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FROM EXPECTED DEMAND TO ACTUAL CONSUMPTION: AN EXPLORATORY STUDY OF FOOD SURPLUS IN EVENT CATERING

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Abstract

Event catering involves substantial demand uncertainty because meal preparation decisions are generally made before actual consumption occurs. Although inaccurate demand forecasting has been identified as an important contributor to food surplus and waste in foodservice operations, relatively limited research has examined this issue using event-level operational data, particularly in temporary, time-sensitive catering environments.

This study explores the gap between expected meal demand, prepared quantities, and recorded food surplus using anonymized operational data from an event catering provider. The dataset comprises 49 catering service records collected between 2025 and 2026, representing 2,351 prepared meals. Descriptive statistics and exploratory non-parametric analyses were employed to examine patterns associated with meal preparation, catering format, food surplus, workforce deployment, and operational exceptions.

The results show that expected meal quantities were identical to prepared quantities in all 49 service records; nevertheless, 439 meals were recorded as remaining after service, representing an aggregate recorded surplus proportion of 18.7%. Food surplus was recorded in 39 of the 49 service observations. Exploratory analysis further revealed substantial differences between catering formats: buffet-style services showed an aggregate surplus proportion of approximately 25.2%, whereas no surplus was recorded for individually packaged meals in the available dataset. This difference should not be interpreted causally because catering formats were not randomly assigned and surplus recording practices may differ across service formats.

The findings highlight an important distinction between expected demand and actual consumption in event catering. The study proposes that event catering operations may benefit from shifting from attendance- or order-based planning toward consumption-oriented demand intelligence that integrates historical event characteristics, catering formats, operational conditions, and actual consumption outcomes. The findings provide preliminary implications for data-driven demand forecasting, service design, and food surplus reduction in event catering.

Keywords

Event Catering; Food Surplus; Demand Forecasting; Consumption Demand; Catering Operations; Food Waste; Data-Driven Decision Making

1. Introduction

Food surplus and food waste have become increasingly important concerns in hospitality and foodservice operations because of their environmental, economic, and managerial implications (Papargyropoulou et al., 2014; Martin-Rios et al., 2018). Foodservice providers must prepare sufficient quantities to maintain

service quality while avoiding excessive production. This balancing problem is fundamentally associated with uncertainty: production decisions are made before actual consumption is fully known.

Demand forecasting is therefore a critical component of foodservice planning. Rodrigues et al. (2024), using long-term daily operational data from three catering services, demonstrated that machine-learning-based demand forecasting could outperform conventional estimates and potentially reduce wasted meals by 14% to 52%, while simultaneously reducing unmet demand. Their findings illustrate that improved demand intelligence can contribute to both service performance and waste reduction.

However, the forecasting challenge may be particularly pronounced in **event catering**.

Unlike restaurants or institutional foodservice operations characterized by relatively recurring demand patterns, event catering is temporary and context dependent. Each event may involve different numbers of participants, service schedules, catering formats, venues, dietary requirements, and operational constraints. Catering providers must often make procurement, preparation, workforce, and logistics decisions before actual on-site consumption behavior becomes observable.

Previous studies have established that event catering represents a meaningful context for food surplus and waste research. Monteiro et al. (2020), examining catered meetings and events in a higher-education context, found that food waste varied across venues and food categories and that characteristics associated with the person ordering catering could influence waste outcomes. Similarly, Leverenz et al. (2020) analyzed data from 239 event caterings and investigated how event type, season, event size, and menu prices were associated with buffet leftovers. These studies demonstrate that food surplus in event catering is not determined solely by the number of meals ordered but may be associated with broader event and service characteristics.

Nevertheless, an important operational distinction remains underexplored: **expected meal demand is not necessarily equivalent to actual consumption demand**.

In many catering operations, the quantity prepared is based on the number of meals requested by the client or the expected number of individuals requiring food. Such information is necessary for planning, but it does not guarantee that all prepared meals will ultimately be consumed. Event schedules may change, personnel may move between locations, meal timing may overlap with operational duties, individual preferences may differ, and catering formats may affect how food is distributed and consumed.

Consequently, a catering provider may accurately prepare the number of meals requested while still generating substantial food surplus.

This distinction shifts the managerial problem from simply asking:

“How many meals were ordered?”

to a more operationally meaningful question:

“How many meals are likely to be consumed under the specific conditions of this event?”

The latter requires information beyond attendance or order quantity. Historical consumption patterns, catering formats, event characteristics, meal periods, service populations, and operational conditions may collectively contribute to more accurate preparation decisions.

This issue is particularly relevant as hospitality and foodservice organizations increasingly adopt data-driven and artificial-intelligence-supported decision systems. Existing evidence suggests that machine learning can improve foodservice demand forecasting and reduce both overproduction and unmet demand (Rodrigues et al., 2024). However, before sophisticated forecasting systems can be developed for event catering, it is necessary to understand what operational patterns exist within actual event-level service records.

The present study addresses this issue through an exploratory analysis of anonymized operational data from an event catering provider. The dataset comprises 49 catering service records collected between 2025 and 2026 and includes information regarding expected meal quantities, prepared meals, recorded food surplus, catering formats, workforce deployment, service timing, and selected operational exceptions.

The study deliberately treats these records as an **exploratory operational case dataset** rather than a representative sample of the broader event catering industry. The objective is not to establish causal relationships or generalize food surplus rates across all catering providers. Instead, the study seeks to identify operational patterns that may help explain the gap between expected meal demand and actual consumption outcomes.

