiple sensory dimensions simultaneously and are often shaped by cultural dining structures.

Recent advances in explainable artificial intelligence (XAI) have highlighted the importance of transparent and interpretable recommendation systems, particularly in domains involving subjective human preferences. In food recommendation contexts, explainability is critical because diners and restaurant operators often require understandable reasoning behind recommendations. Unlike black-box recommendation models based on deep learning or latent embeddings, explainable systems allow users to understand why specific dish combinations are suggested.

Association rule mining (ARM) provides a particularly suitable framework for explainable food recommendation because the generated rules are transparent, interpretable, and directly linked to observable transaction behavior. The Apriori algorithm introduced by Agrawal and Srikant (1994) remains one of the foundational approaches for discovering frequent itemsets and co-occurrence relationships within transactional datasets. Apriori extracts association rules using support, confidence, and lift metrics, allowing statistically significant relationships between items to be identified while preserving interpretability.

In foodservice and retail applications, Apriori has been widely used for market basket analysis, promotional bundling, cross-selling strategies, and recommendation systems. Kurnia et al. (2019) applied Apriori analysis to restaurant transaction data to identify menu combinations suitable for promotional strategies. Similarly, Satria et al. (2023) compared Apriori and FP-Growth methods in food recommendation systems and noted that Apriori provides superior interpretability and managerial transparency despite lower computational efficiency.

Contemporary recommendation systems have also begun integrating contextual variables such as mood, location, and sentiment analysis. Gupta et al. (2021), for example, proposed a

mood-based food recommendation system combining collaborative filtering and contextual analysis to improve personalization. Nevertheless, many existing food recommendation systems still prioritize statistical prediction accuracy while overlooking sensory structure and culturally grounded meal composition behavior.

Despite substantial advances in computational gastronomy, several limitations remain. First, many systems focus primarily on ingredient-level compatibility rather than dish-level meal composition. Second, recommendation systems often operate as black-box models with limited interpretability. Third, sensory interactions involving taste, texture, and aroma are rarely integrated into explainable recommendation frameworks despite their importance in dining behavior.

To address these gaps, this study integrates sensory profiling with association rule mining to construct an explainable AI framework for dish recommendation. Rather than recommending dishes independently, the framework models co-occurrence behavior through interpretable sensory relationships derived from real-world restaurant transactions. By combining transaction-based learning with multisensory knowledge representation, the study contributes to explainable AI, computational gastronomy, and intelligent food recommendation systems.

3. Sensory coding methodology

This study employs a mixed-method computational framework to identify co-occurrence patterns among Thai main dishes by integrating sensory profiling with association rule mining. The methodology consists of three primary components: (1) construction of a sensory attribute dataset categorizing each dish by dominant taste, texture, and aroma; (2) classification of dishes into standardized cooking method categories; and (3) application of the Apriori algorithm to real-

world restaurant transaction data to discover frequent co-ordering patterns. By triangulating these components, the study aims to uncover not only statistically significant pairings but also culturally and sensorially meaningful relationships between dishes. This integrated approach enables the generation of actionable recommendation rules grounded in both empirical transaction behavior and traditional Thai culinary logic.

3.1 Data Collection and Preparation

Transaction data were collected from a Thai restaurant over a year period. Each transaction reflects a unique customer order, consisting solely of main dishes. To maintain analytical consistency, non-main items such as appetizers, beverages, and desserts were excluded from the dataset. This ensured a focused exploration of customer preferences pertaining strictly to core menu offerings.

Each transaction was encoded in a binary matrix format, where rows represent individual orders and columns represent the presence or absence of specific main dishes. Dishes that appeared in fewer than 1% of total transactions were removed to reduce sparsity and eliminate outlier effects. This step was essential in limiting the analysis to high-impact dishes that contribute meaningfully to customer decision-making.

3.2 Application of the Apriori Algorithm

The Apriori algorithm was used to mine frequent itemsets and generate association rules among the main dishes. The algorithm operates in two phases. In the first phase, it identifies all itemsets that meet a user-defined minimum support threshold. In the second phase, it derives association rules from these frequent itemsets that satisfy a minimum confidence criterion.

The analytical process adhered to the following metrics:

Support: Measures how frequently a set of main dishes appears in the dataset.

$$Support(A \rightarrow B) = \frac{Number\ of\ transactions\ containing(A \cup B)}{Total\ number\ of\ transactions}$$

Confidence: Measures the conditional probability that dish *B* is ordered given that dish *A* is ordered.

$$Confidence\ (A \rightarrow B) = \frac{Support(A \cup B)}{Support(A)}$$

Lift: Indicates how much more likely *B* is to be ordered when *A* is ordered, compared to random chance.

$$Lift\ (A \longrightarrow B) = \frac{Confidence(A \longrightarrow B)}{Support(B)}$$

These rules help identify frequent combinations which may reflect shared taste preferences or complementary dish characteristics.

3.3 Parameter Configuration

The algorithm was implemented using the `mlxtend` library in Python, which provides efficient methods for generating frequent itemsets and deriving association rules. After preliminary testing, the following parameters were selected:

Minimum support: 0.05 (5% of total transactions)

Minimum confidence: 0.6 (60%)

Minimum lift: 1.5 (used to filter rules with meaningful strength)

These thresholds were chosen to balance comprehensiveness and interpretability, ensuring that only practically significant and frequently occurring associations were retained.

3.4 Rule Filtering and Interpretation

Once the initial set of rules was generated, a manual filtering process was conducted to remove trivial or symmetric rules (e.g., A → A) and focus on interpretable associations between different main dishes. Particular attention was paid to rules that align with culinary coherence or customer ordering logic, such as combinations that balance flavor profiles or are likely to be shared during group dining occasions.

The final rules were presented as a recommendation framework, enabling restaurant management to consider strategic placement of dishes on the menu, bundling options, or staff suggestions based on established ordering patterns.

4. Findings

Understanding the sensory composition of Thai main dishes requires an integrated analysis of six dominant taste (Salty, Umami, Sour, Spicy, Sweet, Bitter), five texture (Smoothness, Firmness, Slipperiness, Cohesiveness, Creaminess), and six aroma (Seafood, Meat, Vegetable, Grain, Herbs, Fruit) characteristics. Each dish in the dataset was coded according to its primary sensory attributes along these three axes, based on expert consensus and typical ingredient and preparation profiles. Likewise, to provide a foundational structure for analyzing Thai menu composition and co-occurrence behavior, each dish in the dataset was classified into one of 15 preparation-based categories (Spicy Salad, Grilled, Stir-Fried, Curry, Stewed, Steamed, Fried, Relish (Chili Paste), Salad, Rice-Based, Soup, Laab, Boiled, Baked, Others). These categories reflect dominant cooking techniques and culinary functions found in Thai cuisine. This framework allows for a systematic mapping of how Thai cuisine organizes multisensory experiences across dish types.

To help readers better understand the sensory logic underlying typical Thai meal design, a curated list of popular Thai main dishes and their dominant sensory and cooking characteristics is presented in Table 1. It should be noted that these examples are not exhaustive of the dataset but are selected to facilitate the sensory logic description. The dishes include commonly known preparations across cooking methods—stir-fries, curries, soups, salads—and illustrate the interplay of taste, texture, and aroma that typifies Thai culinary structure. This table will also serve as a reference for interpretation in later sections where sensory pairings and association rules are discussed.

