AI-driven Dynamic Pricing during Major Events

A quantitative study on how the hotel industry can maximize revenue during major events with AI-driven dynamic pricing strategies

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Abstract

Major events such as Taylor Swift's sold-out concerts provide powerful illustrations of how spikes in demand create significant revenue opportunities for the hotel industry. However, traditional Revenue Management Systems (RMS) often fall short in maximizing this potential due to their reliance on historical data and internal booking patterns, lacking proactive integration of real-time external event information. This study examines how AI-driven dynamic pricing strategies can optimize hotel revenue during major events, addressing a notable research gap at the intersection of artificial intelligence, dynamic pricing, and event-driven demand forecasting. Through a quantitative analysis of booking and pricing data from a Swedish hotel chain and the design of controlled AI prompts with and without event awareness, the research highlights the critical limitations of current AI systems and proposes the integration of external data sources to improve responsiveness. Results demonstrate that real-time awareness of major events significantly enhances pricing strategies, with AI-informed models capturing higher revenues by adjusting prices proactively. The findings advocate for the development of integrated event data, and suggest managerial implications for leveraging AI technologies more strategically within volatile, uncertain, complex, and ambiguous (VUCA) environments. This thesis contributes both academically and practically to the evolving field of Revenue Management (RM) by showcasing how AI can reshape pricing strategies to better align with dynamic market realities.

Key words: *Artificial Intelligence, Dynamic Pricing Strategies, Events, Hotel Industry, Revenue Management.*

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1. Introduction

Taylor Swift might not be the first name that comes to mind when discussing hotel pricing strategies, yet her sold-out concerts frequently illustrate a powerful lesson in Revenue Management (RM). Whenever the global pop icon arrives in a city for a major performance, hotel occupancy rises, and prices often skyrocket (Stockholm Business Region, 2024). When Taylor Swift performed in Stockholm, the city reported a 98% increase in revenue per available room (RevPAR) compared to the previous year (Stockholm Business Region, 2024). This spike in demand underscores why effective RM is critical in the hospitality industry, especially during major events that drive a sudden influx of visitors.

Hotels have long recognized that concerts, international conferences, sporting events, and other major gatherings can present significant opportunities for profit. Traditionally, the industry has relied on human-driven yield management principles, using past data and manual calculations to set prices in anticipation of increased demand. However, these methods often fall short in capturing the complexity of real-world factors, ranging from last-minute booking behaviors to competitive price shifts across online platforms. As technology evolves, the hotel sector is turning to Artificial Intelligence (AI) to handle these challenges more efficiently, proactively and profitably (Rekiek et al., 2024).

Indeed, AI-driven dynamic pricing systems are reshaping how hotels attempt to balance the delicate interplay between demand and room supply. These systems typically draw from large internal datasets, including historical occupancy rates, competitor pricing, and consumer behavior on online travel agencies, to generate real-time pricing recommendations.

However, current AI-based RMS still lack proactive awareness of external, real-world events unless they are explicitly informed by a human operator. When an event like a Taylor Swift concert is announced, the system is unable to adjust prices in advance, as it does not have a built-in mechanism for detecting upcoming demand shocks. Instead, prices tend to increase only after the surge in bookings has already begun. As a result, while these platforms offer sophisticated forecasting within known parameters, their effectiveness during sudden demand spikes remains limited unless manual interventions are made to update the system.

Despite the promise of these technologies, their widespread adoption raises several important questions (Millauer & Vellekoop, 2019). To what extent do these AI-driven pricing models truly maximize revenue, particularly when traditional methods have ruled for decades? And what role do major events like a Taylor Swift concert play in highlighting both the opportunities and risks associated with rapid, event-driven price adjustments?

This thesis aims to address these questions by exploring how the hotel industry can use AI-driven dynamic pricing strategies to optimize revenue specifically during major events, with the help of Large Language Models, to test alternative options to existing solutions. The study bridges gaps in existing literature by examining the intersection of AI, RM, and Event-Driven Pricing Fluctuations. Ultimately, the goal is to provide both academic insights and practical guidance for hotels, revealing how a sold-out Taylor Swift concert, or any large-scale event, can serve as a testing ground for the industry's most innovative pricing strategies. Through quantitative analysis, case data from a hotel chain in Sweden, and a discussion of emerging best practices, this research contributes to a deeper understanding of how AI can reshape RM in the evolving hospitality landscape.

1.1 Background

By the late 1980s, hotel chains had begun applying yield management principles, adapting them to room capacity, varying price fences, and distribution channels (Kimes, 2003). As it matured, the practice became known as RM to better reflect its broader applications and strategic nature (Kimes, 2003; Ivanov & Zhechev, 2012). Since 2010, RM has evolved rapidly, driven by advancements in AI, big data, and machine learning.

Modern RMS now enhance demand forecasting, price optimization, and real-time decision-making, enabling hotels to adjust room rates dynamically based on demand fluctuations (Kimes, 2003). Recent advancements incorporate big data analytics, AI, and customer-centric strategies, allowing hotels and other sectors to shift their focus from maximizing a single revenue stream (like sold hotel rooms) to optimizing multiple revenue centers, including restaurants, spas, and other event spaces (Wang et al., 2015).

Looking ahead, next-generation RM will incorporate AI-based personalization, allowing hotels to set individualized prices and offers based on previous booking history, digital behaviors, and real-time demand (McGill & Van Ryzin, 1999; Strauss et al., 2018). As major concerts, conferences, and sporting events significantly affect hotel demand and therefore prices, event-driven forecasting models that account for such surges will be critical (Ivanov & Zhechev, 2012; Strauss et al., 2018).

1.2 Purpose & Contribution

There are notable research gaps in the application of AI-driven pricing tools within the hotel RM sector. This became evident during our review of existing studies, where we systematically compiled a literature table summarizing current research. Through this analysis, we identified a gap at the intersection of AI, dynamic pricing strategies, hotel industry, and specifically during major events, highlighting the need for further exploration in this area.

Our study aims to address this gap by examining how AI-driven dynamic pricing strategies can be effectively utilized within the hotel industry to optimize revenue, particularly during major events. By integrating insights from both hospitality management and AI, we seek to contribute to the existing knowledge and provide practical implications for hotel operators looking to leverage AI for more effective RM.

Furthermore, this research is driven by our strong interest in both the hotel industry and AI technologies. We believe that AI has the potential to revolutionize pricing strategies in the hotel industry, and our study aspires to bridge the gap between theoretical knowledge and practical applications. Through this work, we aim to offer valuable insights for academics, hotel managers, and AI practitioners who are interested in the evolving role of AI in RM.

1.3 Research Question

To define the objective of the study, the following research question has been formulated:

> *How can the hotel industry maximize revenue during major events using AI-driven dynamic pricing strategies?*

1.4 Delimitations

Due to constraints in time and resources, the data for this study has been collected from a single hotel chain operator in Sweden. As a result, the findings are primarily reflective of the Swedish hotel market and may not be directly applicable to other regions or markets with different economic conditions, consumer behaviors, or competitive landscapes. While the study provides a general perspective and offers in-depth insights into the collected data, it lacks the granularity and broader applicability that could be achieved by examining multiple hotel chain operators across different markets. A more comprehensive study, including a wider range of geographical locations and business models, could provide a more nuanced understanding of the topic.

Moreover, this research specifically focuses on AI-driven dynamic pricing strategies during events due to the limited scope and time constraints. While this approach allows for a detailed examination of pricing adjustments in response to event-driven demand fluctuations, it does not account for other influential factors that could shape pricing strategies, such as seasonality, inflation, and competitor pricing. Future research could benefit from exploring these additional dimensions, thereby offering a more holistic perspective on the implementation and effectiveness of AI-driven pricing models in the hotel industry.

While sudden demand spikes occur across many industries, including airlines, retail, and e-commerce, this thesis specifically focuses on event-driven demand spikes within the hotel industry. Broader literature on demand volatility has been considered to support the theoretical framing, but empirical analysis is limited to hospitality-related events such as concerts. As such, the findings may not directly apply to other types of demand fluctuations or sectors outside of hospitality

Lastly, this research and upcoming findings are not applicable on third party booking platforms that aggregate hotel prices and offers, with package deals etc.

1.5 Structural Overview

This report is structured into seven sections, each contributing to an in-depth examination of the chosen research question: “How can the hotel industry maximize revenue during major events using AI-driven dynamic pricing strategies?”

The first section serves as an introduction, outlining the background of the study, its relevance, the research question, and any delimitations that frame the scope of the research. This section aims to establish the foundation for the study and justify its significance within the hotel industry. In the second and third section, the theoretical and conceptual framework will be explored through a review of existing literature, drawing upon academic research to build a solid conceptual foundation for understanding AI-driven dynamic pricing and its implications for the hotel industry.

Following this, the fourth section will detail the methodology, explaining how the study was conducted, including the research design, data collection methods, and analytical approach.

This section will ensure transparency in the research process and provide justification for the chosen methods. The fifth section will present the study's findings by showcasing the collected data. This section will provide empirical insights into how AI-driven dynamic pricing is currently utilized during major events within the hotel industry, and how it could be used, using generative AI.

In the sixth section, the findings will be analyzed and discussed in depth. Managerial recommendations will be provided, offering practical insights for industry professionals. Additionally, the discussion will highlight the broader implications of the study and its significance in the context of RM. Finally, the seventh and concluding section will summarize the key findings of the study, address its limitations, and offer suggestions for future research. This final section will reflect on the study's contributions while identifying potential areas for further exploration within AI-driven pricing strategies in the hotel industry.

2. Theoretical Background

The following section outlines four key theoretical themes that explains this study's exploration of how the hotel industry can optimize revenue during major events through AI-driven dynamic pricing strategies. These themes are: Artificial Intelligence, RM, Dynamic Pricing, Events Affecting the Hotel Industry, and the VUCA Framework (Volatility, Uncertainty, Complexity, and Ambiguity). The themes are highly interconnected and will collectively address the core question of how hotels can maximize revenue in periods of increased market activity by strategically balancing supply, demand, and price.

Advancements in *Artificial Intelligence* drive both the speed and accuracy of Revenue Management and dynamic pricing decisions by capturing complex patterns in customer behaviors and market signals. *Revenue Management* lies at the heart of this discussion, providing the underlying principles for balancing capacity constraints with fluctuating demand. Building on these RM foundations, *Dynamic Pricing* emerges as a key mechanism for real-time rate adjustments, enabling hotels to capitalize on demand increases, while mitigating risks associated with oversupply or mispricing. *Events Affecting the Hotel Industry* sheds light on the external factors that amplify the importance of well-structured revenue management. While large-scale events can generate substantial occupancy and revenue gains, they also introduce significant operational and pricing complexities. Finally, the VUCA Framework provides a useful lens for understanding real-time challenges that businesses might face, such as unexpected major events.