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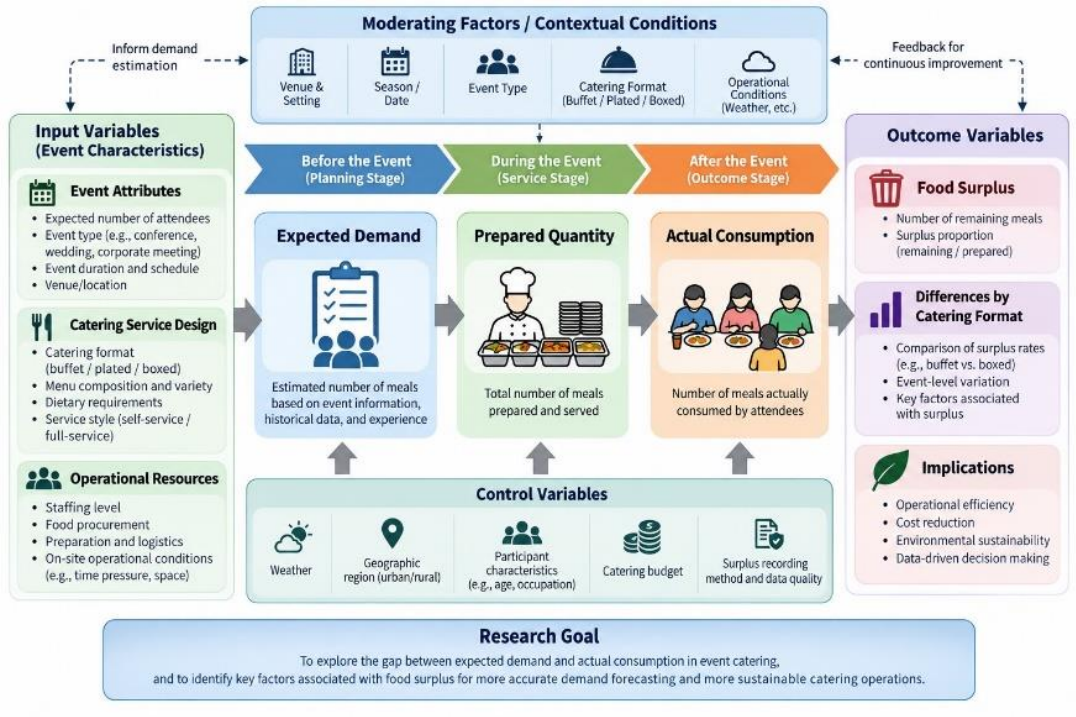


Figure 1. Framework of this paper

This study addresses three research questions:

RQ1. What patterns of food surplus can be observed in event-level catering operations?
RQ2. How does recorded food surplus vary across selected catering and operational characteristics?
RQ3. What implications do these operational patterns provide for data-driven demand forecasting and resource planning in event catering?

The study makes three contributions.

First, it contributes to the relatively limited empirical literature on event catering by using event-level operational records rather than consumer perceptions or hypothetical service scenarios. Whereas previous studies have demonstrated that event characteristics and ordering behavior may influence catering waste, this study focuses specifically on the operational relationship between expected quantities, prepared quantities, and recorded surplus.

Second, the study distinguishes **expected demand** from **actual consumption demand**. This distinction provides a more precise conceptual basis for understanding why food surplus may occur even when catering providers prepare quantities consistent with client orders.

Third, the study provides managerial implications for the digital transformation of event catering. Rather than treating artificial intelligence as an end in itself, the study argues that the primary opportunity for data-driven technology lies in developing better **consumption intelligence**: organizational capability to learn from previous events and progressively improve preparation, service design, and resource allocation decisions.

By connecting event catering, food surplus, and demand intelligence, this study provides an exploratory foundation for future research on AI-enabled forecasting and decision support in temporary and highly variable foodservice environments.

2. Literature Review

2.1 Food Surplus and Waste in Foodservice Operations

Food surplus and food waste represent persistent operational and sustainability challenges in foodservice. Foodservice providers must prepare sufficient quantities to satisfy demand while simultaneously minimizing unnecessary production. When actual consumption is lower than anticipated, overproduction may create surplus food; when preparation is insufficient, service providers face unmet demand,

emergency replenishment, and potential deterioration in service quality. Demand planning therefore involves an inherent trade-off between service assurance and resource efficiency.

An important conceptual distinction should be made between **food surplus** and **food waste**. Food remaining after a catering service does not necessarily become waste because some surplus may subsequently be redistributed, reused where food-safety conditions permit, donated, or otherwise recovered. Accordingly, studies based solely on post-service remaining quantities should avoid automatically classifying all remaining food as waste.

This distinction is consistent with the food waste hierarchy, which separates preventable food surplus from downstream waste-management outcomes and prioritizes prevention and redistribution before disposal (Papargyropoulou et al., 2014).

This distinction is particularly relevant to the present study because the operational dataset records the quantity of meals remaining after service but does not systematically document their final disposal destinations. The term **recorded food surplus** is therefore used when reporting the empirical results, while "food waste" is retained when discussing previous studies that explicitly measured or defined waste.

One important source of overproduction in foodservice is uncertainty regarding future demand. Rodrigues et al. (2024) examined real daily operational data from three catering services over periods ranging from three to nine years and compared machine-learning forecasts with actual demand and existing catering estimates. Their results showed that random forest and long short-term memory models produced improved forecasts that could potentially reduce wasted meals by 14%–52% and unmet demand by 3%–16%. These findings demonstrate that improved forecasting can simultaneously contribute to waste prevention and service reliability.

The relationship between forecasting and food surplus is therefore not merely a sustainability issue. It is also an operational decision problem involving the quality of information available before production occurs.

2.2 Food Surplus in Event Catering

Event catering represents a particularly challenging foodservice context because production and service decisions must be made for temporary and heterogeneous events.

Unlike institutional canteens or recurring restaurant operations, event catering may serve different client groups, venues, schedules, event sizes, catering formats, and meal periods from one service to another. Consequently, historical averages may not always provide sufficient information for predicting consumption at the next event.

Previous empirical research confirms that event-level characteristics are relevant to catering surplus and waste.

Monteiro et al. (2020) examined food waste associated with catered meetings, conferences, and other events in a higher-education setting. Their findings demonstrated variation across venues and food categories and suggested that ordering-related characteristics can influence waste outcomes. This study is important because it shifts attention from consumer plate waste toward decisions made before and during event catering operations.

Leverenz et al. (2020) provided particularly relevant evidence through a four-year case study involving 239 event caterings. The researchers examined event type, season, event size, and menu price in relation to buffet leftovers. Event size showed the strongest influence among the examined variables: smaller events recorded substantially greater buffet leftovers per guest than larger events. The authors also found that a limited number of food product categories accounted for a substantial proportion of buffet leftovers.

These findings have two implications for the present study.