4.1 Sensory Profile Distribution

4.1.1 Taste Profile Distribution: Patterns in Palate Preferences

This distribution reveals that salty and umami flavors are the most dominant in Thai main dishes, jointly accounting for more than 53% of all orders. These flavors are closely associated with dishes featuring fish sauce, soy sauce, oyster sauce, and fermented components, particularly in fried, stir-fried, grilled, and rice-based preparations. They often act as anchor dishes in meal sets due to their deep savoriness and compatibility with rice.

Sour and spicy flavors follow closely, forming a combined share of 34.64%. These profiles are prominent in salads, soups, and certain curries, delivering sharp, aromatic, and refreshing notes. Dishes like *Tom Yum Goong* (1) and *Yum Mamuang* (2) exemplify this group and are typically selected to cut through richness and add palate contrast.

The sweet profile, representing just under 10%, appears in dishes that use palm sugar, sweet soy glaze, or fruit, such as *Massaman curry* (3), *Kai Look Keuy* (4), or *Khao Pad Sapparot* (5).

Though less dominant overall, sweet components often function contextually, balancing spicy or salty items.

Finally, the bitter profile—although least represented (2.43%)—is culturally significant. Found in dishes like *Gang Kee Lek* (6) or *Mara Pad Khai* (7), bitterness signals a connection to medicinal cooking and herbal traditions in Thai cuisine, often appreciated for health or digestive benefits rather than mass appeal.

In sum, Table 2 reflects a culinary logic that prioritizes savory intensity (salty, umami) and sensory stimulation (sour, spicy), with sweetness and bitterness serving as contrastive or functional layers. This balance across taste profiles underpins the compositional diversity of Thai shared meals and validates the relevance of taste as a primary axis in menu modeling.

4.1.2 Texture Profile Distribution: Empirical Patterns and Culinary Significance

The dataset reveals that Thai main dishes exhibit a remarkably balanced distribution across the three dominant texture classes: smoothness (34.56%), slipperiness (33.74%), and firmness (31.66%). This even spread reflects a deliberate emphasis on tactile contrast in Thai meal design, where dishes are selected not just for flavor but also for their mouthfeel contribution to the overall experience.

- Smooth textures, the most prevalent, are characteristic of curries, stews, and stir-fried items, where ingredients are often bathed in rich sauces or coconut milk bases. Dishes such as *Kaeng Khiao Wan Gai* (8) exemplify this category, offering a consistent, cohesive mouthfeel that is both comforting and palatable across a wide demographic.

- Slipperiness, nearly equal in prevalence, is strongly associated with soups and salads that feature brothy liquids, gelatinous ingredients, or mucilaginous vegetables. This texture is prominent in dishes like *Tom Yum Goong* (1), and *Yum Som-O* (9).
- Firm textures, though slightly less frequent, represent an important structural dimension in Thai meals. Found in fried, grilled, and some stir-fried dishes—such as *Gai Tod Kratiem* (10) and *Kor Moo Yang* (11)—firmness offers chewiness and bite, contributing to satiety and perceived protein richness. These items often serve as the "main event" of the meal, anchoring softer or more fluid accompaniments.
- The extremely low representation of cohesiveness and creaminess (each <0.05%) indicates their marginal role in Thai main dishes. These textures are more likely found in desserts or fusion preparations, and their near absence reaffirms the dominant role of clean, contrasting mouthfeels in traditional Thai savory dining.

The findings from Table 3 reinforce the cultural principle of texture modulation in Thai meal planning. Unlike cuisines that prioritize single-texture dishes, Thai cuisine values textural interplay—a meal composed of both crunch and softness, or slippery freshness and structured chew. This has important implications for digital recommendation systems and sensory-aware menu design, particularly in guiding pairings based not only on taste but also on complementary tactile experiences.

4.1.3 Aroma Profile Distribution: The Scent Structure of Thai Cuisine

The data, in Table 4, indicates a strong aromatic dominance of seafood (53.71%), followed by meat-based aromas (33.67%), together accounting for nearly 90% of all dish orders. This distribution reflects the centrality of protein-forward preparations in Thai dining, where aroma acts as a key signal of savory depth, freshness, and complexity.

- Seafood aroma, the most dominant category, is prominent in dishes such as *Tom Yum Goong* (1), *Kaeng Luang Poo Bai Cha Plu* (12), and *Yum Talay* (13). These dishes typically feature shrimp, squid, or crab and convey briny, umami-forward aromas that heighten sensory alertness and evoke freshness. The high percentage reflects both Thailand's geographic proximity to aquatic resources and a strong cultural preference for the aromatic intensity and lightness of seafood-based dishes.
- Meat aroma, though secondary, constitutes one-third of all orders. Dishes such as *Kai Yang* (14), *Pad Kra Pao Moo* (15), and *Moo Krob* (16) exemplify this category. These aromas are typically roasted, caramelized, or umami-rich, contributing depth and familiarity, and often form the structural core of multi-dish meals. Their popularity signals the continued dominance of animal protein as a sensory anchor in Thai culinary construction.
- Vegetable and grain-based aromas, at 5.25% and 3.83% respectively, are generally associated with side dishes or balanced components rather than main items. These include dishes like *Pad Pak Boong Fai Daeng* (17) or *Khao Pad Poo* (18), which contribute supportive aromas rather than dominant olfactory identities.
- Herbal aromas (2.61%)—from ingredients like lemongrass, galangal, and kaffir lime—often play a central flavoring role but are rarely the primary aromatic identity of a dish. While central to dishes like *Tom Kha Kai* (19) or *Yum Ta Krai* (20), herbs are more frequently integrated than foregrounded, making them sensory enhancers rather than dominant notes.

- Fruit aromas (0.93%) are uncommon and typically appear in specialized dishes such as *Kaeng Phet Ped Yang* (21) or *Yum Som-O* (9). These offer aromatic sweetness or floral sharpness, contributing to occasional contrast within a meal.

Overall, the aroma distribution underscores the centrality of animal protein and aquatic ingredients in Thai olfactory culinary identity, while also reflecting cultural values of freshness and flavor layering.

4.2 Cross-Analysis of Sensory Profiles

4.2.1 Cross-Analysis of Taste and Texture Profiles

Thai main dishes are rarely designed with a single dominant sensory cue. Instead, they exhibit a nuanced interplay between taste and texture, creating contrast, balance, and complexity within each dish. Fig. 1 below presents the cross-tabulation of dominant taste and texture profiles, revealing both reinforcing and contrasting sensory strategies embedded in Thai culinary design.

Firmness × Umami: Structural Depth and Savory Impact

The strongest pairing (15.83%) is firm texture with umami taste, often found in dishes like *Pad Kra Pao Moo* (15) or *Kor Moo Yang* (11). The tactile resistance of firm proteins enhances savory impact and creates chewiness that holds seasoning, reinforcing the umami experience.

Smoothness × Salty: Sauce Absorption and Mouthfeel

The second most prevalent combination (17.47%) is smooth texture with salty taste, typical of stir-fries and curries such as *Gai Pad Med Mamuang* (22) or *Khao Pad Goong* (23). Smoothness facilitates cohesive mouthfeel and efficient absorption of sauce, ensuring that seasoning spreads evenly across each bite.

Slipperiness × Sour: Palate Cleansing and Speed of Flavor Release

A notable pattern is slippery texture with sour taste (11.95%), reflecting dishes like *Tom Yum Goong* (1) or *Yum Som-O* (9). The light, moist texture allows acid notes to dominate quickly, creating a refreshing, appetite-whetting sensation that contrasts sharply with oil-based or protein-rich dishes.