This study is grounded in an extensive review of existing literature, primarily gathered from the Stockholm School of Economics library. Additional information was sourced online, including materials from Stockholm Business Region, and was carefully evaluated to ensure trustworthiness, precision, and significance.

Below is a literature table summarizing key articles used to support the theoretical background.

Author(s)	Year	Central Findings	Major themes
Deksnyte & Lydeka	2012	Suggests dynaimc pricing models to optimize pricing in varying contexts	Dynamic Pricing
Den Boer	2015	Adapt pricing based on demand elasticity, competitive responses, and customer segmentation over time	Dynamic Pricing
Ivanov & Zhechev	2012	Identifies gaps in integrating real-time data and personalization into traditional models.	Revenue Management
Kopalle et al	2023	Defines the scope of dynamic pricing in contemporary markets, with managerial insights into implementation challenges and opportunities	Dynamic Pricing
Laurin et al	2018	Highlighting that organizations must prepare for a wide range of unpredictable future scenarios rather than relying solely on forecasts	VUCA
Li et al	2024	Evaluates how large language models (LLMs) perform in tasks requiring nuanced perception and contextual understanding	Generative AI, LLMs
Millauer & Vellkop	2019	Recommends a balanced approach integrating human expertise with AI insights to ensure responsible and effective revenue decisions	AI, Revenue Management, Managerial Implications
Rekiek et al	2024	Significant improvements in revenue management and pricing strategies through AI and data-driven automation in the hotel industry	AI, Dynamic Pricing
Zhang & Lu	2021	Artificial intelligence technologies, outlining key innovations, applications across sectors, and the challenges of deployment. It underscores future directions including ethics, explainability, and integration into business and service processes	AI

2.1 Artificial Intelligence

AI has developed into a transformative technology since its formal introduction in 1956, where scholars first proposed the concept of machines simulating human intelligence (Zhang & Lu, 2021). The area of AI includes many "disciplines", such as computer science, logic, psychology, and philosophy, aiming to replicate human cognitive processes such as learning, decision-making, and problem-solving (Zhang & Lu, 2021).

Over the decades, AI has played a significant role in technological advancements, impacting various sectors and industries. Notably, the rapid progress in AI-related fields such as machine learning, natural language processing, and robotics has propelled its application in real-world scenarios, enhancing labor efficiency and optimizing human resource structures (Zhang & Lu, 2021). As AI continues to evolve and develop, its integration with emerging technologies like big data, IoT, and cloud computing is expected to drive further innovation and societal transformation (Zhang & Lu, 2021).

AI is restructuring the hotel industry by transforming RM and demand forecasting, through data-driven decision-making that optimizes profitability and operational efficiency. AI-based models have improved the accuracy of predicting demand and booking trends, as they can analyze multiple variables, such as competitor pricing and local events (Rekiek et al., 2024). Unlike traditional forecasting methods, which struggle to capture the complexities of market fluctuations, AI-driven models process real-time data and generate dynamic pricing strategies that maximize occupancy rates and revenue (Rekiek et al., 2024).

Furthermore, AI enables automated RM, allowing hotels to centralize decision-making and reduce operational costs while increasing efficiency (Millauer & Vellekoop, 2019). However, the transition to AI-powered systems presents challenges, including cybersecurity risks, the dependency on data accuracy, and concerns about job displacement (Millauer & Vellekoop, 2019). As AI continues to evolve, striking a balance between automation and human expertise will be essential in ensuring both financial success and customer satisfaction in the hotel industry.

2.2 Dynamic Pricing

Dynamic pricing, as defined by Den Boer (2015), is the practice of setting optimal prices for products or services and adjusting them frequently with minimal effort. This approach applies to both online and physical stores using digital technology to update prices continuously, and while responding to market changes. Kopalle et al. (2023) explain this, framing dynamic pricing as an ongoing adjustment of prices to accommodate four key market demand drivers: People (segments or individual consumers), Product configurations, Periods (time), and Places (locations). From this perspective, dynamic pricing aims to match consumer price sensitivity at each point of variation.

Building on these definitions, Deksnyte & Lydeka (2012) emphasize the multifaceted nature of dynamic pricing, categorizing relevant definitions into four distinct groups: those seeking revenue maximization, those driven by demand parameters, those focused on supply management, and those balancing supply with demand. This evolution from a purely theoretical framework to a sophisticated strategy underscores the role of both economic and behavioral factors, consumer behavior, market structure, and perceptions of fairness shape its implementation.

Giampaolo et al. (2016) illustrate dynamic pricing's importance in the hotel industry, where hotels adjust room rates in real time based on demand fluctuations, competitor pricing, and available inventory. While these tactics often boost revenue, they also affect consumer reference prices, influencing how fair or unfair these fluctuations appear. This aligns with Kopalle et al. (2023) discussion on price adjustments driven by distinct market factors and connects to the article by Deksnyte and Lydeka (2012), categorization of pricing strategies. Thus, dynamic pricing not only enhances profitability but also shapes fairness perceptions and market structures, underscoring its strategic importance in both research and practice.

2.2.1 Demand Spikes Beyond Hospitality

While this study focuses on event-driven demand spikes within the hotel industry, the phenomenon of sudden, short-term demand surges is well documented across other sectors. Airlines face pronounced demand variability driven by seasonality, day-of-week patterns and special events, and their RMS must also cope with operational irregularities such as cancellations, diversions, defections from delayed flights and no-shows (McGill & Van Ryzin, 1999).

Retailers, especially online vendors and stores with electronic shelf labels, use dynamic pricing to manage everyday traffic (Den Boer, 2015), hence E-commerce platforms adjust prices dynamically during promotional periods such as flash sales and markdown events (Kopalle et al., 2023).

These industries have developed robust strategies to anticipate and respond to such surges, often combining real-time data analytics with inventory and pricing optimization. Although the specific triggers and operational constraints differ, the underlying principles such as volatility, urgency, and limited capacity are consistent. Insights from these broader contexts inform the conceptual basis for understanding how pricing systems, especially those powered by AI, can respond to dynamic, unpredictable spikes in demand.

2.3 Revenue Management

Revenue Management is defined as the strategic use of pricing and related techniques to influence customer demand, thereby increasing both revenue and profitability (Huefner, 2014). While it is often discussed alongside cost management, RM is fundamentally distinct in that it seeks to optimize revenues rather than reduce expenses, making it critical for industries where capacity is fixed and product perishability is high (Huefner, 2014).

Hotels, airlines, car rental companies, and entertainment venues are prime examples of sectors where unsold inventory, be it a vacant hotel room or an empty airline seat, cannot be recovered once the selling period has passed. Hence, the importance of RM lies in its ability to balance supply and demand efficiently, segment customers based on their purchasing behavior, and maximize total profitability (Ivanov & Zhechev, 2012).

Hotels must predict demand fluctuations based on seasonality, competitor rates, and special events (McGill & Van Ryzin, 1999; Ivanov & Zhechev, 2012). AI-driven forecasting further refines these predictions in real time, enabling hotels to adjust prices swiftly to capitalize on fluctuations (Boyd, 2003). However, frequent price changes and complex rate fencing can create distrust if customers perceive pricing as unfair or inconsistent (Huefner, 2014; Kimes, 2003). While consumers accept demand-based pricing in airlines more readily, hotels face greater scrutiny, as reference prices form quickly through online comparisons (Kimes, 2003; Boyd, 2003). Rate parity agreements, imposed by many OTAs, further limit pricing flexibility and can lead to uniform rates across channels, affecting profit margins (Boyd, 2003).

Additionally, overreliance on third-party distributors can cannibalize direct sales, forcing hotels to pay high commissions (Boyd, 2003). Balancing short-term revenue maximization with long-term brand equity is another concern as excessive discounting may permanently lower customers' perceived fair price levels (Huefner, 2014). On the operational side, implementing advanced RM solutions entails substantial complexity: integration with big data analytics, AI, and automated decision-making tools can challenge even well-resourced hotels (McGill & Van Ryzin, 1999). Human decision-making remains vital, ensuring that pricing does not alienate loyal customers or violate consumer protection laws (Ivanov & Zhechev, 2012).

2.4 Events Affecting the Hotel Industry

External events such as concerts, sports events, and festivals, significantly affect hotel performance by causing sudden spikes in demand. Alananzeh (2022) states that events generate substantial economic returns and drive hotel occupancy. This is supported by the Taylor Swift case study in Stockholm, which reported a 98% increase in revenue per available room (RevPAR) during her concerts compared to the previous year (Stockholm Business Region, 2024).

Major events also boost the overall tourism economy (Hoff et al., 2025). For instance, Taylor Swift's concerts generated an economic impact of 848 million kronor through increased spending on hotels, dining, and local services. With roughly 69% of that revenue coming from foreign tourists. About 88% of visitors stayed overnight for an average of three days, with 90% of foreign tourists using hotels compared to 47% of Swedish tourists. Additionally, 75% of foreign visitors traveled by air (Stockholm Business Region, 2024).

Spending on accommodation and daily consumption was substantial: Swedish tourists contributed about 265 million kronor, while foreign tourists accounted for approximately 583 million kronor. Moreover, activities like dining out, shopping, and independent sightseeing were significantly more popular among foreign visitors. This demonstrates how events can benefit not only individual hotels but also stimulate broader economic activity throughout the hotel industry (Stockholm Business Region, 2024).

However, external events also bring challenges. The sudden increase in guests can strain resources and intensify competition, requiring hotels to quickly adjust their services and pricing strategies. For hotels to capture a larger share of event-driven demand, Alananzeh (2022) notes that technology plays a key role.

AI helps hotels forecast demand and adjust pricing in real time during peak periods. This enables hotels to secure higher rates and optimize resource allocation during major events. In summary, external events provide significant revenue opportunities for hotels while also introducing operational challenges. Balancing these factors through smart pricing strategies and effective resource management is essential for hotels to fully benefit from major events.

2.5 VUCA Framework

In an increasingly dynamic and unpredictable market, traditional strategic planning often falls short in addressing the real-time challenges businesses face. The concept of VUCA, Volatility, Uncertainty, Complexity, and Ambiguity, provides a useful lens for understanding and navigating these conditions. Originally rooted in military leadership contexts, VUCA has since been widely adopted in business strategy to describe environments marked by rapid change and instability (Bennet & Lemoine, 2014; Laurin et al., 2018).

Volatility refers to the frequency and intensity of change within an environment. It is characterized by instability and unexpected disruptions that require organizations to respond swiftly and flexibly. According to Laurin et al. (2018), while the nature of change may be clear, its speed and scale often challenge the limits of existing processes, demanding organizational slack and rapid adjustment mechanisms.

Uncertainty arises when the cause and effect of events are known, but the outcome remains unpredictable. Laurin et al. (2018) point out that uncertainty is not just a situational characteristic, it is a defining feature of contemporary business environments, driven by new entrants, evolving technologies, and shifts in consumer behavior.