First, food surplus in event catering should not be understood solely as a function of the number of meals prepared. **Event characteristics matter.**

Second, the temporary and heterogeneous nature of events means that the relationship between expected attendance and actual food consumption may vary from event to event.

Despite these insights, empirical event-catering research remains relatively limited compared with research on restaurants, hotels, institutional foodservice, and household food waste. Moreover, existing studies have largely focused on the quantity and determinants of leftovers or waste. Less attention has been directed toward the informational process preceding production: how expected meal demand is translated into preparation quantities and how actual consumption outcomes can subsequently improve future planning.

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2.3 Demand Forecasting in Catering Operations

Demand forecasting is central to catering operations because several important decisions must be made before actual demand is observable. Procurement quantities, ingredient preparation, workforce allocation, transportation, and meal production all depend to some extent on estimates of future requirements.

A conventional approach is to rely on reservations, client orders, expected attendance, historical experience, or managerial judgment. These sources provide essential planning information, but each contains uncertainty.

This issue becomes especially important when the unit being predicted is unclear.

For example, an event organizer may provide the number of people expected to require meals. The catering provider may subsequently prepare approximately the same number of meals. Operationally, this represents accurate fulfillment of the client's requested quantity. However, if not all meals are consumed, accurate fulfillment of the **order quantity** does not necessarily imply accurate prediction of **consumption demand**.

This distinction can be expressed as three separate quantities:

Expected or ordered demand → Prepared quantity → Actual consumption

Food surplus may arise when:
Prepared quantity > Actual consumption

even when:
Prepared quantity ≈ Expected or ordered demand.

This distinction is central to the present study.

Rodrigues et al. (2024) provide evidence that machine-learning models can improve foodservice demand forecasting when sufficient historical operational data are available. Their research used variables including temporal and contextual information to learn recurring patterns and predict future demand.

However, transferring such approaches to event catering is not straightforward. Many event-catering services involve relatively heterogeneous and non-recurring events. The relevant predictors may therefore extend beyond calendar patterns to include event type, service population, catering format, meal period, venue conditions, and other contextual characteristics.

Before developing sophisticated predictive models, it is therefore necessary to identify whether meaningful demand–consumption patterns can be observed in actual event-level operational data.

2.4 From Expected Demand to Consumption Intelligence

Based on the preceding literature, this study proposes a distinction between **order-based planning** and **consumption-oriented planning**.

Order-based planning answers the question:
How many meals has the client requested?

Consumption-oriented planning addresses a different question:
Given the characteristics of this event, how many meals are likely to be consumed?

The second question does not eliminate the importance of client orders. Contractual quantities remain fundamental to catering operations. Instead, consumption information can provide an additional decision layer that supports discussions regarding preparation margins, catering format, replenishment strategy, portion design, procurement, and surplus prevention.

For the purposes of this exploratory study, we use the term consumption intelligence as a provisional managerial lens: the systematic use of historical event-level consumption outcomes and contextual information to improve future catering decisions.

At this stage, consumption intelligence is not proposed as a new formal theory or validated construct. Rather, it serves as a conceptual lens for interpreting the operational gap between expected demand, prepared quantities, and actual consumption.

The proposed learning process is:

Expected demand
↓
Preparation decision
↓
Actual event consumption
↓
Recorded surplus
↓
Post-event operational data
↓
Learning across events
↓
Improved future demand decisions

This feedback-loop perspective differs from one-off forecasting. Each completed event generates information that may improve decisions for subsequent events.

Such an approach also creates a foundation for future data-driven and AI-supported catering systems. Artificial intelligence is therefore treated in this study as a potential future decision-support mechanism rather than an intervention whose effects are tested using the current dataset.

This distinction is important because the present research does not evaluate an implemented AI forecasting system. Instead, it identifies operational patterns that may indicate where future data-driven forecasting and decision support could generate managerial value.

3. Methodology

3.1 Research Design

This study adopts an exploratory single-case operational data approach to investigate food surplus and demand–consumption patterns in event catering.

An exploratory design was selected because the purpose of the study is not to test a predetermined causal model or estimate population-level effects. Instead, the study examines naturally occurring operational records to identify patterns that may inform future research on event-catering demand forecasting and resource planning.

The unit of analysis is an individual catering service record. Each observation represents a specific catering service delivered within an event context.

The analysis proceeded in three stages.

First, descriptive statistics were used to characterize service scale, preparation quantities, recorded food surplus, workforce deployment, catering formats, and operational exceptions.

Second, exploratory comparisons were conducted to examine whether recorded surplus patterns differed across selected operational characteristics.

Third, the observed patterns were interpreted in relation to previous event-catering and foodservice-demand literature to identify implications for future data-driven decision support.

Because the study uses observational data from a single provider, all inferential analyses are treated as exploratory rather than confirmatory.

3.2 Data Source and Confidentiality

The dataset was obtained from a Taiwanese event-catering service provider undergoing progressive digitalization of its operational processes.

The original records included information related to catering activities conducted between 2025 and 2026. To protect commercial confidentiality, all directly or indirectly identifying information was removed before analysis.

The study does not disclose the company's name, client identities, performers or entertainment groups, event names, venues, exact event dates, contractual relationships, or combinations of contextual characteristics that could reasonably enable identification through publicly available information.

Where necessary, results are aggregated to further reduce re-identification risk.

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The final analytical dataset consisted of **49 catering service records**, representing **2,351 prepared meals**. The records contained variables concerning expected meal quantities, prepared quantities, remaining meals after service, catering format, workforce deployment, labor input, service timing, and selected operational exceptions.

The company was not selected to represent the entire event-catering industry. It serves as an information-rich operational case through which demand and surplus patterns can be explored.

3.3 Variables and Operational Definitions

Expected Meal Demand
Expected meal demand represents the number of meals communicated or anticipated prior to service and used as a basis for operational preparation.

Prepared Meals
Prepared meals represent the number of meal portions prepared for each catering service.

Recorded Food Surplus
Recorded food surplus refers to meals or meal portions remaining after the catering service.
Because the dataset does not systematically record whether remaining meals were subsequently donated, redistributed, safely reused, or discarded, recorded surplus is **not treated as equivalent to final food waste**.

Surplus Proportion
For observations with available information, surplus proportion was calculated as:
Surplus proportion = Recorded surplus / Prepared meals × 100

This indicator represents the proportion of prepared meals remaining after service.