Spicy Profiles: Split Across Textures

Spicy taste is spread across all three dominant textures: Firmness (4.79%), offers structure to carry spice oils and chili heat; Smoothness (8.19%), common in spicy stir-fries and curries; Slipperiness (2.95%), seen in hot-sour soups, where chili is suspended in broth.

Bitter and Creamy/Cohesive Profiles: Peripheral Roles

Bitterness (2.42% with firmness) remains a niche but culturally significant taste, often found in herbal or medicinal dishes such as *Mara Pad Khai* (7). Creaminess and cohesiveness are nearly absent, confirming that rich, uniform mouthfeels are not central to Thai savory cuisine.

4.2.2 Cross-Analysis of Aroma and Texture Profiles

In Thai cuisine, aroma and texture are deeply interwoven to shape multisensory meal experiences. The cross-tabulation of these attributes (Fig. 2) reveals strategic pairings that enhance flavor perception, tactile satisfaction, and cultural expectations.

Firmness × Meat Aroma: Structural and Satiating

The most dominant aroma–texture pairing (26.08%) is meat aroma with firm texture, found in dishes like *Kai Yang* (14), *Moo Ping* (24), and *Pad Kra Pao Moo* (15). These dishes deliver

satisfying bite resistance, chewy textures, and roasted or seared aromas, forming the structural backbone of many Thai meals.

Slipperiness × Seafood Aroma: Fluid Intensity

An equally notable pairing (33.06%) is seafood aroma with slippery texture, exemplified in dishes such as *Tom Yum Goong* (1) and *Pla Muek Neung Manao* (25). This combination allows oceanic and briny aromas to rapidly diffuse across the palate, while the moist, soft texture provides a broth-driven or steamed sensation, often sharpened by sour or spicy flavors.

Smoothness × Seafood Aroma: Savory Fluidity

At 20.63%, smooth texture with seafood aroma is also prevalent. Dishes like *Kaeng Luang Poo* (12) or *Kai Tun Poo* (26) exemplify this duo. The gentle texture allows the briny or umami notes of crab or shrimp to persist without overpowering, contributing to a rich yet balanced mouthfeel.

Vegetable & Herb Aromas: Distributed Across Textures

- Firmness + Vegetable (2.65%): Found in dishes such as *Pad Pak Boong* (17) or *Yum Tua Plu* (27), where crunch reinforces freshness.
- Smoothness + Herbs (1.72%): Reflects subtle herbal broths or stews like *Kai Toon Sam Kler* (28) or *Tom Kha Kai* (19).
- Firmness + Herbs (0.89%): Present in grilled or stir-fried dishes with strong basil or lemongrass presence such as *Yum Ta Krai* (20).

Fruit Aroma: Slippery or Smooth Carriers

While less common, fruit aroma pairings (0.53% slippery; 0.40% smooth) reveal culturally specific contrasts, such as, *Kaeng Phet Ped Yang* (21) and *Yum Som-O* (9). These dishes use moist textures to carry sweet–aromatic notes that act as cooling or palate-resetting agents in spicy or oily meals.

4.2.3 Cross-Analysis of Aroma and Taste Profiles

The pairing of dominant taste and aroma attributes in Thai dishes plays a crucial role in shaping the holistic sensory experience. While aroma acts as the anticipatory signal of flavor identity, taste contributes the immediate palatal impact. The cross-tabulation of these two dimensions (Fig. 3) demonstrates how aroma–taste couplings are strategically deployed in Thai cuisine to deliver layered complexity, coherence, and contrast.

Umami × Meat Aroma: Foundational Pairing

The strongest aroma–taste pair (17.38%) is umami taste with meat aroma, anchoring dishes such as *Kaeng Masaman Nuea* (3), *Kai Toon Sam Kler* (28), and *Pad Prik Thai Dam Moo* (29). These dishes emphasize savory depth, often reinforced through slow cooking, stewing, or braising techniques that intensify both aroma and taste. This pairing serves as the structural core in Thai meals, offering a sensory anchor of richness and protein-based satisfaction.

Sour × Seafood Aroma: Bright, Briny, Refreshing

The second most frequent combination (14.83%) is sour taste with seafood aroma, appearing in iconic dishes like *Tom Yum Goong* (1) and *Pla Muek Neung Manao* (25). This

pairing exemplifies the Thai strategy of layering acidity over marine-derived aromas to produce refreshing and vibrant profiles. It also functions as a palate cleanser within multi-dish meals, balancing richer, oil-based items.

Salty × Seafood Aroma: Layered Brininess

Salty taste with seafood aroma (15.46%) is another dominant pair, common in fried or stir-fried preparations such as *Pad Kapi Goong* (30) and *Tod Mun Pla* (31). The pairing intensifies the perception of natural brininess and creates contrast when served alongside lighter salads or soups. When reinforced with herbs or chili, this combination achieves multidimensional sharpness.

Sweet × Seafood or Grains: Soothing & Familiar

Notably, sweet taste frequently co-occurs with seafood aroma (6.92%) and grain aroma (1.82%), as found in dishes like *Goong Pad Nam Prik Pao* (32) or *Khao Pad Sapparot* (5). These combinations often appear in rice-based or stir-fried formats where sweetness is used to round out spicy or savory components

Spicy × Seafood and Meat Aromas: Sensory Amplification

Spicy taste is often coupled with seafood (9.11%) and meat (5.47%) aromas, a hallmark of dishes such as *Pad Cha Pla* (33). The combination delivers a sharp flavor impact, as spicy heat enhances the aromatic volatility of proteins and herbs.

Bitter × Vegetable Aroma: Cultural Specificity

Although rare overall (2.43%), the bitter taste with vegetable aroma pairing is notable in dishes like *Mara Pad Khai* (7). These combinations are culturally valued for their medicinal or detoxifying properties, even if they do not appeal to all diners. Their inclusion in the dataset highlights the regional and health-linked nuance of Thai culinary practice.

This analysis reveals a coherence between aroma and taste functions in Thai cuisine:

- Protein-based aromas (meat, seafood) pair primarily with umami, salty, or spicy tastes, forming strong, savory anchors.
- Vegetal and herbal aromas are distributed across sour, bitter, and salty tastes, often contributing balancing or contrastive effects.
- Fruit aromas, though rare, accompany spicy or sweet taste profiles, functioning as reset points within intense flavor sequences.

4.3 Tri-Dimensional Sensory Profile Analysis: Insights from a Thai Restaurant Menu

To deepen the understanding of sensory architecture, a triple-frequency analysis was conducted to identify the most prevalent Taste-Texture-Aroma combinations across the dataset. Fig. 4 below presents the top 15 sensory triads, ranked by frequency, that emerged from the cross-tabulation of aroma type, dominant taste, and leading textural quality.

This analysis confirms the dominance of seafood-based aroma across multiple taste–texture pairings, especially in combinations involving slipperiness and sour, salty, or umami flavors. These patterns are characteristic of soups and boiled seafood dishes, such as *Tom Yum Goong* (1) or *Kaeng Som Cha Om Goong* (34), where broth-like consistencies and citrus-herb flavor dominate.

The top-ranked triad—*Meat–Umami–Firmness* (15.49%)—represents grilled or stir-fried protein-centered dishes, such as *Pad Prik Thai Dam Moo* (29) or *Moo Krob* (16). These items act as anchor dishes, offering savory richness and structural bite.