Complexity reflects the interdependence of numerous factors, actors, and systems that influence business operations. Laurin et al. (2018) argue that even established companies with deep expertise can struggle with complexity if they lack systems for collaborative problem-solving and knowledge sharing.

Ambiguity, the fourth element, involves situations with unclear causal relationships and multiple interpretations. It is particularly challenging because there is no historical precedent to guide decisions. As Laurin et al. (2018) note, navigating ambiguity requires flexibility, strategic foresight, and the willingness to act without full clarity.

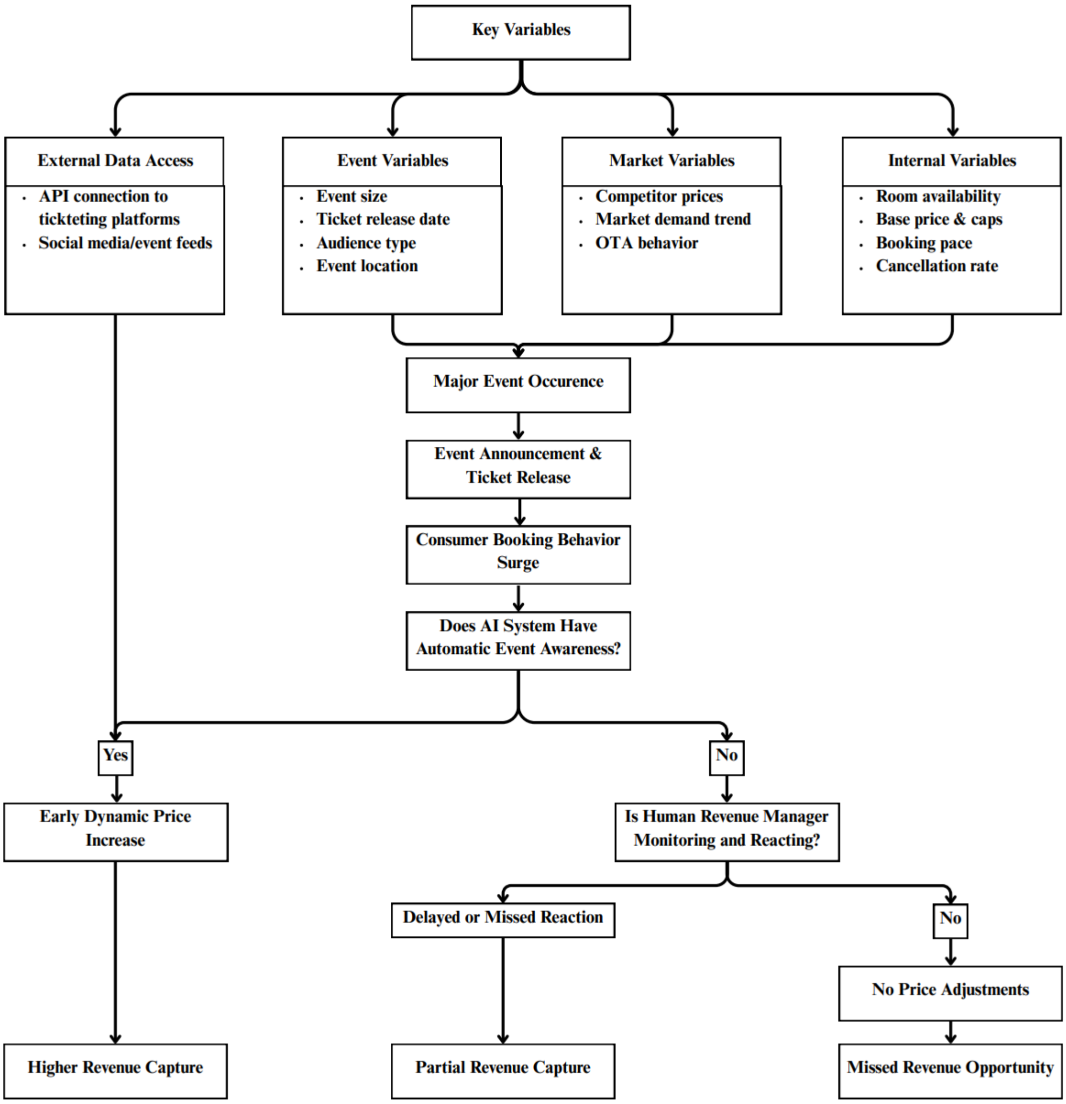
Laurin et al. (2018) and Bennet and Lemoine (2014), suggest that scenario planning, cross-functional collaboration, and fostering a shared understanding of potential disruptions can significantly enhance a company's ability to thrive under VUCA conditions. Leaders must embrace paradoxes, challenge assumptions, and empower their teams to act decisively in the face of uncertainty.

3. Conceptual Framework

This section presents the conceptual framework that underpins the thesis central proposition.

3.1 Purpose of the Framework

Figure 3.1 presents the conceptual framework, which serves to illustrate and apply the central argument of the thesis: an RMS with an AI-enabled pricing engine is more consistent and better at capturing the full revenue uplift from major demand shocks compared to an RMS without automatic event awareness. The framework visualises timing as the critical independent variable, contrasting the event-aware RMS (left side) with the non-event-aware RMS (right side). The revenue capture nodes represent the outcome, i.e., the dependent variable (“Higher, Partial or Missed Revenue Capture”).



3.2 Key Variables

The variables as defined as following:

- Event Variables define the type, scale, and timing of the event, which directly shape the expected booking surge.
- Market Variables capture competitive forces and market-wide demand patterns that influence pricing boundaries.
- Internal Variables reflect the hotel's current booking status and strategic pricing rules, such as rate caps or pacing targets.
- External Data Access refers to the technical ability to automatically integrate outside information into the pricing logic, which is a central theme of this thesis.

Collectively, these inputs form the information space in which any pricing decision taken must take account of, regardless if it's a human or AI.

3.3 Causal Mechanism

Firstly, an exogenous shock occurs: an event is announced or tickets are released, altering the booking pace almost instantly. From there, we arrive at the decision node: does the RMS recognize the event signal in advance? If yes, it results in an early dynamic price increase, where the AI raises rates while demand is still inelastic, effectively securing the price premium. If the RMS does not have any automatic event awareness, dependence on human monitoring becomes vital. If no reaction occurs, a missed revenue opportunity results, and if the reaction is delayed, it leads to a partial revenue capture. In the end, the three outcomes are: Higher, Partial, or Missed revenue capture.

3.4 The Importance of Timing

Under normal conditions, RM pricing assumes a gradual pickup based on supply and demand, which in turn is influenced by external factors such as travel reasons and purposes. There is a balance between selling the most rooms, at the highest prices, while keeping guest satisfaction high; this is Revenue Management. The RMS will therefore try to follow all instructions set by the Revenue Manager, while also considering historical data and booking patterns.

On the other hand, during major events, tickets are released, bookings surge, and inventory is rapidly depleted in just a few days. Without advance knowledge of the event, traditional RMS are too slow to react. External data access would enable the RMS to scan event calendars, ticketing site APIs, and social media to increase prices proactively, thereby addressing the current timing disadvantage associated with traditional RMS.

3.5 Alignment with the Research Question

The research question presented in Chapter 1, “How can the hotel industry maximize revenue during major events using AI-driven dynamic pricing strategies?” is addressed by the independent variable “Early Dynamic Price Increase.” The remaining two branches are manual in nature and illustrate how much revenue is lost when the reaction to demand is delayed.

4. Methodology

This section explains the research method used and the approach to answer the research question.

4.1 Research Design

This study uses a quantitative research approach to analyze the impact of major events on hotel booking and pricing trends. The research is based on numerical data collected from an anonymous hotel chain operating in Sweden. Given the structured nature of the data and the focus on identifying trends and relationships between booking behavior, pricing, and event occurrences, a quantitative approach is chosen as the most suitable.

Following prior research by Li et al. (2024), we will use an alternative approach in addition, by using generative AI, and in these four different models (GPT-4o, GPT-o3, Gemini Flash 2.0, Gemini Pro 2.5). Drawing inspiration from the article by Li et al. (2024), who successfully showed that large language models (LLMs) could replace human participants in market research by accurately capturing complex perceptions through targeted prompts, our study will explore a similar AI-driven approach but in a new context: hotel pricing strategies, and more specifically, during major events.

Following the methodological approach proposed by Li et al. (2024), who evaluated how LLMs perform in tasks requiring nuanced perception and contextual understanding, we adapted their prompt-based experimental design to test LLM behavior in hotel pricing contexts. Specifically, we mirrored their use of controlled, paired prompts to isolate the impact of a single variable, and in our case, event awareness, while holding all other factors constant. Like Li et al. (2024), we emphasized internal validity by keeping the structure and tone of each prompt nearly identical.

4.2 Selection of AI Models and Rationale

To evaluate the role of event awareness in AI-generated hotel pricing, we primarily used OpenAI's GPT-4o to analyze our hypotheses. However, to ensure the validity of our findings and to gain broader perspectives on generative AI performance, we also tested the same prompts using three additional models (Krugmann and Hartmann, 2024; Sonoda et al., 2024; Zou et al., 2025) available as of April 2025: Gemini Flash 2.0, GPT-o3, and Gemini Pro 2.5. These models were selected to allow for comparison between high-speed general-purpose

LLMs and those optimized for more complex reasoning tasks, thereby assessing how model capabilities influence the interpretation and application of event data in pricing strategies.

The selected models were categorized into two groups based on their design focus:

1) Lightweight Models: GPT-4o and Gemini Flash 2.0

These models are optimized for speed, accessibility, and multimodal functionality, making them representative of the type of tools that may be more easily adopted in commercial applications due to their cost-efficiency and responsiveness. However, they are also known to operate with more general logic and shallower reasoning structures, which may limit their ability to fully process complex, multi-layered prompts.

2) Advanced Reasoning Models: GPT-o3 and Gemini Pro 2.5

These models are designed for deep reasoning, tool integration, and advanced decision-making, making them more capable of handling nuanced prompts involving future event scenarios, hypothetical consumer behavior, and multi-variable optimization. Their use in this thesis allows us to test whether more sophisticated models produce meaningfully different pricing strategies compared to lighter alternatives.

The rationale behind this mixed selection is twofold. First, it allows us to compare how different classes of AI models interpret identical prompts under both event-informed and non-event conditions. Second, it provides insight into the practical trade-offs between speed and sophistication in generative AI applications for RM. For example, a lightweight model may offer quick outputs suitable for real-time pricing decisions, while a more advanced model might uncover deeper pricing opportunities at the cost of speed or computational resources.