Catering Format
Catering format represents the operational mode through which food was provided. For exploratory analysis, formats were grouped into broader categories where necessary to maintain confidentiality and sufficient analytical cell sizes.

Service Scale
Service scale was operationalized using the number of prepared meals associated with each service record.

Workforce and Labor Input
Workforce deployment represents the number of personnel assigned to the catering service. Labor input represents recorded working hours associated with service preparation and execution.

Operational Exceptions
Operational exceptions refer to recorded deviations from planned service, such as last-minute meal additions, service or transportation delays, meal-related errors, or workforce-related issues.

Realized Consumption Outcome
Actual food consumption was not directly measured in the operational records. Accordingly, the study does not treat prepared meals minus recorded surplus as a direct measure of food intake. Instead, the relationship between prepared quantities and post-service recorded surplus is interpreted as an operational indicator of the extent to which pre-event demand corresponded with realized service outcomes. The term *realized consumption outcome* is therefore used cautiously to describe this relationship without implying direct measurement of individual food consumption.

3.4 Data Analysis

Data analysis was conducted in two levels.

First, descriptive statistics were calculated to summarize the operational dataset. These included frequencies, totals, means, medians, ranges, and aggregate surplus proportions where appropriate.

Second, exploratory non-parametric analyses were used because the sample was small, subgroup sizes were uneven, and the distributional assumptions required for conventional parametric tests could not be confidently established.

For comparisons between two independent service groups, the **Mann–Whitney U test** was used where sufficient observations were available.

For relationships between continuous or ordinal operational measures, **Spearman's rank correlation coefficient (ρ)** was used.

Where variables contained very small subgroup sizes, statistical significance testing was avoided and results were reported descriptively.

A two-sided significance threshold of **$p < .05$** was used for exploratory statistical tests. However, p-values are interpreted cautiously because the study was not designed as a confirmatory hypothesis-testing investigation and involves multiple observational dependencies and potential confounding factors. Effect sizes and descriptive patterns are therefore emphasized alongside statistical significance.

3.5 Analytical Strategy

The empirical analysis was organized around the three research questions.

For RQ1, descriptive analysis was used to characterize the overall magnitude and distribution of recorded food surplus.

For RQ2, exploratory comparisons examined whether surplus patterns varied according to selected catering and operational characteristics, including catering format and service scale where data quality permitted.

For RQ3, empirical patterns were interpreted in conjunction with previous research on event catering and demand forecasting to identify implications for data-driven resource planning.

Importantly, the analysis does not attempt to demonstrate that any particular catering format, event characteristic, or operational practice **causes** food surplus.

Observed differences may reflect unmeasured factors such as menu composition, contractual requirements, client preferences, event schedules, service populations, or differences in recording practices.

Accordingly, the empirical results are interpreted as **pattern identification within an operational case**, rather than causal effect estimates.

3.6 Research Ethics and Data Protection

The study follows a data-minimization approach to protect commercial confidentiality.

Only variables necessary to address the research questions are included in the analysis. Identifying and commercially sensitive information is excluded from the manuscript, and individual events are not described using combinations of characteristics that could facilitate re-identification.

The study reports aggregate statistics wherever possible.

Operational records are used exclusively to investigate service-level patterns and are not used to evaluate or publicly rank individual clients, employees, performers, events, or venues.

These procedures allow the study to retain the analytical value of real-world operational data while reducing potential disclosure risks associated with commercially sensitive event-catering relationships.

4. Results

4.1 Descriptive Characteristics of the Catering Operations

The final dataset consisted of 49 event-catering service records collected between 2025 and 2026. Across all observations, 2,351 meals were expected and 2,351 meals were prepared. The number of prepared meals per service ranged from 10 to 148, with a mean of 47.98 meals and a median of 35 meals.

A total of 439 meals were recorded as remaining after service. Based on the total number of prepared meals, the aggregate recorded surplus proportion was therefore 18.67%. At the service-record level, the mean surplus proportion was 20.33%, with a median of 24.00%. Some degree of recorded surplus occurred in 39 of the 49 observations (79.6%).

The operations involved a total recorded workforce deployment of 126 person-assignments across the 49 service records, corresponding to an average of 2.57 workers per service. Total recorded labor input was 373 hours, with a mean of 7.61 labor hours per service record.

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Table 1 summarizes the principal characteristics of the operational dataset.

Table 1. Descriptive Characteristics of the Event-Catering Records

Indicator	Result
Number of service records	49
Observation period	2025–2026
Total expected meals	2,351
Total prepared meals	2,351
Mean prepared meals per service	47.98
Median prepared meals per service	35
Range of prepared meals	10–148
Total recorded food surplus	439 meals
Aggregate surplus proportion	18.67%
Mean service-level surplus proportion	20.33%
Median service-level surplus proportion	24.00%
Services with recorded surplus	39 (79.6%)
Mean workforce deployment	2.57 workers
Total recorded labor input	373 hours
Mean labor input per service	7.61 hours

These results indicate that recorded surplus was not an isolated occurrence within the observed catering operations. However, because the dataset records remaining meals rather than their final disposition, the 439 meals are reported as food surplus and should not be interpreted as 439 meals of final food waste.

4.2 Expected Demand, Preparation, and Recorded Surplus

A particularly notable result emerged from the comparison between expected meal demand and preparation quantities.

For all 49 service records, the number of prepared meals was identical to the expected number of meals. In other words:
Expected meals = Prepared meals in 49 of 49 observations.

At the aggregate level:
Expected meals = 2,351
Prepared meals = 2,351

This indicates that the catering provider consistently translated the pre-service expected quantity directly into the number of meals prepared within the observed dataset.

Nevertheless, 439 meals remained after service.

This creates a clear empirical distinction among three operational quantities:
Expected demand → Prepared quantity → realized consumption outcomes

Although the first two quantities were perfectly aligned in the observed records, the recorded post-service surplus indicates that the final consumption outcome did not always correspond to the quantity expected before the event.