Several clusters deserve specific attention:

- Seafood–Salty–Smoothness (8.43%) and Seafood–Spicy–Smoothness (6.54%) reflect dishes *Lon Pla Insee Khem* (35) and *Choo Chee Pla Kapong* (36) like where layered seasoning meets tender seafood textures.
- Vegetable–Bitter–Firmness (2.42%) appears exclusively in traditional dishes like *Mara Pad Khai* (7), reflecting cultural significance despite lower prevalence.
- Multiple Sweet–Slippery combinations with Seafood or Fruit (Ranks 7, 14) suggest inclusion of sweetness not as a dominant taste but as a counterbalance to spice and acidity, such as in *Pla-Heang Taeng-Mo* (37) or *Kaeng Phet Ped Yang* (21).

These triads emphasize how Thai cuisine balances: Firm protein structures with umami/savory base tones; Slippery broths or salads with sour/spicy highs, and; Smoothness across dishes that rely on coconut milk, stir-frying, or poaching.

Each triad reflects a modular sensory cluster that can act as a building block in Thai meal composition. The integration of these dimensions also reveals how certain sensory triads fulfill specific roles within the structure of a meal is as shown in Table 5.

4.4 Distribution of Dish Categories in the Dataset: A Restaurant-Based Perspective

4.4.1 Distribution of Preparation-based Categories

For preparation-based categories, as mentioned earlier, each dish in the dataset was classified into one of 15 preparation-based. This classification system enables systematic analysis of co-selection tendencies and sensory balance across diverse culinary forms.

As shown in Table 6, the most dominant category was fried dishes, accounting for 3,802 entries or 23% of the total dataset. This prevalence underscores the popularity of deep-fried and pan-fried items such as *Moo Krob* (16) and *Tod Mun Pla* (31), which deliver crispy textures and high flavor intensity. Fried dishes are often chosen as main protein items or served as indulgent side dishes, and their high frequency confirms their central role in Thai restaurant meals.

The second most frequent category was spicy salad (e.g., *Yum Neua Yang* (2)), comprising 3,244 dishes or 20%. These dishes offer bold combinations of sour, spicy, and herbal flavors, often served cold or at room temperature, and typically deliver slippery or firm textures. Their popularity reflects the Thai culinary principle of balancing richness with freshness and acidity.

Stir-fried dishes ranked third at 15% (2,413 dishes), including staples such as *Pad Kra Pao Moo* (15) and *Pad See Ew Moo* (39). These dishes are valued for their intense seasoning, quick preparation, and versatility in protein and vegetable inclusion. Stir-fried items often appear in both individual rice plates and shared multi-dish meals.

Grilled items (10%) such as *Kai Yang* (14) and *Kor Moo Yang* (11) ranked fourth, followed by stewed (7%) and salad (7%) categories. These categories offer a range of textures and cooking times, from long-simmered broths to lighter, herb-forward plates. Curry and boiled dishes followed closely, each comprising 6% of the dataset, with items like *Kaeng Khiao Wan Gai* (8) and *Tom Yum Goong* (1) representing staple forms of moisture-rich preparations.

Lower-frequency categories included steamed (4%), rice-based dishes (4%), and relishes (2%), with laab-style salads (2%), soups (1%), baked dishes (1%), and miscellaneous/others (1%) rounding out the tail end of the distribution. While these categories are less common overall, many represent culturally significant or regionally specific preparations that serve important balancing or ceremonial functions in meals.

To enable analytical clarity in subsequent sections, each category was assigned a symbolic code (A–O), which will be used in all visualizations and rule-mining outputs. The distribution pattern observed suggests a tiered structure in Thai restaurant offerings, with fried, spicy salad, and stir-fried categories forming the functional core, supported by contrasting wet, grilled, or herbal items that provide balance in flavor, texture, and moisture. These findings reinforce the Thai culinary ethos of constructing meals through deliberate juxtaposition rather than linear sequencing, a pattern that will be further examined through co-occurrence and association rule analysis.

4.4.2 Co-Occurrence Patterns

To investigate the combinatorial logic behind Thai meal construction, we analyzed the pairwise co-occurrence probability between main dish categories based on restaurant transaction data as shown in Table 7. Each co-occurrence represents the proportion of transactions where two dish categories appeared together, indicating diners' tendencies to build meals around multi-dish harmony rather than singular selections.

4.4.2.1 Prominent Co-Occurrence Patterns

The strongest pairing observed was between spicy salad and fried dishes, with a co-occurrence probability of 53.60%, the highest in the dataset. This frequent pairing reflects Thai

diners' preference for contrast-based composition—combining acidic, slippery, and herb-forward elements from spicy salads with the firm, crispy, and protein-dense textures of fried dishes. This pattern supports earlier sensory findings, where contrast in taste (sour vs. salty) and texture (slippery vs. firm) frequently drives dish selection.

Following this, spicy salad also co-occurred significantly with stir-fried (42.77%), grilled (34.13%), and stewed (32.62%) dishes. Each of these combinations introduces either moisture (stewed), roasted umami (grilled), or high seasoning intensity (stir-fried) into the meal structure. The recurring presence of spicy salad as a base component highlights its functional role in providing acidity and freshness across varied combinations.

Other high-frequency pairings included:

- Stir-fried with fried dishes: 44.83%, indicating a tendency to pair richly seasoned, smooth-textured stir-fries with crispy fried items to enhance texture layering.
- Grilled with fried dishes: 35.32%, reflecting a shared role as protein anchors in Thai meals, offering chewiness (grilled) and crispness (fried).
- Stewed with fried dishes: 31.87%, where sauced or braised items are complemented by drier, structure-enhancing accompaniments.

Interestingly, the data reveals that curry dishes, while popular, were less frequently co-ordered with other moisture-rich categories such as boiled, stewed, or steamed dishes—likely due to their functional overlap in flavor concentration and texture. Instead, curry was more often paired with fried (28.99%), stir-fried (25.36%), or spicy salad (27.61%) categories.

4.4.2.2 Low Co-Occurrence Combinations

Pairings between similarly wet or soft-textured dish types exhibited notably lower co-occurrence rates. For instance: Stewed and steamed is 10.96%, Curry and steamed below 19%, Boiled and rice-based dishes is 10.39%. These lower probabilities suggest that redundancy in texture or mouthfeel—such as pairing two sauce-heavy dishes—is avoided in favor of combinations that increase sensory diversity. Thai diners appear to intentionally construct meals where each dish complements the others in moisture, intensity, and structure.

When these distribution patterns were analyzed in relation to pairing behavior, clear co-occurrence logics emerged that mirror long-standing principles in Thai culinary design—particularly the emphasis on balance through contrast. The most common pairing in the dataset was between spicy salads and fried dishes, observed in more than half of all transactions involving a spicy salad. For example, *Yum Woon Sen* (40) was frequently ordered with *Moo Krob* (16), offering a pairing that juxtaposes acidity, slipperiness, and freshness with saltiness, crunch, and indulgent depth.

Stir-fried dishes also commonly co-occurred with fried items, while grilled dishes were frequently paired with spicy salads. In each of these cases, the pairing involved one dish with intense umami or salt-based seasoning.

Certain categories function as supporting or harmonizing elements rather than central features. For instance, curries and stews were often paired with fried or stir-fried dishes, offering smooth, rich, or sweet-spicy notes that tempered the crispness or boldness of the accompanying item. Grilled meats and soups served similar balancing roles. In contrast, pairings between categories with overlapping characteristics—such as steamed with stewed, or salad with boiled—were rare, likely due to their redundancy in mouthfeel or seasoning profile.