The comparative performance of these four models, illustrated in Appendix 8.3: Overview of Graphs, adds an important layer of nuance to our conclusions. It not only demonstrates that event awareness significantly improves revenue capture potential, but also that model choice itself plays a material role in how effectively that awareness is translated into pricing logic. A detailed technical comparison of these models is available in Appendix 8.4: Technical Comparison of AI Models, while the full set of output graphs for both event and non-event scenarios is consolidated in Appendix 8.3.

4.3 Data Collection

This study is based on proprietary operational data provided by a leading Swedish mid-market hotel group. The data were extracted directly from the chain's internal RMS and include transaction-level details on booking behaviour, price formation, occupancy levels, and demand forecasts generated by the AI-enabled pricing system.

To isolate the impact of event-driven demand shocks, two occupancy dates were purposively selected:

1. 18 May 2024 (Event Date): coinciding with a large-scale city-wide event that generates peak demand.
2. 20 May 2023 (Non-Event Date): a comparable date with no major events, serving as a baseline for analysis.

For each date, we extracted four key variables at daily resolution:

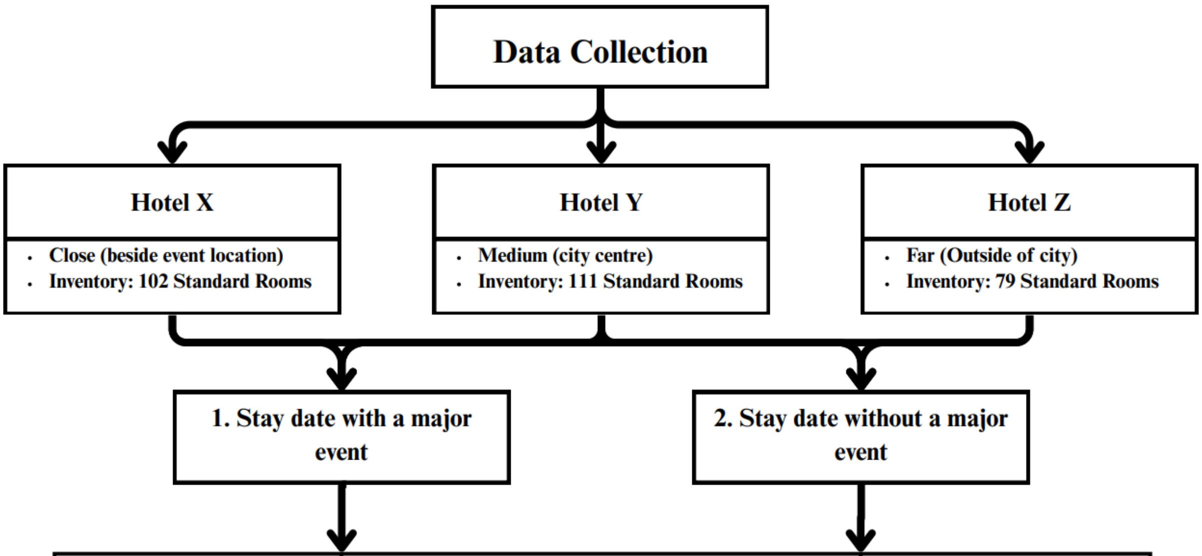
- Average Daily Rate (ADR) quoted at 00:00 on the day before arrival
- Public rate, representing the lowest publicly available rate after dynamic price optimisation
- Sold rooms, measuring the number of room-nights booked
- Forecasted occupancy, reflecting end-of-day demand forecasts by the chain's AI-driven RMS

The dataset covers three hotels within the same chain:

- Hotel X, located within walking distance of the event venue
- Hotel Y, situated in the city center near T-Centralen
- Hotel Z, positioned outside the city in a suburban area

To ensure comparability, only standard-category rooms were included across all properties. The hotel names and geographic coordinates have been anonymized in accordance with a confidentiality agreement signed with the data provider.

An overview of the data structure, hotel segmentation, selected stay dates, and variables is provided in Figure 3.1 below. The resulting dataset comprises 2,928 observations (366 days × 4 variables × 2 dates), forming a balanced panel that captures both routine and event-induced pricing dynamics across different geographic contexts.



Variable	Description	Unit
ADR	Average Daily Rate quoted at 00:00 on the day before arrival	SEK
Public rate	Lowest publicly available room rate after dynamic price optimisation	SEK
Sold rooms	Total number of room-nights booked	Rooms
Forecasted occupancy	End-of-day occupancy forecast generated by the chain's AI-enabled RMS	Rooms

Figure 4.1: Overview of Data Collection Structure, Stay Dates, and Variables

4.4 Structure of Analysis

Our thesis investigates whether an AI model that utilizes external data sources can more effectively predict hotel room pricing compared to a model that does not. If this proves true, it would suggest that hotel chains should enhance their AI systems by integrating external datasets, such as information from event organizers, to better anticipate demand surges linked to events.

Li et al. (2024) demonstrated that large language models (LLMs) can effectively replicate human responses in market research by accurately capturing consumer perceptions through carefully designed prompts. Their approach showed significant potential for improving efficiency and reducing costs in market research. Drawing inspiration from Li et al. (2024), this study explores a similar AI-driven approach but in a new context: hotel pricing strategies.

Currently, hotels already use AI systems to decide room rates dynamically, but these systems have a major limitation. They lack direct access to external information about future events (such as large concerts, festivals, or conferences) that significantly influence room demand. This is problematic, since such events cause heavy price fluctuations that current AI models cannot predict. This limitation arises because existing pricing algorithms rely solely on human input, historical data and internal booking patterns, entirely missing critical information available externally.

Given the success of Li et al. (2024) in accurately predicting complex human perceptions through advanced prompt engineering of LLMs, we find it interesting to test whether similar methods could enable hotels to proactively adjust prices for major events. Specifically, by carefully engineering prompts that incorporate event details, including timing, location, anticipated demographics, and scale, hotels could leverage LLM-generated forecasts to set more precise, future-oriented pricing strategies.

Investigating this possibility is important, because if proven effective, hotels would have a strong incentive to establish Application Programming Interfaces (APIs) directly connecting their AI pricing systems to organizations that manage or sell tickets for major events. Such integrations would significantly enhance their ability to anticipate demand and pricing fluctuations, set competitive rates, and maximize revenue opportunities in ways that are currently not possible.

To examine this, together with the collected data, we generated two AI prompts: one where the model has full knowledge of the event, and one where it is instructed to disregard it. We then compare the approaches (the two prompts from each LLM, and the hotel's own AI system) to find differences and eventual possibilities.

4.5 Prompt Design

To test the impact of external event data on AI-generated pricing, we created two distinct prompts:

1. Event Prompt
2. Non-Event Prompt

The Event Prompt simulates a scenario in which the AI has access to event information one year in advance, as if provided directly by the event organizer. This includes:

- The event name (Taylor Swift - Eras Tour)

- The event date (May 18, 2024)
- Ticket announcement and release dates
- Audience demographics (Millennials, Baby Boomers, Gen X)
- Geographic demand (national vs. international)
- Event classification (e.g., superstar)
- Competitor behavior assumptions
- Hotel location and baseline pricing one year prior to stay date

The Non-Event Prompt simulates a scenario where the AI has no knowledge of the event. The AI is instructed to disregard Event-related details, and the model is asked to create a pricing strategy as if it were a regular night.

To isolate the effect of event awareness on AI-generated pricing behavior, both the Event and Non-Event Prompts were constructed to be structurally and linguistically identical, ensuring that any variation in output could be attributed solely to the presence or absence of an event.

During initial testing, however, the AI occasionally inferred event-related logic despite the instruction to disregard such details. To enforce consistent non-event behavior, a secondary prompt was introduced after the Non-Event Prompt, stating, "Did you not read the first sentence?" This addition, along with the instruction to disregard event details, served as the only point of variation between the two versions. By minimizing discrepancies in the prompts, we maximized internal validity and created a controlled environment in which differences in pricing strategies could be confidently attributed to event awareness alone.

To ensure the robustness of our experiment, each prompt was executed repeatedly until the outputs stabilized. Once consistency was confirmed, we applied both the Event and Non-Event prompts to every hotel in the study. In one Non-Event run for Hotel X, however, Gemini Flash 2.0 unexpectedly raised prices immediately after the (supposedly absent) event-announcement date. We retained this outlying result for transparency, as it illustrates the model's occasional tendency to "hallucinate" event-driven logic despite explicit instructions to ignore such information.

The full text of both prompts, as well as the hotel-specific input parameters used for each scenario, are provided in Appendix 8.1: Full Prompts and Appendix 8.2: Hotel-Specific Prompt Parameters for reference.

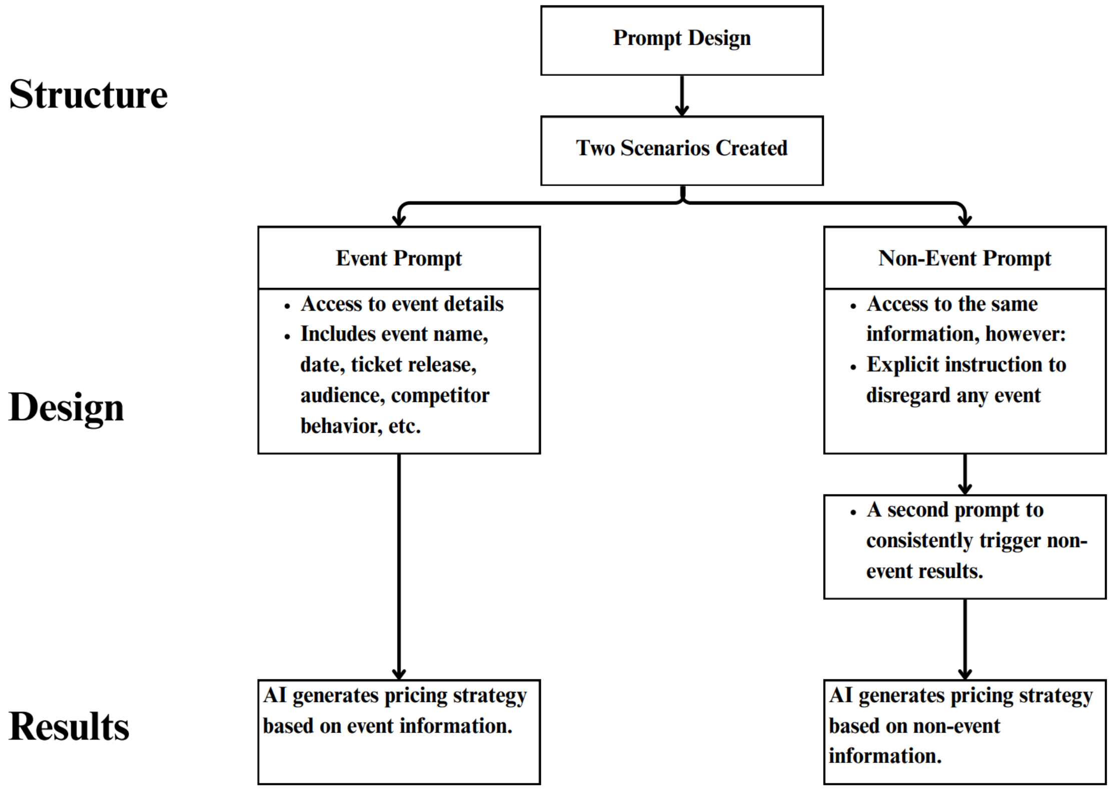


Figure 4.2: Overview of Prompt Structure for Event and Non-Event Scenarios

4.6 Generative AI Disclosure

In this thesis, generative AI tools, primarily OpenAI's ChatGPT, were used to improve the clarity and fluency of the written language, as well as to obtain comparative insights & results, as described earlier (Kasneci et al., 2023). This method was recommended by Professor Lily Gao, and supported by relevant literature (Li et al., 2024; Kasneci et al., 2023) (see methodology 4.1). The use of AI contributed to a more precise and professional presentation of our findings, as well as helping us reflect by generating alternative viewpoints to compare with collected data and our own conclusions.