The aggregate relationship can be expressed as:

2,351 expected meals
↓
2,351 prepared meals
↓
439 meals recorded as surplus
↓
18.67% aggregate recorded surplus

This finding does not indicate that the provider incorrectly fulfilled client orders. On the contrary, the preparation records show close adherence to the quantities expected before service. Rather, the results identify a potential **demand–consumption gap**: pre-event expected demand may not fully represent the quantity ultimately consumed under actual event conditions.

The distinction is important because improving preparation decisions may require information beyond the initial expected or ordered quantity.

4.3 Recorded Surplus Across Catering Formats

The 49 service records were subsequently classified into two broader catering-format categories to permit exploratory comparison while avoiding excessively small analytical groups.

Thirty-nine observations involved buffet-style catering, whereas 10 observations involved individually packaged meals.

Buffet-style services accounted for 1,739 prepared meals and 439 recorded surplus meals, resulting in an aggregate surplus proportion of **25.24%**.

The individually packaged meal group accounted for 612 prepared meals. No post-service surplus was recorded for these 10 observations in the available dataset.

Table 2. Recorded Food Surplus by Catering Format

Catering format	Service records	Prepared meals	Recorded surplus	Aggregate surplus proportion
Buffet-style service	39	1,739	439	25.24%
Individually packaged meals	10	612	0	0.00%
Total	**49**	**2,351**	**439**	**18.67%**

A Mann–Whitney U test was conducted as an exploratory comparison of service-level surplus proportions between the two catering formats. The difference was statistically significant (U = 390.00, two-sided $p < .001$).

The corresponding rank-biserial correlation was 1.00, reflecting complete separation of the observed service-level surplus distributions: every individually packaged observation had a recorded surplus proportion of zero, whereas the buffet observations contained positive surplus values.

This result should nevertheless be interpreted with substantial caution.

Catering format was not randomly assigned, and the two groups may differ in event characteristics, service populations, menu design, operational requirements, and other unobserved factors. In addition, the method used to record remaining meals may be more straightforward for buffet services than for individually packaged meals.

Accordingly, the analysis does **not** establish that buffet-style catering causes greater food surplus. It demonstrates only that a substantial format-related difference was observed within this operational dataset.

4.4 Service Scale and Recorded Food Surplus

To examine whether larger catering services were associated with greater proportional surplus, Spearman's rank correlation was calculated between the number of prepared meals and the service-level surplus proportion.

The relationship was negligible and statistically non-significant:
Spearman's ρ = −.031, p = .835.

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Thus, within the available 49 observations, there was no evidence of a monotonic relationship between catering service scale and the proportion of meals remaining after service.

Table 3. Exploratory Association Between Service Scale and Surplus Proportion

Variables	Spearman's ρ	*p*
Prepared meals × surplus proportion	−.031	0.835

This finding indicates that service size alone does not explain the observed variation in surplus within the case dataset.

The result should not be interpreted as evidence that event size is irrelevant to food surplus more generally. Instead, it suggests that other characteristics of the catering context may be necessary to explain surplus patterns in the observed operations.

In particular, catering format, meal characteristics, event schedules, service populations, and other contextual variables may interact with preparation quantities in ways that cannot be captured by service scale alone.

4.5 Operational Exceptions

The operational records were also examined for deviations from planned service.

Most services were completed without a recorded operational exception. However, the dataset contained a small number of last-minute meal additions, delivery or service delays, meal-related errors, workforce shortages, and other on-site incidents.

Specifically, last-minute meal additions were recorded in two service observations. One observation recorded a service or delivery delay, one recorded a meal-related error, and one recorded a workforce shortage.

Because these events occurred infrequently, inferential comparisons between services with and without operational exceptions were not considered appropriate.

Table 4. Selected Operational Exceptions

Operational exception	Number of records
Last-minute meal addition	2
Service/delivery delay	1
Meal-related error	1
Workforce shortage	1

The low frequency of these events does not imply that operational responsiveness is unimportant. Rather, the available sample provides insufficient variation for estimating their statistical relationship with food surplus.

For confidentiality reasons, narrative descriptions of individual incidents are not reported.

4.6 Summary of Findings

The exploratory analysis produced four principal findings.

First, recorded food surplus was common within the observed event-catering operations. Across 49 service records and 2,351 prepared meals, 439 meals remained after service, corresponding to an aggregate surplus proportion of 18.67%.

Second, expected meal quantities and preparation quantities were identical in all 49 observations. This finding indicates that the provider consistently prepared according to expected demand but that expected demand did not necessarily correspond to actual consumption outcomes.

Third, a substantial difference was observed between catering formats. Buffet-style services recorded an aggregate surplus proportion of 25.24%, whereas no surplus was recorded for individually packaged meals in the available observations. Although the difference was statistically significant, the observational nature of the dataset prevents causal interpretation.

Fourth, catering service scale was not significantly associated with surplus proportion. The number of prepared meals showed virtually no monotonic relationship with the proportion of meals remaining after service.

Taken together, these findings suggest that the operational challenge may extend beyond estimating event size alone.

The empirical pattern can instead be represented as:
Accurate fulfillment of expected demand

does not necessarily imply
accurate prediction of actual consumption.

The results therefore provide preliminary empirical support for distinguishing **expected demand** from **consumption demand** in event-catering operations.

This distinction forms the basis of the discussion that follows.

5. Discussion

5.1 The Demand–Consumption Gap in Event Catering

The most important finding of this study is not simply the presence of recorded food surplus, but the relationship among expected demand, preparation quantity, and actual consumption outcomes.

Across all 49 service records, the expected number of meals was identical to the number of meals prepared. This pattern indicates that the focal catering provider consistently translated pre-event demand information into preparation quantities. Nevertheless, 439 meals remained after service, corresponding to an aggregate recorded surplus proportion of 18.67%.

This finding highlights an operational distinction that is easily overlooked in catering demand planning:

accurately fulfilling expected demand is not necessarily equivalent to accurately predicting actual consumption.

The observed surplus therefore should not be interpreted simply as evidence of poor production planning. From the provider's perspective, preparing the number of meals communicated before an event may represent appropriate contractual and service behavior. Reducing preparation quantities without additional information could generate meal shortages and compromise service reliability.

The more fundamental problem is therefore informational. The quantity requested before an event represents **expected or ordered demand**, whereas the quantity eventually consumed represents **realized consumption demand**. The two quantities may diverge because of changes in event schedules, participation patterns, meal timing, individual preferences, operational duties, catering format, or other contextual circumstances.