These pairing dynamics suggest that diners in this restaurant made selections not only based on the standalone appeal of individual dishes, but also with consideration for their interplay—including textural contrast (e.g., slippery vs. firm), aromatic layering (e.g., herbal vs. roasted), and taste balance (e.g., sour vs. umami). This behavior aligns with a culturally embedded logic of meal construction, in which variety and contrast are central to satisfaction.

Furthermore, these observed combinations validate the use of category-level association rule mining. High-frequency rules derived through the Apriori algorithm—such as spicy salad → fried dish or stir-fried → grilled dish—closely mirror the co-occurrence patterns found in the dataset. This convergence between statistical modeling and culinary convention strengthens the case for using association rules not just as behavioral summaries but as tools for designing realistic, culturally grounded food recommendation systems.

In sum, the distribution and pairing patterns observed in this restaurant menu suggest insights serve not only as a descriptive foundation for the study but also as a practical guide for predictive modeling and menu optimization, which can be further visualized in Fig. 5.

The observed patterns confirm that Thai consumers engage in multi-dish meal design that prioritizes complementarity in preparation, texture, and taste. These behaviors validate the subsequent application of association rule mining (Apriori algorithm) and reinforce the cultural preference for balancing light and heavy dishes, dry and sauced preparations, and contrasting textures in a single sitting.

In the next section, we operationalize these co-occurrence patterns through Apriori rule generation, identifying the most statistically significant and sensory-consistent pairings used in Thai meal construction.

4.5 Apriori Rule Generation and Interpretation Based on Dish Categories: Contextual Modeling of Thai Meal Behavior

To determine which types of dishes tend to be ordered together, also to model the implicit structure of Thai meal composition as it unfolds in a real-world, menu-driven setting, the algorithm was parameterized with a minimum support threshold of 5% and a minimum confidence threshold of 40%, ensuring that only rules with both prevalence and reliability were retained. Each rule followed the format $A \rightarrow B$, where category A was the antecedent and B the consequent. Rule strength was evaluated using three key metrics:

Support: the proportion of all transactions that included both A and B,

Confidence: the likelihood that B appears in a transaction given A,

Lift: the strength of the rule relative to random chance, where a value above 1 indicates positive association.

The strongest rule identified in the dataset was:

Spicy Salad → *Fried Dish* (Support: 18.7%, Confidence: 53.6%, Lift: 2.33)

This rule indicates that more than half of all transactions involving a spicy salad also included a fried dish, and that this pairing is over twice as likely to occur compared to random chance.

Another high-confidence rule was:

Stir-Fried → *Fried Dish* (Support: 16.8%, Confidence: 44.8%, Lift: 1.95)

This rule highlights the tendency for diners to pair intensely seasoned, soft-textured stir-fried dishes reflecting a desire for layered richness and alternating mouthfeel.

Additional rules aligned with traditional Thai meal structuring logic:

- *Grilled* → *Spicy Salad* (Confidence: 34.1%, Lift: 1.26),

- *Stewed* → *Fried* (Confidence: 31.9%, Lift: 1.39),
- *Curry* → *Fried* (Confidence: 28.9%, Lift: 1.26).

These rules emphasize how grilled meats, with their roasted aromas and firm textures, are often balanced by moist, acidic salads, while smooth, umami-rich stews and curries are anchored by crispy fried sides. Notably, many of the antecedents in the strongest rules were sensory-forward categories—such as spicy salads, stir-fries, and curries—while the consequents were often balancing or supporting elements, including fried or grilled items. This directional asymmetry suggests a behavioral logic in which diners first select a bold, defining dish, and then choose accompanying items to complete the sensory composition of the meal.

4.6 Integrated Sensory Interpretation of Top Association Rules

To operationalize these findings, we developed a rule-based recommendation system grounded in the tri-dimensional sensory model and empirical association rules. The system transforms culturally embedded pairing logic into a computational framework that informs menu design, digital ordering systems, and personalized recommendations.

a. Rule System Architecture

The recommendation system is structured into a multi-layered hierarchy:

Primary Rules: Based on strong cultural pairings with high-confidence values.

Secondary Rules: Governed by sensory balance, especially texture contrast.

Tertiary Rules: Focused on aroma diversity.

Tri-Dimensional Rules: Derived from cross-tabulation of taste, aroma, and texture.

Each rule includes:

Condition: Attributes of the selected dish (e.g., spicy, stir-fried).

Recommendation: Suggested sensory attributes or categories.

Confidence Score: Derived from data.

Cultural Weight: Reflecting importance in Thai meal construction.

Sample Primary Rules:

P1: Spicy + Stir-Fried → Boiled + Sour

P2: Meat + Firm → Seafood + Slippery

P3: Sweet → Salty or Spicy counterbalance

Sample Secondary Rules:

S1: Smooth → Slippery or Firm

S2: Avoid Slippery + Slippery

Sample Tertiary Rules:

T1: Grain aroma → Meat/Seafood/Vegetable complement

T2: Avoid consecutive Meat aromas

Sample Tri-Dimensional Rule:

TD1: Meat + Firm + Spicy → Seafood + Slippery + Sour

b. Recommendation Algorithm

The algorithm processes dish selections in the following hierarchy:

- Apply Primary Rules → Apply Texture Rules → Apply Aroma Rules

- Aggregate, score, and rank recommendations based on rule confidence, validation logic, and cultural weight.
- Validation Function applies bonuses for contrast and penalties for redundancy.

c. Example Use Case

A diner selects *Pad Kra Pao Moo* (15) (Spicy, Firm, Meat, Stir-Fried):

Rule P1 triggers: Suggests *Tom Yum Goong* (1) (Boiled, Sour)

Rule P2 triggers: Suggests seafood with slippery texture (e.g., *Yum Talay* (13))

Tertiary Rule T2 suggests avoiding another meat dish → reinforces *Tom Yum Goong* (1)

Final Recommendation: *Tom Yum Goong* (1) with 89% confidence

d. System Impact

This study demonstrates how explainable AI can uncover the sensory and cultural logic underlying meal composition behavior. Frequent dish pairings—such as spicy salads with fried dishes—reflect deliberate balancing strategies that combine contrasting textures, flavors, and preparation styles to reduce sensory fatigue and support communal dining experiences.

By integrating taste, texture, and aroma into association rule mining, the framework explains not only which dishes co-occur but also why such combinations emerge. For example, sour and slippery seafood salads are commonly paired with firm and salty fried dishes, illustrating sensory equilibrium through contrasts in acidity, texture, and richness. Similarly, pairings between stir-fried and boiled dishes suggest preferences for alternating moisture levels and cooking methods within a meal.

The resulting explainable recommendation system models these sensory interactions through transparent and interpretable rules, allowing recommendations to be understood in terms

of cultural and multisensory logic rather than opaque algorithmic predictions. This provides practical applications for intelligent menu design, digital ordering platforms, and AI-driven food recommendation systems seeking culturally adaptive recommendations.

Ultimately, the study demonstrates that traditional data mining approaches such as the Apriori algorithm become substantially more meaningful when enriched with sensory knowledge representation and cultural context, transforming raw transactional data into behaviorally grounded and explainable culinary intelligence.