Potential risks included over-reliance on AI-generated content, the introduction of inaccuracies, and the risk of unintentional plagiarism. To mitigate these risks, all AI-generated outputs were critically reviewed, cross-checked against academic sources, and edited to align with the project's goals and original voice.

Through this process, we gained valuable insights into how AI can serve as a supportive tool in academic work, enhancing productivity, encouraging critical reflection, and improving linguistic quality, while highlighting the importance of maintaining academic integrity and human oversight throughout.

5. Findings

This section presents the key findings of our research, focusing on the limitations and performance of an AI-driven RMS in handling primarily high-demand scenarios. A crucial discovery is the system's lack of automated integration with external data sources related to major events that can drastically influence demand, such as concerts. By analyzing actual booking data and comparing it with AI-generated pricing simulations, we demonstrate how the absence of real-time event awareness led to early sell-outs at suboptimal rates. These findings point to a significant gap in current RM practices and pave the way for future improvements in system proactiveness and data integration.

5.1 Lack of External Data

A key finding in our research is the insufficient integration of external data in the AI-driven RMS. While the system makes pricing decisions based on predefined inputs, historical data, and, to a limited extent, external factors, it lacks an automated mechanism for detecting and responding to newly announced external major events. This limitation becomes particularly significant in scenarios where large-scale events impact demand and pricing, such as popular concerts.

Currently, the system does not autonomously recognize new event announcements. Instead, a Revenue Manager must manually input relevant event data, such as a concert from a high-profile artist like Taylor Swift, and then authorize the system to adjust prices to new relevant price spans. This manual intervention introduces a lag in market response, reducing the system's and the company's ability to capitalize on sudden demand surges.

AI-based RM systems typically operate within a predefined price range set by the RM organization. When extraordinary events occur, the system requires explicit authorization from the Revenue Manager to override these constraints. Our analysis of the data indicates that due to this operational inflexibility, price adjustments might fail to materialize before available inventory is sold out. As a result, the system's delayed response leads to missed revenue optimization opportunities, highlighting a critical inefficiency in the current AI-driven system and pricing framework.

This major finding will be further discussed and analyzed in the upcoming section, especially for future research and managerial implications.

5.2 Empirical Results from the Hotel's AI Pricing System

The hotel data analyzed concerns the stay date of May 18, 2024, one of the dates during which Taylor Swift held a concert at Strawberry Arena in Solna, Stockholm. The dataset includes key performance indicators such as the public selling price, the Average Room Rate (ARR) of all sold room nights, the number of room nights sold, and the forecasted room nights. These KPIs are presented by booking date, covering a period of 365 days prior to the actual stay date. This allows for a detailed analysis of booking behavior over time, including when reservations were made and at what price.

For comparative purposes, data from the Same Time Last Year (STLY) is also included, seen in Appendix 8.3: Non-Event Data (Figure 8.17), reflecting a similar stay date in the previous year that did not coincide with a major event. This provides a baseline for evaluating typical booking and pricing patterns in the absence of exceptional demand drivers, in this case major events.

One of the most interesting observations from the data is that a significant portion of the room inventory for the event date was sold out on the same day that concert tickets were released. Notably, these bookings were made at considerably lower rates than the public selling prices available just days later. These early bookings were made at prices far below what could have been achieved with more dynamic pricing strategies.

This phenomenon can be attributed to a delay in the RMS response to the event. The system is not inherently aware of major external events unless manually informed by a human (Revenue Manager) with a new input to the system. In this case, consumers were able to secure bookings before the Revenue Manager had the opportunity to adjust pricing parameters in the system. Had the RMS been equipped with real-time access to this external event data, it could have responded more proactively, and in turn, adjusting prices accordingly and potentially driving significantly higher revenue.

The actual selling prices for the hotel rooms were not adjusted in a timely manner. Focusing on the hotel located near the major event, the ARR ended up at 2082 SEK as a result. However, the public selling price on the final day before the event had reached 4510 SEK. On July 11, 2023, the day when tickets for the event were released, the public selling price was 1750 SEK. By the following day, after all rooms had already been sold out, the price had increased to 2650 SEK, followed by further rate escalations. However, these adjustments came too late to impact revenue. This pattern was consistent across all hotels, caused by delayed system reactions that led to missed revenue opportunities. This system works well in “normal conditions”, when there is no major event, because this is what the system is used to handle, and has knowledge and history about, seen in the more plain curve for STLY, seen in Appendix 8.3: Non-Event Data (Figure 8.17).

During this period, nearly all hotels in Stockholm were sold out, and the city recorded record-breaking revenues in connection with the Taylor Swift concert. Because the hotel sold out rooms too early and at prices below market potential, the final ARR was limited to 2082 SEK. This figure could likely have been significantly higher if relevant external data, such as ticket release information, had been integrated into the RMS at the time of release.

5.3 Prompt Results

While this section focuses specifically on GPT-4o to illustrate event and non-event driven pricing behavior across all hotels, we defer detailed discussion of other AI model outputs to Section 5.4, where we compare all models' responses for Hotel X to provide a broader perspective.

5.3.1 Event Prompt Results (GPT-4o)

GPT-4o was prompted with full knowledge of a major Taylor Swift concert taking place on May 18, 2024. For Hotel X (closest to the event venue), Hotel Y (city center location), and Hotel Z (located outside the city), the model generated daily room rates starting 365 days out (May 18, 2023) through the event date (May 18, 2024). The data reveal the following overall trends, seen in Appendix: 8.3.1 Event Data.

For roughly the first month, all three hotels maintained relatively stable or only slightly increasing prices. During this period, Hotel X remained in the 1520 SEK range, Hotel Y at about 3992 SEK, and Hotel Z near 990–1000 SEK.

The day of the concert announcement triggered a noticeable jump in prices.

- Hotel X: Increased from 1520 SEK to roughly 1976 SEK.
- Hotel Y: Moved from 3992 SEK to around 4878 SEK.
- Hotel Z: Rose from about 1007 SEK to the low 1300s.

The AI logic suggests that even the public awareness of a “superstar event” justifies a more assertive pricing stance, as demand for prime booking windows may begin to build post-announcement.

The most substantial overnight jump occurred on the exact ticket release date.

- Hotel X: Jumped from 1976 SEK to 3040 SEK.
- Hotel Y: Spiked significantly from 4878 SEK to 7540 SEK.
- Hotel Z: Doubled from 1329 SEK to over 2691 SEK.

From that point onward, prices continued to escalate steadily each day for Hotel Z, and in chunks for Hotel X and Y, reflecting the model’s assumption of a fast booking wave once tickets were available for purchase.

Between August 2023 and April 2024, all three hotels’ rates show incremental climbs, reflecting sustained anticipation of high demand. Hotel X’s daily rate rose into the 4000+ SEK range, while Hotel Y’s rates increased most aggressively, breaking 13,000 SEK in May 2024. Hotel Z’s prices also approached nearly 5000 SEK by the final weeks.

5.3.2 Non-Event Prompt Results (GPT-4o)

In this scenario, GPT-4o was explicitly instructed to disregard any details related to a major event, treating May 18, 2024, as a standard stay date. Consequently, the model’s pricing recommendations remained relatively stable and followed a gradual upward trend over the 365-day period, without any dramatic spikes or sudden adjustments tied to ticket announcement or release dates, seen in Appendix: 8.3.2 Event Data.

- Hotel X started at around 1174 SEK and increased only slightly each day.
- Hotel Y remained close to 1775 SEK, with minimal early fluctuations.
- Hotel Z consistently hovered near 890 to 900 SEK.

Unlike the Event Prompt scenario, there were no abrupt jumps around June 20 or July 11. The model consistently incremented the rates in line with typical, non-event seasonality patterns, reflecting a normal day’s pricing logic.

Over the summer and into autumn, all three hotels’ rates slowly inched upward, mirroring modest demand projections. By the end of the year, Hotel X progressed to the mid-1300 SEK range, Hotel Y hovered near 1900 SEK, and Hotel Z rose to around 1100-1200 SEK. These modest rate increases align with standard RM practices that nudge prices upward as the booking date nears, yet do not factor in any event-driven demand surges.

In the final weeks before May 18, 2024, Hotel X reached a maximum recommended rate of around 1645 SEK, Hotel Y peaked at roughly 2366 SEK, and Hotel Z topped out near 1480 SEK. Importantly, the model did not display any extraordinary or last-minute surges, reinforcing that it was never "informed" of a major event and therefore had no reason to foresee a booking rush.

5.4 Hotel AI vs. GPT-4o: Event and Non-Event Pricing Comparison

The hotel RMS system, not being connected with external data, could as such not anticipate the event announcement, ticket sales and event date. Bookings surged immediately after July 11, 2023 (ticket release date), but room rates remained low until RM intervened manually. As a result, rooms sold out too early and ARR ended at 2082 SEK, substantially below the final posted public price (4510 SEK). Large chunks of inventory were thus sold at lower rates than the market would have supported once the concert demand became evident.

On the other hand, for a typical stay date without a major demand shock like a major event, the hotel's AI generally performs as intended, gradually adjusting prices over time based on historical patterns and observed bookings. As such, when there is no sudden external trigger like a high-profile concert, the system's reliance on internal data alone is sufficient to match "normal" fluctuations in demand. This was evident in the Non-Event data gathered from the hotels, where no significant event occurred, and the AI's pricing strategy aligned with standard seasonal trends, leaving little room for major mispricing

If we compare GPT-4o's "Event Prompt" to the hotels actual event outcome, we see that GPT-4o (Event Prompt) proactively raised rates as soon as the concert announcement and ticket sales dates arrived (June 20 and July 11, 2023, respectively). Rates for Hotel X jumped from around 1520 SEK to 3040 SEK overnight on the ticket release date, with even steeper climbs for Hotel Y. Had the hotel applied this event-informed approach, it would have captured higher revenue on the early bookings that actually sold out at low rates. By contrast, the hotel's actual AI sold the rooms to its maximum price span (set by RM), until RM increased the price span so the system could work more freely and broadly, which was too late. This reactive stance drove the final ARR down to 2082 SEK, demonstrating the revenue gap caused by missing timely event data.