This interpretation complements previous event-catering research. Monteiro et al. (2020) demonstrated that leftover food at catered meetings and events differed across venues and food categories and that more experienced event organizers generated approximately 11% less food waste on average. Their findings suggest that food surplus is partly influenced by information and decision quality before service, rather than exclusively by consumer behavior during consumption.

The present study extends this perspective by locating the information problem explicitly between **pre-event demand estimates and realized consumption**. This distinction may be particularly important for temporary event catering, where providers have fewer opportunities than recurring institutional foodservice operations to learn stable daily demand patterns.

Accordingly, demand forecasting in event catering may need to evolve from predicting how many meals are requested toward estimating how much of the requested quantity is likely to be consumed under specific event conditions.

5.2 Why Event Size Alone May Be Insufficient

A second noteworthy finding concerns catering service scale.

In the present dataset, the number of prepared meals showed virtually no monotonic relationship with the service-level surplus proportion (Spearman's $\rho = -.031$, $p = .835$). In other words, larger catering services were not systematically associated with either higher or lower proportional surplus within the observed case.

This finding differs from the pattern reported by Leverenz et al. (2020). Using records from 239 event caterings in Germany, they found event size to be the strongest of the examined influences on buffet leftovers. Smaller events with fewer than 100 participants generated approximately 280 g of buffet leftovers per guest, whereas events exceeding 500 participants generated approximately 74 g per guest.
The difference between the two studies should not be interpreted as contradictory evidence or as a failure

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to replicate the earlier finding.

Several contextual differences may explain why event size did not emerge as an important correlate in the present case.

First, the current dataset includes catering services with different service formats and operational conditions, whereas Leverenz et al. specifically examined buffet leftovers.

Second, the two studies measure surplus differently. Leverenz et al. used weight-based monitoring of buffet leftovers, whereas the present operational records capture meal- or portion-based remaining quantities.

Third, event size may interact with menu composition, replenishment practices, event schedules, catering formats, and service populations. A simple relationship between number of meals and surplus proportion may therefore disappear when these contextual characteristics vary substantially.

Most importantly, the present finding suggests that **headcount or service scale alone may provide an insufficient basis for consumption forecasting**.

This has direct managerial relevance. If preparation rules are dominated by expected attendance while actual consumption is shaped by multiple contextual characteristics, simply improving attendance estimates may not substantially reduce surplus.

Future event-catering forecasting models may therefore benefit from incorporating event-level contextual variables rather than relying predominantly on service size.

5.3 Catering Format as an Operationally Relevant Context

The largest descriptive difference observed in the dataset concerned catering format.

Buffet-style services recorded an aggregate surplus proportion of 25.24%, whereas no post-service surplus was recorded for individually packaged meals in the available observations. The difference in service-level surplus proportions was statistically significant in the exploratory Mann–Whitney analysis. However, this finding requires particularly cautious interpretation.

The study does not establish that buffet-style catering inherently causes greater food surplus. Catering format was not randomly assigned, the subgroup sizes were unequal, and buffet services may differ systematically from packaged-meal services in event purpose, service population, menu design, timing, replenishment practice, and recording procedures.

Nevertheless, the observed pattern is operationally plausible and broadly consistent with research indicating that service design influences the mechanisms through which surplus is generated.

Buffet operations involve a structural tension between minimizing surplus and maintaining visible food availability. Food must often remain available until late in the service period to preserve perceived abundance, choice, and service quality. Consequently, managers may continue replenishment even when remaining demand is uncertain.

Research in other foodservice settings similarly identifies buffet or service-stage surplus as an important operational problem. Studies of foodservice waste have shown that serving-stage waste can constitute a substantial share of overall food waste, while waste-tracking interventions can help organizations identify and reduce buffet leftovers.

Recent hospitality research further suggests that buffet waste is shaped not only by demand variability but also by operational mechanisms such as defensive preparation, abundance signaling, and late replenishment (Liang et al., 2026). This reinforces the view that food-surplus prevention requires attention to **service design and operational timing**, rather than demand forecasting alone.

The practical implication is therefore not that event caterers should necessarily replace buffet services with packaged meals.

Buffets may provide flexibility, variety, hospitality value, and service advantages that are important in particular event contexts. Instead, the results suggest that forecasting strategies should be **format sensitive**.

For example, buffet-style operations may require decisions concerning batch preparation, replenishment thresholds, serving-container size, menu modularity, and the timing at which replenishment is reduced or discontinued. Individually packaged catering may require a different forecasting logic because the unit of production is directly tied to a discrete meal portion.

Consequently, catering format should be considered an input to demand and preparation decisions rather than merely a delivery choice made after demand has been forecast.

5.4 From Demand Forecasting to Consumption Intelligence

The findings provide a basis for reconsidering what should actually be predicted in event-catering operations.

Previous research demonstrates that machine-learning methods can improve demand forecasting in food catering. Rodrigues et al. (2024), using three to nine years of real daily records from three catering services, found that machine-learning models could potentially reduce wasted meals by 14%–52% while also reducing unmet demand by 3%–16% compared with baseline forecasting approaches.

This evidence clearly demonstrates the potential value of data-driven forecasting.

However, applying such approaches to event catering requires careful definition of the prediction target.

If a model simply predicts the number of meals ordered, yet the number ordered systematically differs from actual consumption, improved prediction of orders may not fully address the surplus problem.
The findings of the present study therefore suggest a progression from:

order forecasting
to
consumption-oriented demand forecasting.

For this purpose, the study uses **consumption intelligence** as a conceptual lens describing an organization's capacity to systematically learn from the relationship between event characteristics, preparation decisions, actual consumption outcomes, and recorded surplus.
Consumption intelligence can be represented as a continuous learning process:

Expected demand
↓
Preparation quantity
↓
Event and service conditions
↓
Actual consumption outcome
↓
Recorded surplus
↓
Post-event learning
↓
Improved future decisions

The critical feature of this process is the feedback loop.

Each event becomes not only a catering assignment but also a source of operational learning. Over time, accumulated records may reveal patterns associated with particular catering formats, meal periods, event types, service populations, preparation practices, or other characteristics.