5. Conclusion

This study integrates association rule mining with tri-dimensional sensory profiling—taste, texture, and aroma—to uncover culturally meaningful dish-pairing patterns in Thai cuisine. Analyzing real restaurant transactions, we found that co-occurrence rules, such as meat–umami–firmness or seafood–sour–slipperiness, reflect structured sensory and cultural logics, not random preferences. By embedding these insights into a transparent, rule-based recommendation system, we provide tools for personalized menu suggestions, culturally aligned digital ordering, and explainable menu design—avoiding black-box predictions in favor of interpretable logic. While based on data from a single restaurant, the framework offers scalable potential. Future improvements include expanding to other restaurant formats and integrating contextual factors like diner mood or meal occasion. Adaptive algorithms and NLP could further enhance personalization and responsiveness. Ultimately, this work shows how pairing data mining with sensory and cultural understanding leads to smarter, more human-centered food experiences—where Thai meals are not only flavorful but sensorially and culturally coherent.

From an industry perspective, advanced AI-driven recommendation systems may contribute to multiple areas of gastronomy and hospitality management. Restaurants may use intelligent recommendation engines to optimize menu engineering, cross-selling strategies, inventory planning, and customer personalization simultaneously. Fine-dining establishments could employ sensory-aware AI systems to design tasting menus with carefully sequenced sensory progression, while casual dining restaurants may use AI-driven personalization to improve operational efficiency and customer satisfaction.

Importantly, future gastronomic AI systems must remain culturally adaptive rather than universally standardized. Food preferences and meal structures vary substantially across regions, social groups, and culinary traditions. Consequently, culturally grounded sensory representation and explainable recommendation logic will remain essential for preserving culinary diversity within increasingly digitalized hospitality systems.

Overall, the convergence of explainable AI, sensory science, computational gastronomy, and multimodal recommendation technologies is expected to fundamentally reshape how food experiences are designed, recommended, and consumed. Future intelligent gastronomy systems may not only predict what consumers want to eat but also understand why specific combinations are meaningful, pleasurable, and culturally appropriate.

Declaration of Generative AI and AI-Assisted Technologies

The authors declare that generative AI and AI-assisted technologies were used in the preparation of this manuscript in the following ways:

- **Text Generation and Refinement**: OpenAI's ChatGPT (GPT-4) was used under author supervision to assist in drafting and revising sections of the manuscript, including the abstract, literature review, methodology framing, and discussion. The AI was used as a writing assistant to improve clarity, structure, and coherence, especially for organizing complex ideas related to association rule mining, sensory science, and culinary logic.
- **Reference Formatting**: AI tools assisted in generating and checking APA-style references based on provided bibliographic data.

All content generated with AI tools was critically reviewed, edited, and approved by the authors to ensure accuracy, integrity, and alignment with the research objectives. The authors bear full responsibility for the integrity and originality of the content presented in this manuscript

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Competing Interests

The authors declare that they have no competing interests.

Clinical Trial Registration

Not applicable.

Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

Data Availability

The datasets generated and/or analyzed during the current study are not publicly available because they contain proprietary commercial transaction data from a participating restaurant but are available from the corresponding author on reasonable request and with permission from the data owner.

Code Availability

The code developed for the association rule mining and recommendation framework is available from the corresponding author upon reasonable request.

Author Contributions (CRediT)

Kullapapruk Piewthongngam: Conceptualization, Writing – Original Draft, Writing – Review & Editing.

S. Intarasothonchun: Methodology, Modeling, Formal Analysis.

P. Mahasuweerachai: Conceptualization, Data Curation, Menu Categorization, Variable Selection.

Pongphan Sathatip: Menu Categorization, Literature Review, Validation.

All authors read and approved the final manuscript.

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Ethical Approval and accordance

Not Applicable

Table 1. Sensory and Cooking Method Profiles of Representative Popular Thai Main Dishes

Thai Name	Dish Explanation	Dominant			Cooking Method
		Taste	Texture	Aroma	
(1) Tom Yum Goong	Spicy lemongrass shrimp soup.	Sour	Slippery	Seafood	Boiled
(2) Yum Mamuang	Green mango salad.	Sour	Firm	Fruit	Salad
(3) Kaeng Masaman Nuea	Braised beef in massaman curry.	Umami	Smooth	Meat	Stewed
(4) Kai Look Keuy	Fried boiled egg with tamarind sauce.	Sweet	Smooth	Herb	Fried
(5) Khao Pad Sapparot	Pineapple fried rice.	Sweet	Slippery	Grain	Stir-fried
(6) Gang Kee Leak Neua Yang	Salted beef and Cassia leaves curry.	Bitter	Smooth	Herb	Curry
(7) Mara Pad Khai	Stir-fried bitter melon with egg.	Bitter	Firm	Vegetable	Stir-fried
(8) Kaeng Khiao Wan Gai	Green curry with chicken and Thai eggplant.	Spicy	Smooth	Herb	Curry
(9) Yum Som-O	Spicy pomelo salad.	Sour	Slippery	Fruit	Salad
(10) Gai Tod Kratiem	Fried chicken with garlic.	Salty	Firm	Meat	Fried
(11) Kor Moo Yang	Grilled pork neck with dipping sauce.	Salty	Firm	Meat	Grilled
(12) Kaeng Luang Poo Bai Cha Plu	Southern yellow crab curry with betel leaf.	Umami	Smooth	Seafood	Curry
(13) Yum Talay	Seafood salad with chili-lime dressing.	Sour	Slippery	Seafood	Salad
(14) Kai Yang	Grilled chicken.	Salty	Firm	Meat	Grilled
(15) Pad Kra Pao Moo	Stir-fried pork with holy basil and chili.	Spicy	Firm	Meat	Stir-fried
(16) Moo Krob	Crispy pork belly with golden crackling.	Umami	Firm	Meat	Deep-fried
(17) Pad Pak Boong Fai Daeng	Stir-fried morning glory with fermented bean sauce.	Salty	Firm	Vegetable	Stir-fried
(18) Khao Pad Poo	Crab fried rice.	Umami	Smooth	Grain	Stir-fried
(19) Tom Kha Kai	Chicken coconut galangal soup.	Salty	Smooth	Herb	Boiled
(20) Yum Ta Krai	Spicy lemongrass salad.	Sour	Firm	Herb	Salad
(21) Kaeng Phet Ped Yang	Red curry with duck and lychee.	Sweet	Smooth	Fruit	Curry

(22) Gai Pad Med Mamuang	Chicken stir-fried with cashew nuts.	Sweet	Smooth	Meat	Stir-fried
(23) Khao Pad Goong	Shrimp fried rice.	Umami	Smooth	Grain	Stir-fried
(24) Moo Ping	Grilled pork skewers with sweet soy glaze.	Sweet	Firm	Meat	Grilled
(25) Pla Muek Neung Manao	Steamed squid with garlic and lime.	Sour	Slippery	Seafood	Steamed
(26) Kai Tun Poo	Savory egg custard with crabmeat.	Umami	Smooth	Seafood	Steamed
(27) Yum Tua Plu	Wing bean salad.	Nutty	Firm	Vegetable	Salad
(28) Kai Toon Sam Kler	Chicken stew with Chinese herbs.	Umami	Smooth	Meat	Stewed
(29) Pad Prik Thai Dam Moo	Stir-fried pork with black pepper and oyster sauce.	Umami	Firm	Meat	Stir-fried

Table 1. Sensory and Cooking Method Profiles of Representative Popular Thai Main Dishes (continued)