Moving on, in the Non-Event Prompt, GPT-4o's rates rose gradually and stayed modest. Final prices ended up around 1645 SEK for Hotel X, ~2366 SEK for Hotel Y, and ~1480 SEK for Hotel Z. This trajectory is comparable to a typical night (no large spikes, only incremental increases). It aligns well with how the hotel's AI normally behaves when no event is anticipated. Crucially, neither GPT-4o nor the hotel's AI sees a reason for sudden jumps if they are unaware of an external demand catalyst. Both models essentially rest on stable or seasonally adjusted trends, highlighting the importance of accurate, timely event data to trigger more aggressive pricing.

In essence, when GPT-4o is informed about a major demand driver like a Taylor Swift concert, it aligns its rates to that high-demand reality, producing significant early rate hikes that better capture heightened willingness to pay. The hotel's AI, by contrast, cannot do this automatically, leading to underpriced and prematurely sold-out rooms. Furthermore, the hotel's real-world example shows how dependence on a revenue manager's input causes a time lag. Rooms get booked at below-optimal prices between the ticket release date and the AI's eventual price update. Without a surge in demand, both GPT-4o's Non-Event Prompt and the hotel's AI produce similar, gradually ascending curves, indicating that standard dynamic pricing handles routine occupancy patterns reasonably well.

Overall, these findings underscore the value of automated external data integration. If the hotel's AI could detect events immediately (e.g., via direct feeds from ticketing platforms) and dynamically elevate pricing to match real-time demand surges, it would bridge the significant revenue gap observed in the actual event scenario.

- Hotel X Comparison (Event)

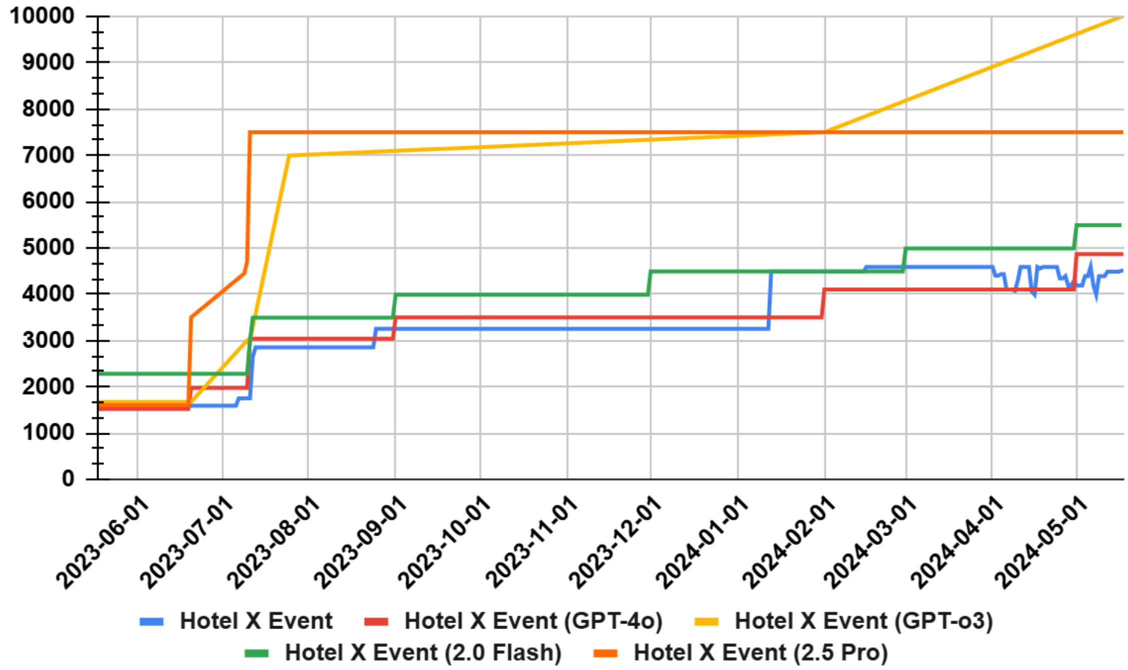


Figure 9.6: Hotel X Model Comparison (Event Data, Full Period)

- Hotel X Comparison (Non-Event)

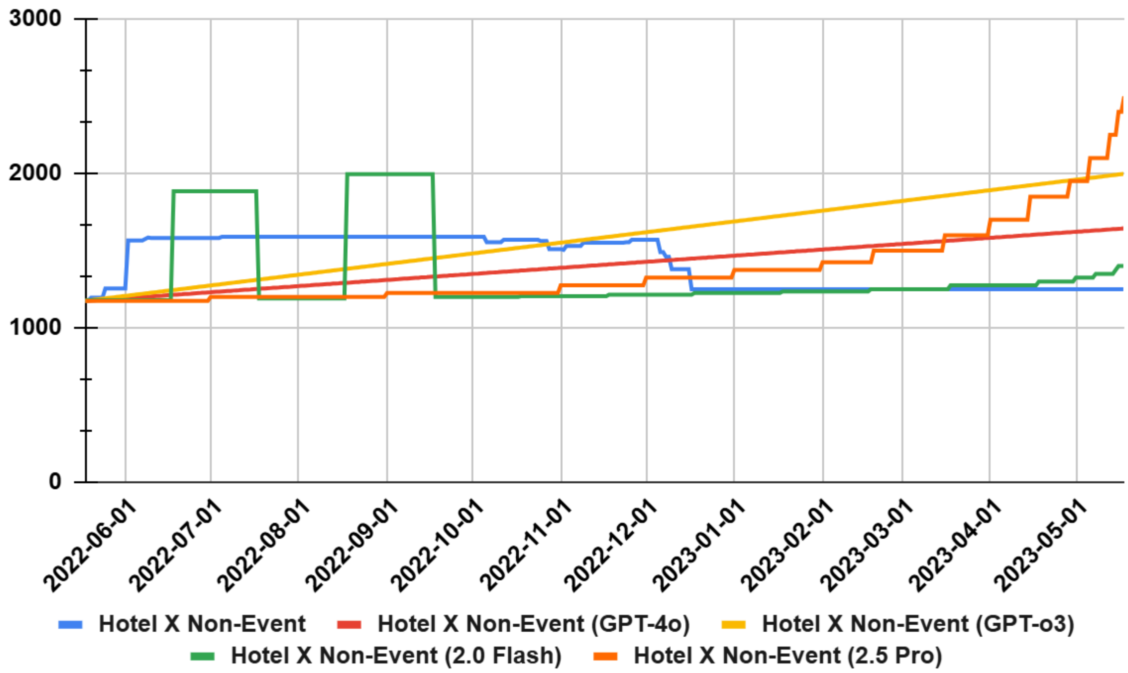


Figure 9.22: Hotel X Model Comparison (Non-Event Data, Full Period)

5.5 Hotel X, AI Model Pricing Strategies (Event Scenario)

The following section compares the pricing strategies generated by the four AI models (GPT-4o, GPT-o3, Gemini Flash 2.0, and Gemini Pro 2.5) for Hotel X when prompted with full awareness of the Taylor Swift Eras Tour event, see Appendix: 8.2.1 Hotel-Specific Prompt Parameters (Event) (Figure 8.6 & 8.13).

GPT-4o applied a structured, phased pricing strategy aligned with key demand signals. Prices remained at a baseline of 1520 SEK until the event announcement on June 20, 2023, after which they rose to 1976 SEK. A second major increase occurred on the ticket release date (July 11, 2023), reaching 3040 SEK. The model then escalated prices incrementally through early 2024, culminating in a final rate of 4864 SEK in the last weeks before the event. The strategy emphasized an early-mover advantage post-announcement and ticket release, but maintained steady price increases throughout the year.

Gemini Flash 2.0 adopted a more aggressive early-pricing approach. It set the starting rate at 2280 SEK immediately after the event announcement period began, then increased the price to 2990 SEK on the ticket release date. Post-ticket release, the model quickly raised prices to 3490 SEK, followed by incremental increases to 3990 SEK (September-November 2023), 4490 SEK (December-February), 4990 SEK (March-April), and a final rate of 5490 SEK in the two weeks before the concert. The model anticipated full sell-out by May 18, 2024, and closed availability entirely on that date.

GPT-o3 implemented the most aggressive spike in pricing during the ticket-sale window. Starting with a modest pre-announcement rate of 1672 SEK, it introduced a daily ramp to 3000 SEK after the June 20 announcement. On the ticket release date, pricing surged rapidly from 3000 SEK to 7000 SEK within a two-week window. During the post-surge phase (August 2023 to January 2024), the model maintained rates between 7000-7500 SEK, inching upward 1% monthly. A final climb to 10,000 SEK began in February 2024, reaching its peak on May 18. GPT-o3's strategy was explicitly designed to capture revenue early through dynamic price escalation, even if it would lead to an early sell-out.

Gemini Pro 2.5 followed a highly dynamic and velocity-sensitive pricing strategy. Prices began at 1600 SEK prior to the announcement, then jumped to 3500 SEK on June 20, 2023. A daily incremental increase of 30-50 SEK brought the rate to approximately 4700 SEK by July 10. On the ticket release date, the model immediately implemented a peak price of 7500

SEK. Depending on booking velocity, the model recommended real-time price adjustments, allowing prices to rise to 8500 or even 9500 SEK in response to rapid sell-out rates. If sell-out did not occur by September 2023, Gemini Pro 2.5 maintained high pricing into the lead-up to the event.

Across all four models, the Taylor Swift concert was consistently classified as a “Superstar Event,” triggering pricing strategies that incorporated significant jumps around key dates. GPT-4o and Gemini Flash 2.0 followed more gradual, structured increases, while GPT-o3 and Gemini Pro 2.5 pursued steep, dynamic escalations designed to capture peak willingness to pay within short timeframes. While all models anticipated sell-out before the event, only GPT-o3 and Gemini Pro 2.5 explicitly modeled pricing strategies that optimized for early sell-out at maximum revenue, rather than balancing gradual rate growth with inventory pacing.

These AI-generated strategies, while varied in their pricing aggressiveness and timing, were further subjected to professional scrutiny. The following section presents the results of expert validation to assess the plausibility of each model’s predictions from a RM standpoint.