This perspective also provides a more realistic role for artificial intelligence in event catering.
AI should not be viewed primarily as an isolated technological feature or as an automated replacement for managerial judgment. Its potential value lies in learning patterns across heterogeneous historical events that may be difficult for managers to recognize consistently through experience alone.

In this sense, the sequence toward AI-enabled catering may be conceptualized as:

Operational data accumulation→ Data quality and standardization
→ Consumption pattern identification→ Predictive decision support
→ Managerial adjustment→ New operational outcomes→ Continuous model learning

Importantly, the current study does not test this AI-enabled process. The available operational records represent the empirical basis for identifying the decision problem, not evidence that AI has already solved it.

This distinction prevents technological overclaiming while still identifying a clear direction for future research.

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5.5 Managerial Implications for Event-Catering Operations

The findings suggest several implications for practitioners.

First, event-catering providers should distinguish **contractual meal quantity** from **forecast consumption quantity**.

The former determines what the provider is obligated to prepare or make available; the latter represents an analytical estimate of what is likely to be consumed. These quantities should not necessarily be used interchangeably.

The purpose of a consumption forecast is therefore not automatically to prepare fewer meals than contracted. Rather, it can support discussions regarding safety margins, phased preparation, replenishment strategies, portioning, procurement, and service design.

Second, post-event surplus should be treated as an operational data asset rather than merely as an undesirable outcome.

Providers can establish a standardized post-event feedback record containing variables such as:

- meals expected;
- meals prepared;
- actual or estimated meals consumed;
- remaining meals;
- catering format;
- meal period;
- broad event characteristics;
- service population;
- menu characteristics;
- operational disruptions; and
- relevant scheduling conditions.

When accumulated consistently, these variables may create the training foundation for future predictive analytics.

Third, buffet-style services deserve particular managerial attention. Given the substantial descriptive difference observed in this study, providers may consider monitoring not only total preparation quantity but also replenishment timing, batch size, remaining service time, and food remaining at individual service stages.

Fourth, food-surplus reduction should be balanced against service reliability.

Foodservice production planning involves competing risks. Excess preparation creates cost and sustainability problems, while insufficient preparation may produce unmet demand and damage service quality. Previous operations research similarly recognizes this tension between overproduction and shortage in buffet environments(Birisci & McGarvey, 2018).

The managerial objective should therefore not be **zero surplus at any cost**.

A more appropriate objective is to identify an acceptable preparation buffer that simultaneously minimizes unnecessary surplus and maintains required service levels.

This represents a decision-support problem rather than merely a waste-reduction problem.

5.6 Theoretical Contribution

Although exploratory, this study offers three conceptual contributions.

First, it introduces the **demand–consumption gap** as a useful distinction for event-catering research. Existing event-catering studies have identified variables associated with leftovers and waste, while demand-forecasting research has demonstrated the potential of advanced prediction methods. The present study connects these streams by showing that expected demand can be accurately translated into preparation quantities while still differing substantially from realized consumption.

Second, the study highlights the need to conceptualize event-catering demand as **context dependent**. The lack of an observed relationship between service scale and surplus proportion, together with the substantial difference across catering formats, suggests that consumption cannot necessarily be inferred from headcount alone.

Third, the study proposes **consumption intelligence** as a preliminary managerial lens linking operational data, demand forecasting, service design, and organizational learning.

This concept should not yet be regarded as a validated theoretical construct. Further research is

required to establish its dimensions, measurement, predictive validity, and applicability across organizations.

Nevertheless, it provides a useful conceptual bridge between traditional event-catering operations and future data-driven decision support.

The contribution can therefore be summarized as follows:

Traditional planning
Expected attendance/order
→ Preparation
Observed operational problem
Expected demand
→ Preparation
→ Consumption gap
→ Surplus
Proposed data-driven logic
Event context + historical outcomes
→ Consumption intelligence
→ Preparation and service decisions
→ Actual outcome
→ Learning

This expanded perspective moves the research question beyond **"How can food surplus be reduced?"** toward a more fundamental question:

"How can event-catering providers learn the relationship between what is expected, what is prepared, and what is actually consumed?"

The latter provides a foundation for future research on predictive analytics, AI-enabled decision support, and sustainable event-catering operations.

6. Conclusions

6.1 Conclusions

This study explored the relationship among expected meal demand, preparation quantities, and recorded food surplus in event-catering operations using 49 anonymized service records from a Taiwanese event-catering provider. The dataset represented 2,351 prepared meals across heterogeneous event-catering contexts.

Three main conclusions can be drawn.

First, recorded food surplus was a recurrent operational phenomenon in the observed services. A total of 439 meals remained after service, corresponding to an aggregate recorded surplus proportion of 18.67%. Surplus was recorded in 39 of the 49 service observations. Because the dataset does not document the final disposition of all remaining meals, these quantities should be interpreted as **food surplus rather than final food waste**.

Second, the study identified a clear distinction between expected demand and actual consumption outcomes. Expected meal quantities and prepared quantities were identical in all 49 observations, indicating that the provider consistently prepared according to pre-event expectations. Nevertheless, substantial surplus remained after service. This suggests that accurate fulfillment of expected demand does not necessarily represent accurate prediction of actual consumption.

Third, the exploratory results indicate that contextual characteristics may be relevant to this demand–consumption gap. A substantial difference in recorded surplus was observed between buffet-style and individually packaged services, whereas service scale itself showed virtually no monotonic association with surplus proportion. These findings suggest that headcount alone may be insufficient for understanding consumption behavior in heterogeneous event-catering environments.

Taken together, the study answers the three research questions by demonstrating that: (1) recorded surplus occurred frequently in the observed event-catering operations; (2) surplus patterns differed across selected operational contexts, particularly catering format, while no clear relationship with service scale

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was observed; and (3) these patterns point toward the need for more context-sensitive, consumption-oriented approaches to demand planning.

The central conclusion of the study can therefore be expressed simply:
Expected demand is not necessarily consumption demand.

For event-catering providers, the next stage of data-driven decision making may consequently require moving beyond the question of how many meals are ordered toward understanding how event conditions influence how many meals are ultimately consumed.

6.2 Practical Implications

The findings provide several implications for event-catering operators.