Thai Name	Dish Explanation	Dominant			Cooking Method
		Taste	Texture	Aroma	
(30) Pad Kapi Goong	Shrimp paste stir-fry.	Salty	Firm	Seafood	Stir-fried
(31) Tod Mun Pla	Fried fish cakes.	Salty	Firm	Seafood	Fried
(32) Goong Pad Nam Prik Pao	Shrimp in red chili paste.	Sweet	Smooth	Seafood	Stir-fried
(33) Pad Cha Pla	Fried fish with chili and basil.	Spicy	Firm	Seafood	Fried
(34) Kaeng Som Cha Om Goong	Sour curry with shrimp and acacia omelet.	Sour	Slippery	Seafood	Boiled
(35) Lon Pla Insee Khem	Salted Mackerel Coconut Dip	Salty	Smooth	Seafood	Boiled
(36) Choo Chee Pla Kapong	Choo Chee Red Curry with Seabass	Spicy	Smooth	Seafood	Curry
(37) Pla-Heang Taeng-Mo	Dried fish with watermelon.	Sweet	Slippery	Fruit	Salad
(38) Laab Moo	Spicy minced pork salad.	Spicy	Firm	Meat	Laab
(39) Pad See Ew Moo	Stir-fried soy sauce noodles with pork.	Sweet	Smooth	Grain	Stir-fried
(40) Yum Woon Sen	Thai spicy glass noodle salad	Sour	Slippery	Seafood	Salad

Table 2. Distribution of Main Dishes by Dominant Taste Profile

Taste Profile	Number of Orders	Percentage (%)
Salty	3,113	27.62%
Umami	2,865	25.42%
Sour	2,110	18.72%
Spicy	1,795	15.92%
Sweet	1,115	9.89%
Bitter	274	2.43%

807 **Table 3. Distribution of Main Dishes by Dominant Texture Profile**

Texture	Number of Orders	Percentage (%)
Smoothness	3,896	34.56%
Firmness	3,569	31.66%
Slipperiness	3,803	33.74%
Cohesiveness	3	0.03%
Creaminess	1	0.01%

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Table 4. Distribution of Main Dishes by Dominant Aroma Profile

Aroma Profile	Number of Orders	Percentage (%)
Seafood	6,054	53.71%
Meat	3,795	33.67%
Vegetable	592	5.25%
Grain	432	3.83%
Herbs	294	2.61%
Fruit	105	0.93%

Table 5. Sensory Roles in Meal Composition for Thai Main Dishes

Role	Common Sensory Profile	Function in Meal
Anchor dish	Umami–Smooth–Meat or Grain	Structural base, often rich and filling
Contrast enhancer	Sour–Slippery–Seafood or Herb	Refreshes palate, introduces sharp acidity
Texture variation	Firm–Salty–Meat	Adds crunch or chew, often deep-fried or grilled
Balance/restraint	Sweet–Smooth–Seafood or Grain	Soothes, rounds out heat or acid
Medicinal or cultural	Bitter–Smooth–Vegetable	Traditionally valued, not always dominant in flavor

Table 6. Number of Dishes by Category and Assigned Symbol

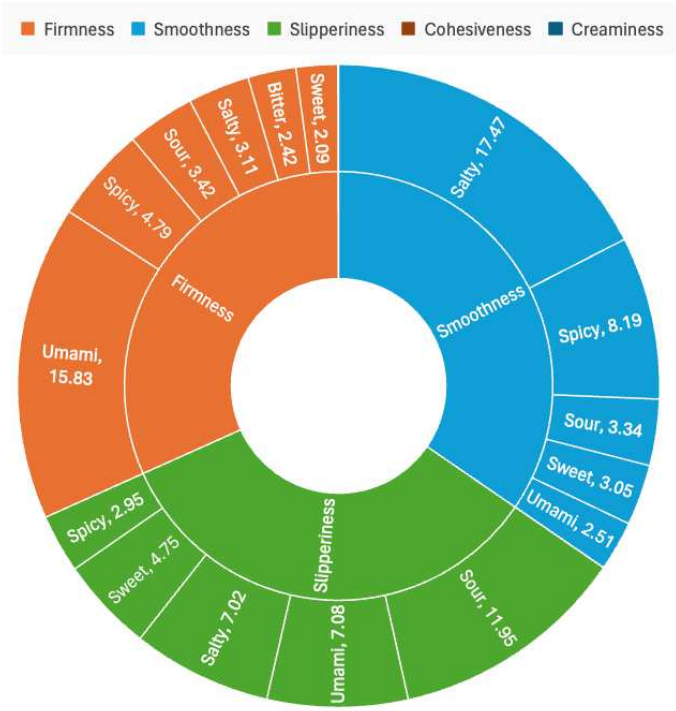
Dish Category	Frequency	Percentage (%)	Symbol	Symbol
Spicy Salad	3,244	20.00	A	
Grilled	1,589	10.00	B	
Stir-Fried	2,413	15.00	C	
Curry	996	6.00	D	
Stewed	1,072	7.00	E	
Steamed	550	4.00	F	
Fried	3,802	23.00	G	
Relish (Chili Paste)	207	2.00	H	
Salad	1,042	7.00	I	
Rice-Based	679	4.00	J	
Soup	75	1.00	K	
Laab	305	2.00	L	
Boiled	929	6.00	M	
Baked	125	1.00	N	
Others	41	1.00	O	

Table 7. Co-Occurrence Probability Between Dish Categories

Cooking Method	Boiled	Curry	Fried	Grilled	Rice -Based	Salad	Spicy Salad	Steamed	Stewed	Stir -Fried
Boiled			23.04	12.59	10.39	10.58	21.48		15.28	20.6
Curry			28.99	18.16	10.39	14.59	27.61		18.91	25.36
Fried	23.04	28.99		35.32	21.1	27.93	53.6	17.09	31.87	44.83
Grilled	12.59	18.16	35.32		13.59	20.66	34.13	11.33	20.98	28.37
Rice-Based	10.39	10.39	21.1	13.59		10.46	20.6		13.71	16.91
Salad	10.58	14.59	27.93	20.66	10.46		27.3		16.66	21.98
Spicy Salad	21.48	27.61	53.6	34.13	20.6	27.3		17.09	32.62	42.77
Steamed			17.09	11.33			17.09		10.96	15.34
Stewed	15.28	18.91	31.87	20.98	13.71	16.66	32.62	10.96		27.24
Stir-Fried	20.6	25.36	44.83	28.37	16.91	21.98	42.77	15.34	27.24	

Note: Only pairs with non-zero values are shown. Co-occurrence is defined as the percentage of total transactions in which both dish types appear.