5.6 Expert Validation

To ensure the quality and relevance of the model outputs, a validation process was conducted with the involvement of two independent experts in Revenue Management. These professionals brought extensive industry experience and were tasked with evaluating whether each model’s predictions were plausible within the operational and strategic context of RM.

Each expert independently reviewed a subset of anonymized model predictions, without being informed of which model had generated them. This blind evaluation was designed to eliminate potential biases and focus purely on the substance of the output.

The experts assessed each prediction using a binary plausibility scoring system:

- Score of 1 (Plausible): The prediction was judged to be credible, aligned with RM principles, and potentially actionable in a real-world revenue optimization scenario.
- Score of 0 (Implausible): The prediction was found to be unrealistic, irrelevant, internally inconsistent, or misaligned with standard RM practices.

Following the independent scoring, the results were consolidated to form a professional validation benchmark, offering insights into each model’s practical reliability.

LLM	Expert Prediction Score
GPT-4o	1
GPT-o3	0
2.0 Flash	1
2.5 Pro	0

6. Discussion

This discussion highlights the critical role of integrating external event data into AI-driven RMS to maximize hotel revenues during major events. The analysis revealed that the lack of automated external data feeds results in reactive pricing strategies, causing missed revenue opportunities. Building on the findings, the discussion proposes the development of an Event Forecasting Platform to bridge this gap, enabling proactive, real-time price adjustments. By comparing actual hotel outcomes with AI-prompted simulations, the study demonstrates the substantial revenue gap caused by delayed responses to external demand surges. Furthermore, it emphasizes that future dynamic pricing strategies should not solely rely on AI automation but also require human expertise and strategic data collaborations across industry actors. Overall, embracing proactive data integration is presented as a strategic necessity for optimizing pricing performance in volatile and uncertain environments.

6.1 Integration of External Data

A key insight from this study is the critical need for real-time integration of external data, such as major event announcements, into AI-driven RMS. As highlighted in section 5.1, the current systems rely heavily on internal datasets and historical patterns, which renders them reactive rather than proactive. Without automated access to external signals, like ticket releases or public event calendars, AI systems struggle to anticipate spikes in demand, resulting in suboptimal pricing and lost revenue opportunities.

This limitation was confirmed by the empirical findings in section 5.2. Despite the presence of an AI-based RMS, the hotel failed to adjust prices in time when Taylor Swift concert tickets were released. The system sold out rooms shortly after ticket release, at prices far below the potential maximum. Although the final public selling price reached over 4500 SEK per room, the ARR stagnated at just 2082 SEK. This reflects a substantial revenue gap, attributable to delayed pricing adjustments caused by the lack of external data integration.

From a theoretical standpoint, this inefficiency contradicts the potential of AI discussed in section 2.1. AI is expected to outperform traditional methods by processing large, diverse data sets and identifying complex patterns (Zhang and Lu, 2021; Rekiek et al., 2024). Yet, as the current system lacks an API or data pipeline to ingest event-related data, it falls short in the potential of maximizing revenue during major events. Section 2.4 emphasized that major events significantly drive hotel demand, an insight supported by the Taylor Swift case, which led to a 98% increase in RevPAR (Region Stockholm, 2024). However, without programmatic access to such external variables, the system operates in a siloed environment and misses these surges.

Furthermore, this issue aligns with the VUCA framework (section 2.5), particularly the dimensions of volatility and uncertainty (Bennet and Lemoine, 2014; Laurin et al., 2018). In volatile environments, like cities hosting major events, static systems that require human input are simply too slow. Uncertainty increases when systems lack situational awareness, which could be reduced through structured data flows from external event organizers. These findings support the argument for developing direct integrations (e.g., APIs) between RMS platforms and ticketing or event platforms, enabling automated price adaptations the moment new events are announced.

In conclusion, the lack of integration between RMS systems and external data sources represents a significant bottleneck in fully realizing the value of AI in dynamic pricing. Addressing this gap would allow AI systems to behave more like predictive engines rather than reactive calculators. As an added incentive, such integrations could even evolve into business partnerships, where hotels get early event signals in exchange for data-sharing agreements or revenue-based commissions. Ultimately, enhancing AI with external awareness is not just a technical upgrade, it is a strategic necessity for maximizing profitability during major events.

6.2 Event Forecasting Platform

A potential solution to bridge the disconnect between RMS and external data sources is the development of an Event Forecasting Platform.

This platform would act as an API-based plug-in, allowing hotels to gain advanced insights into regional events that could impact future demand. Instead of relying purely on traditional forecasting tools (e.g. seasonal trends, competitor pricing, or historical occupancy), the platform aggregates real-time information from sources like ticketing platforms, event organizers, convention centers, and social media channels.

Once connected to the hotel's RMS, the system would continuously monitor and update key event data, including announcement dates, ticket sale releases, estimated attendance, and relevant demographic details. With this data flowing directly into the hotel's AI-powered pricing algorithms, room rates can be automatically adjusted well ahead of demand spikes.

Through partnerships with key players in the event industry, the platform identifies upcoming events, estimates ticket sales using machine learning and expert input, and transmits this intelligence directly into the hotel's RMS. This proactive, data-driven approach helps hotels move beyond static or delayed pricing strategies, addressing a critical gap in current RMS capabilities that often lack forward-looking event data and depend heavily on manual input.

By integrating dynamic event forecasting, hotels can shift from reactive to anticipatory pricing, unlocking more precise revenue opportunities and staying ahead of demand surges before they materialize.

The Event Forecasting Platform could be initiated by a tech-focused startup, a hospitality technology provider, or even a strategic consortium involving RMS vendors, event data aggregators, and hospitality groups. A startup with expertise in data engineering, machine learning, and API development could move quickly to build a scalable solution, particularly if partnered with ticketing platforms or social media analytics firms.

Alternatively, existing RMS providers are well positioned to lead this initiative, given their direct integration with hotel systems and understanding of pricing logic. A collaborative approach could also work, where event organizers, destination marketing organizations, and hotel chains co-develop the platform to ensure data access, technical robustness, and industry adoption from day one.

6.3 Possible Outcomes vs Actual Results

The comparison between the actual revenue outcomes of the hotel's AI system and the simulated results generated by GPT-4o underscores the critical impact of external data integration in revenue optimization. As shown in section 5.4, the hotel's RMS, which lacked real-time awareness of the Taylor Swift concert and ticket release dates, responded too late to the sudden demand spike. This delay caused rooms to sell out at prices far below the market's willingness to pay. The final ARR stagnated at 2082 SEK, while public selling prices soared to over 4500 SEK in the final days. In contrast, GPT-4o, when prompted with full knowledge of the event (including announcement and ticket release dates), predicted sharp and timely price increases raising rates from 1520 SEK to over 3000 SEK overnight after ticket release, with further rises leading up to the event. While this suggests a clear opportunity to capture significantly higher revenue through early, event-informed pricing, it is important to acknowledge the limitations of the GPT-4o forecast. The model was given retrospective event data, meaning it was influenced by information already known to have had a market impact, which may have biased its projections. Nonetheless, the exercise illustrates the theoretical potential of VUCA-responsive AI systems (section 2.5), capable of acting dynamically in volatile and uncertain conditions, rather than relying solely on historical booking trends. Furthermore, from a RM perspective (section 2.2), the failure to anticipate and react to the event exemplifies the constraints of internal-data-only systems in highly perishable inventory markets. While GPT-4o's simulated forecast cannot be taken as a definitive alternative outcome, it highlights the substantial revenue gap that arises when AI systems are siloed from critical external inputs, reinforcing the strategic value of real-time event data integration in future RMS designs.

6.4 Managerial Implications

A managerial implication is the evolving balance between AI-driven automation and human expertise in RM, particularly when it comes to sharing confidential information across organizational and industry boundaries. While AI can process datasets and react faster than any human, its full potential is only realized when it's fed with real-time, context-specific information, often held by humans or external collaborators. In practice, this requires a shift in mindset where event organizers, hotel managers, and AI vendors collaborate more openly, potentially sharing sensitive data like ticket release dates or artist schedules under strict confidentiality agreements. However, this introduces challenges related to data privacy, trust, and competitive advantage. Revenue Managers thus play a critical role, not just as overseers of pricing algorithms, but as strategic connectors who bridge AI capabilities with high-quality, external human intelligence. The future of dynamic pricing lies not in replacing humans, but in enhancing their decision-making power through intelligent systems that can act on shared, timely, and reliable information.

6.5 Theoretical contribution

This study contributes to the theory of revenue management by introducing the concept of event-aware dynamic pricing, a capability made possible by integrating large-scale external data directly into AI-powered pricing systems. Our framework highlights that detecting external events in real time is not just helpful, but essential for reacting to sudden changes in demand. If there's a delay between an event (like a major concert or sports match) and the system's pricing response, potential revenue is lost. Importantly, we show how large language models (LLMs) can play a key role by making sense of unstructured information, such as news or social media, that traditional systems can’t easily process. This shifts the focus of revenue management from reacting to change, to anticipating it. Our framework lays the groundwork for future research on how different combinations of data speed, event impact, and model intelligence influence revenue in industries where capacity is limited and timing is critical.

7. Conclusion

7.1 Summary

This thesis set out to explore how the hotel industry can maximize revenue during major events through the use of AI-driven dynamic pricing strategies. To investigate this, we collected and analyzed real-world booking and pricing data from a major Swedish hotel chain, focusing on two comparative stay dates: one coinciding with a major event (Taylor Swift’s concert) and one during a typical, non-event period. In parallel, we utilized generative AI to simulate pricing strategies under two distinct scenarios: one where the AI had full knowledge of the event and one where it was instructed to disregard it.

The comparison between the actual hotel data and the AI-prompted results revealed critical insights. The main finding was that current AI-driven RMS, which lack automated integration with external event data, are reactive rather than proactive. As a result, hotels missed significant revenue opportunities during the event. Rooms were sold out early at suboptimal prices because the RMS did not automatically recognize and respond to the sudden demand surge triggered by the concert's ticket release.

Our findings strongly indicate that integrating external event data through real-time APIs into hotel RMS systems is not just beneficial but essential. By having access to event-related information such as ticket sale dates and audience demographics, AI systems could dynamically adjust prices ahead of surges in demand, ultimately maximizing revenue potential.

This conclusion is strongly backed by existing academic literature. Research by Rekiek et al. (2024) and Millauer & Vellekoop (2019) emphasizes the transformative role of AI in demand forecasting and revenue optimization, while works like Alananzeh (2022) and Stockholm Business Region (2024) highlight the significant economic impact of major events on hotel performance.

This thesis contributes to both theory and practice by demonstrating that connecting AI-driven RMS to external event data can substantially increase hotel revenue. It also suggests how hospitality firms can modernize their dynamic pricing strategies to meet the demands of today's VUCA (Volatile, Uncertain, Complex, and Ambiguous) business environment.