First, providers should distinguish between the **contractual quantity** that must be supplied and the **forecast consumption quantity** that supports operational decision making. A consumption forecast should not be used mechanically to reduce contracted quantities. Instead, it can inform preparation margins, procurement, batch production, replenishment, portioning, and communication with clients.

Second, post-event surplus should be systematically recorded. Event-catering companies frequently accumulate operational experience across individual events, but such experience may remain dispersed among employees or recorded inconsistently. A standardized event-level dataset can convert operational experience into organizational knowledge.

At minimum, future records should distinguish among expected meals, prepared meals, estimated or measured meals consumed, remaining quantities, catering format, meal period, broad event characteristics, menu characteristics, workforce deployment, service timing, and operational exceptions.

Third, providers using buffet-style catering should pay particular attention to service-stage decisions. Rather than determining the entire surplus outcome only through the initial preparation quantity, operators may be able to intervene through smaller preparation batches, staged replenishment, smaller serving containers, monitoring of remaining service time, and differentiated replenishment thresholds.

Fourth, digitalization should begin with reliable operational data rather than with AI technology itself.

The findings of this study suggest the following progression:
Standardized operational records→ Reliable historical database
→ Identification of consumption patterns→ Predictive analytics→ Decision support
→ Continuous operational learning

For small and medium-sized event-catering providers in particular, this sequence may be more realistic than immediately implementing complex AI systems without sufficient historical data.

Finally, the objective of demand optimization should not be zero surplus regardless of service consequences. Event caterers must simultaneously manage the risk of overproduction and the risk of insufficient food availability. The appropriate managerial objective is therefore to improve the balance between **resource efficiency and service reliability**.

6.3 Limitations

Several limitations should be considered when interpreting the findings.

First, the study is based on 49 service records from a single event-catering provider. The sample does not represent the broader event-catering industry, and the findings should therefore be interpreted as evidence from an exploratory operational case rather than population-level estimates.

Second, the observational dataset was originally generated for operational rather than academic research purposes. Some variables that may influence consumption—including detailed menu composition, participant characteristics, precise consumption counts, replenishment behavior, and event-program dynamics—were not consistently available.

Third, recorded remaining meals cannot be equated with final food waste. The dataset does not systematically document whether surplus food was subsequently redistributed, reused, donated, or discarded. Consequently, the present study deliberately uses the term **recorded food surplus** when describing its empirical results.

Fourth, the substantial difference observed between buffet-style and individually packaged

services should be interpreted cautiously. Catering formats were not randomly assigned, subgroup sizes were unequal, and the zero recorded surplus among packaged-meal observations may partly reflect differences in how remaining food was operationally defined or recorded. The result therefore represents an exploratory association rather than evidence of a causal effect of catering format.

Fifth, the available dataset contains a relatively limited number of operational exceptions. Statistical relationships involving last-minute changes, delays, errors, and workforce shortages could therefore not be meaningfully estimated.

Sixth, the analysis did not evaluate the effectiveness of an implemented artificial-intelligence forecasting system. Although the findings provide implications for future AI-enabled demand forecasting, no causal claim regarding the performance or impact of AI can be made from the present data.

Finally, multiple service observations were generated by the same organization and may involve recurring organizational routines or client relationships. The observations should therefore not be assumed to be fully independent representations of the event-catering market.

These limitations constrain generalizability but do not eliminate the value of the dataset for exploratory pattern identification. Rather, they define the boundary conditions within which the findings should be interpreted.

6.4 Future Research

The present study provides several directions for future research.

A first priority is to expand event-level data collection across a larger number of events, catering providers, event types, and service formats. Multi-provider datasets would allow researchers to determine whether the demand–consumption gap observed in this case also occurs across different organizational and market contexts.

Second, future research should measure **actual consumption** more directly. Rather than relying solely on ordered, prepared, and remaining quantities, future data collection could distinguish food prepared, food served, food consumed, edible surplus, redistributed food, and final waste. Weight-based measurement may be particularly valuable for buffet operations.

Third, future studies should examine the contextual predictors of actual consumption. Potential variables include event type, meal period, participant characteristics, catering format, menu composition, venue conditions, event schedule, service duration, weather conditions where relevant, and historical consumption patterns.

With a sufficiently large and standardized dataset, predictive models could then compare conventional managerial estimates with statistical and machine-learning approaches. Model performance should be evaluated not only through forecast error but also through operational outcomes such as surplus reduction, shortage prevention, labor efficiency, procurement efficiency, and service reliability.

Fourth, future research could investigate catering formats in greater detail. Rather than treating buffet and packaged meals as simple categories, researchers could examine preparation batches, replenishment frequency, serving-container size, menu diversity, portion flexibility, and the timing of final replenishment.

Fifth, the preliminary concept of **consumption intelligence** introduced in this study requires further conceptual and empirical development. Future research could examine whether consumption intelligence can be operationalized as an organizational capability involving data collection, pattern recognition, forecasting, managerial interpretation, operational response, and post-event learning.

Such research could eventually test the following learning cycle:

Event data→ Consumption prediction→ Preparation and service planning
→ Operational execution→ Consumption and surplus outcomes
→ Feedback→ Model and managerial learning

Finally, qualitative expert research may complement larger operational datasets. Expert interviews, modified Delphi studies, or multi-criteria decision methods could be used to identify the organizational, technological, and managerial conditions required for successful implementation of AI-enabled event-catering systems.

Accordingly, the present study should be regarded as a first step in a broader research program. It establishes the operational problem—the gap between expected demand and actual consumption—while future studies can investigate increasingly sophisticated approaches for predicting, managing, and

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ultimately reducing that gap.

6.5 Final Statement

Event catering operates under an unavoidable condition of uncertainty: food must be planned and prepared before actual consumption is known.

The findings of this study suggest that improving event-catering sustainability is therefore not simply a matter of preparing less food. It requires better information about the relationship between event conditions and actual consumption.

By transforming post-event operational records into cumulative organizational knowledge, catering providers may gradually move from experience-based estimation toward consumption-oriented, data-driven decision making.

In this transition, the value of artificial intelligence lies not in replacing professional judgment, but in helping managers learn systematically from events that have already occurred.

The path toward smarter event catering may therefore begin not with AI itself, but with learning what the data from each event can tell us about the next one.

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