Fig. 1. Cross-Tabulation of Taste and Texture Profiles in Thai Main Dishes (Percentage of Total Orders)


Firmness
Smoothness
Slipperiness
Cohesiveness
Creaminess
Salty, 17.47
Spicy, 8.19
Sour, 3.34
Sweet, 3.05
Umami, 2.51
Sour, 11.95
Umami, 7.08
Salty, 7.02
Sweet, 4.75
Spicy, 2.95
Umami, 15.83
Spicy, 4.79
Sour, 3.42
Salty, 3.11
Bitter, 2.42
Sweet, 2.09
Smoothness
Slipperiness
Firmness

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Fig. 2. Cross-Tabulation of Aroma and Texture Profiles in Thai Main Dishes (Percentage of Total Orders)

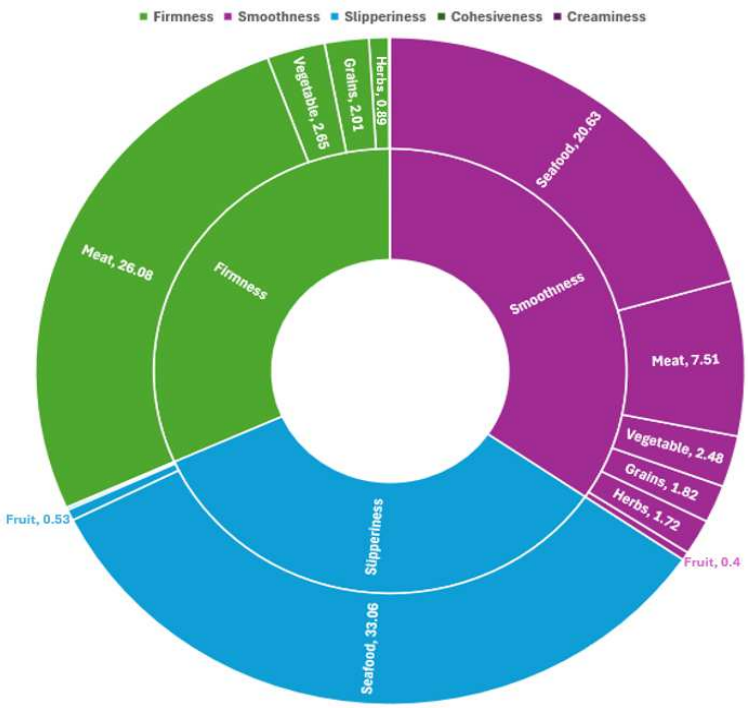


Fig. 3. Cross-Tabulation of Aroma and Taste Profiles in Thai Main Dishes (Percentage of Total Orders)

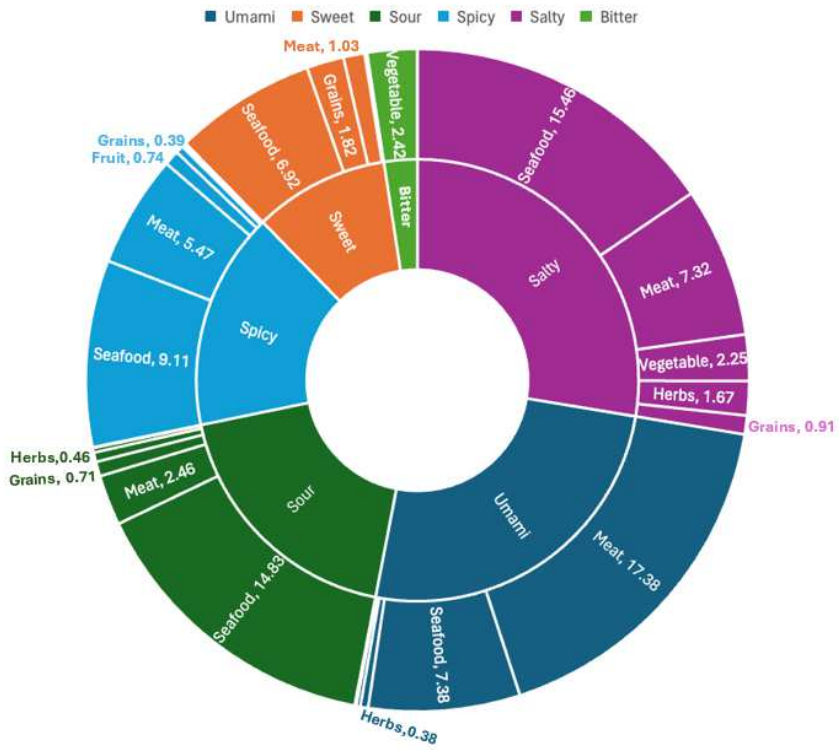
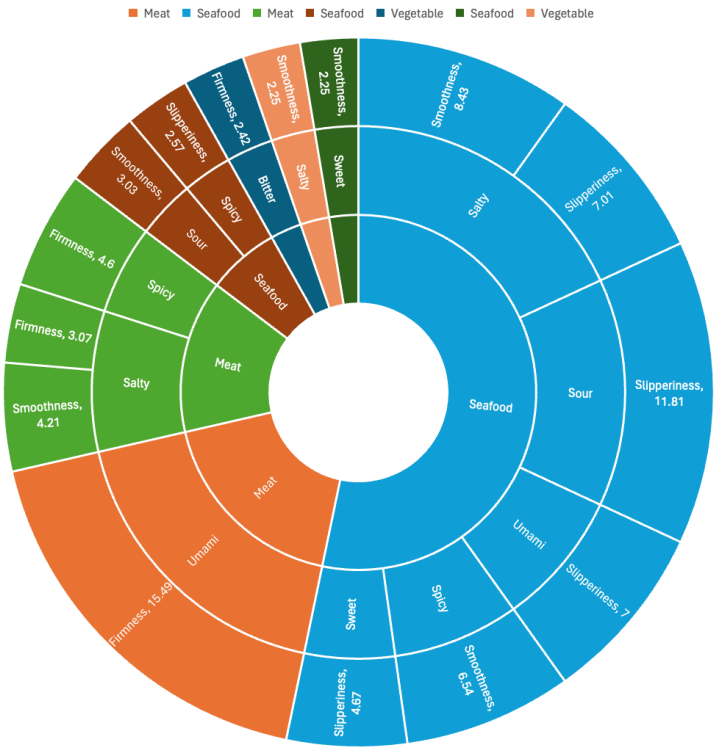
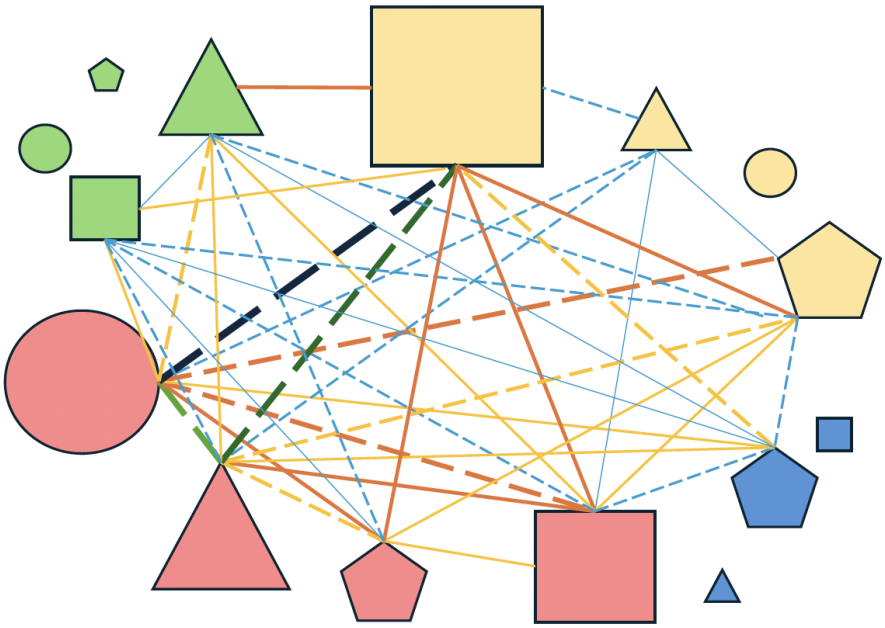


Fig. 4. Cross-Tabulation of Aroma, Taste, and Texture Profiles in Thai Main Dishes (Percentage of Total Orders)



839 **Fig. 5. Network Graph Distribution and Pairing Patterns of Dish Categories**



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