7.2 Future Research & Limitations

While this study offers valuable insights, it also has several limitations that future research should address.

Firstly, the depth of our data analysis was constrained by the scope of the dataset, which was limited to one hotel chain operating in a single country (Sweden). Future research could benefit from broader and more diverse datasets, covering multiple hotel chains across different geographic regions, to test the generalizability of the findings in varied market conditions.

Secondly, while our study focused specifically on major events, other influential factors such as seasonality, competitor pricing reactions, customer loyalty behaviors, and broader macroeconomic variables were outside the scope.

We also only examined one major event, featuring a global superstar, Taylor Swift. This presents an important limitation: it remains unclear how pricing strategies generated by generative AI would respond to smaller-scale events. What happens, for example, when a less prominent artist visits Sweden? Does AI still recommend increased pricing even though demand may not justify it? Investigating whether AI models overestimate demand sensitivity in lower-profile contexts is essential to avoid unnecessary price inflation and potential customer dissatisfaction.

Additionally, the use of AI prompts to simulate pricing strategies is an emerging method with its own limitations. The LLMs used retrospective event information, which may have introduced bias into the simulation outcomes. Future research could explore more robust, real-time AI forecasting methods, or even integrate actual live event feeds into experimental designs to enhance validity.

Future research could extend our work by statistically modeling the relationship between event prompt inputs and AI-generated pricing outputs using regression or time-series analysis. While our approach mirrors the perceptual prompt-pairing method of Li et al. (2024), incorporating inferential statistics, such as ANOVA to detect inter-model variation, could offer more robust validation of AI sensitivity to external signals. Additionally, expanding the range of events and integrating randomized control prompts could transform our design into a formal experimental framework suitable for statistical hypothesis testing.

Overall, deeper and broader investigations into AI-enhanced RM, particularly regarding the integration of real-time external data, will be crucial for fully realizing the potential of dynamic pricing in the hotel industry.

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9. Appendix

9.1 Full Prompts

9.1.1 Event Prompt

The Event Prompt simulates an AI model with access to detailed event information. The full prompt is as follows:

You are asked to create an optimal pricing strategy for hotel rooms for an event night.

Event Details

- Event: Taylor Swift - Eras Tour
- Event Date: May 18, 2024
- Venue: Friends Arena, Solna, Stockholm
- Audience: Millennials, Baby Boomers, and Gen X
- Inventory: X standard rooms (depends on hotel X,Y,Z)

Additional Information

- The event was announced on June 20, 2023.
- Ticket sales open on July 11, 2023.
- Starting occupancy is zero on May 18, 2023.
- Competitors will not know about the event until the public announcement but may react dynamically afterward.
- A standard room usually costs SEK X (depends on hotel X,Y,Z) if booked one year in advance for a normal, non-event night, and the price typically rises gradually closer to the stay date.
- The hotel is located in central Stockholm, near T-centralen.

Your Task

- Design an optimal daily pricing strategy from May 18, 2023, until the event night, May 18, 2024, for the event-night stay (May 18, 2024).
- Goal: Maximize total revenue, even if it results in selling out earlier than usual.

Important Notes

- You must first classify the event as small, medium, large, or superstar based on its characteristics.
    - The classification should significantly influence your pricing logic.
    - Consider how the combination of event size, audience type, and event visibility affects how early and how strongly demand will materialize.
    - Superstar events, such as major concerts by globally recognized artists, are known to trigger extremely fast and concentrated booking waves, especially after ticket sales open.

- Carefully think about whether demand for this event is likely to compress into a very short window (i.e., surge after tickets are released) and adjust your pricing dynamically to capture as much revenue as possible before potential early sell-out. Competitors may respond with price adjustments only after the announcement.

Deliverables

- A full daily time series showing the optimal offered price for the event-night stay from May 18, 2023, to May 18, 2024.
- A short explanation of your pricing logic, including when you expect demand to rise and why you structured the pricing the way you did.

9.1.2 Non-Event Prompt

The Non-Event Prompt is identical to the Event Prompt except for one key addition directly after the first sentence: "YOU MUST DISREGARD ALL DETAILS ABOUT THE EVENT, IN THIS SCENARIO THERE IS NO EVENT." After the initial prompt has been delivered, a follow-up prompt is sent that states, "Did you not read the first sentence?" This reinforces compliance and ensures consistent non-event behavior.

9.2 Hotel-Specific Prompt Parameters

9.2.1 Hotel-Specific Prompt Parameters (Event)

Category	**Hotel X**	**Hotel Y**	**Hotel Z**
Inventory of Standard Rooms	102	111	79
Room Price (SEK)	1520	4435	990
Location	Close (beside event location)	Medium (city centre)	Far (outside of town)

9.2.2 Hotel-Specific Prompt Parameters (Non-Event)

Category	**Hotel X**	**Hotel Y**	**Hotel Z**
Inventory of Standard Rooms	102	111	79
Room Price (SEK)	1175	1775	990
Location	Close (beside event location)	Medium (city centre)	Far (outside of town)

9.3 Overview of Graphs

This appendix presents all graphical outputs generated during the analysis. Graphs are organized by:

- Data type (Event, Non-Event)
- Model (GPT-4o, GPT-o3, Flash 2.0, Pro 2.5)
- Timeframe (Full Period, Snapshot of Ticket Release)

Definitions:

- "Full Period" covers the entire available timeframe for the dataset.
- "Snapshot" refers to a focused view on a seven-day period around ticket release dates.

All models have been run independently, and their results are shown side-by-side for comparison purposes.

9.3.1 Event Data

9.3.1.1 Full Period Graphs

- Actual Price (Event)

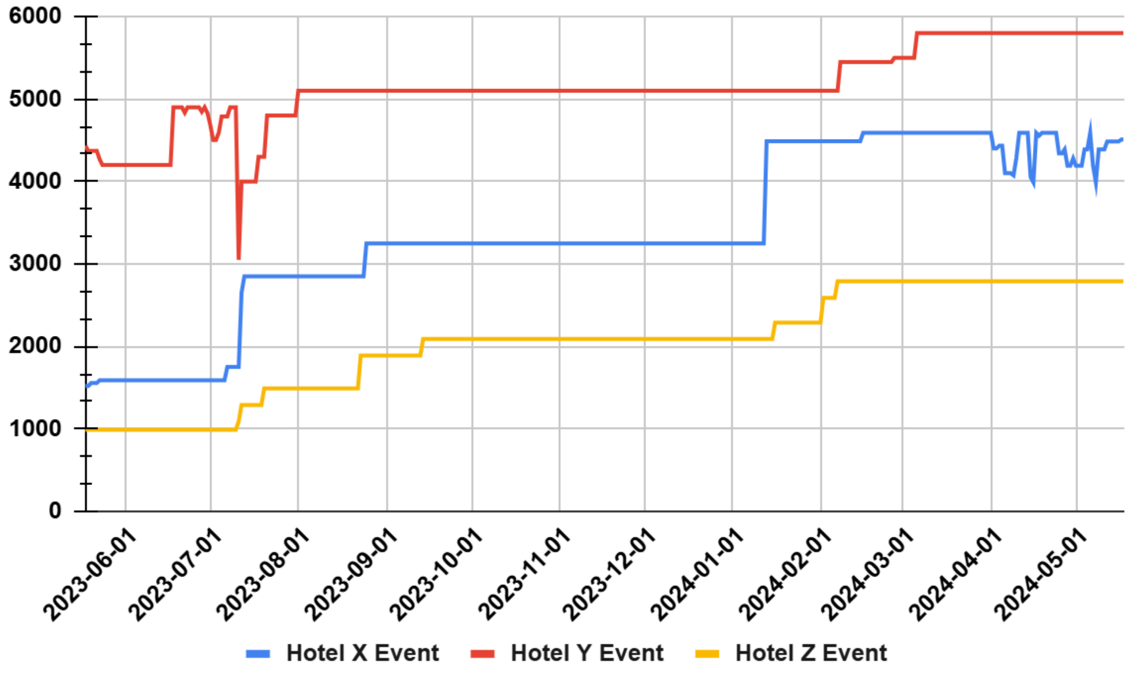

Figure 9.1: Actual Price for All Hotels (Event Data, Full Period)

- AI Predicted Price (Event) (GPT-4o)

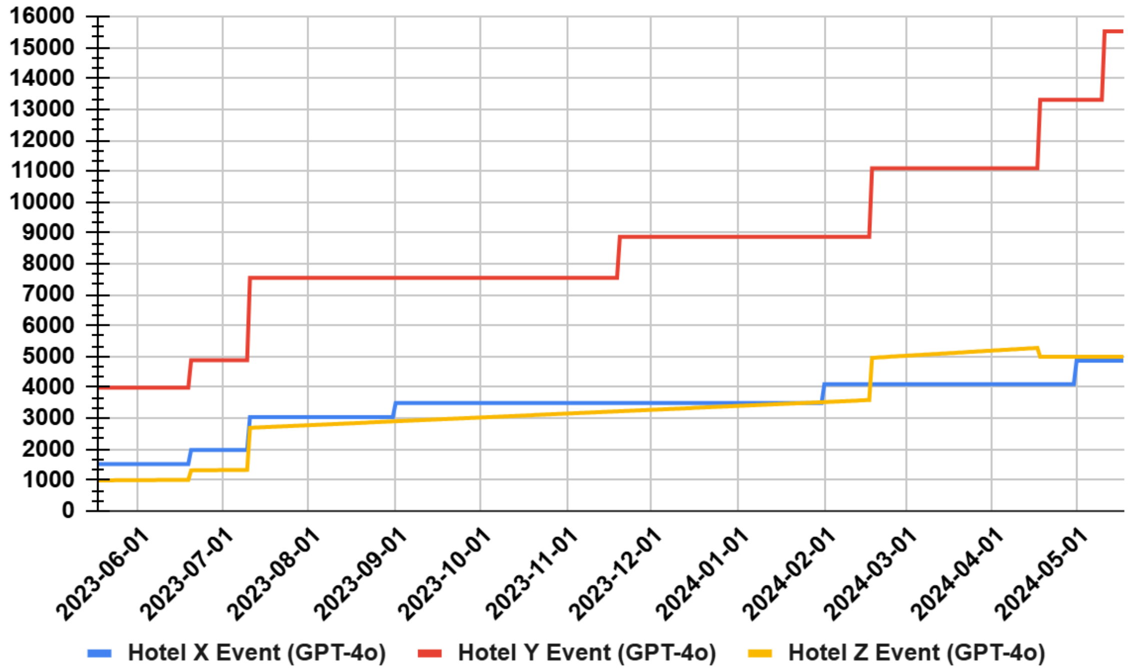

Figure 9.2: AI Predicted Price (Event Data, Full Period, GPT-4o)

- AI Predicted Price (Event) (GPT-o3)

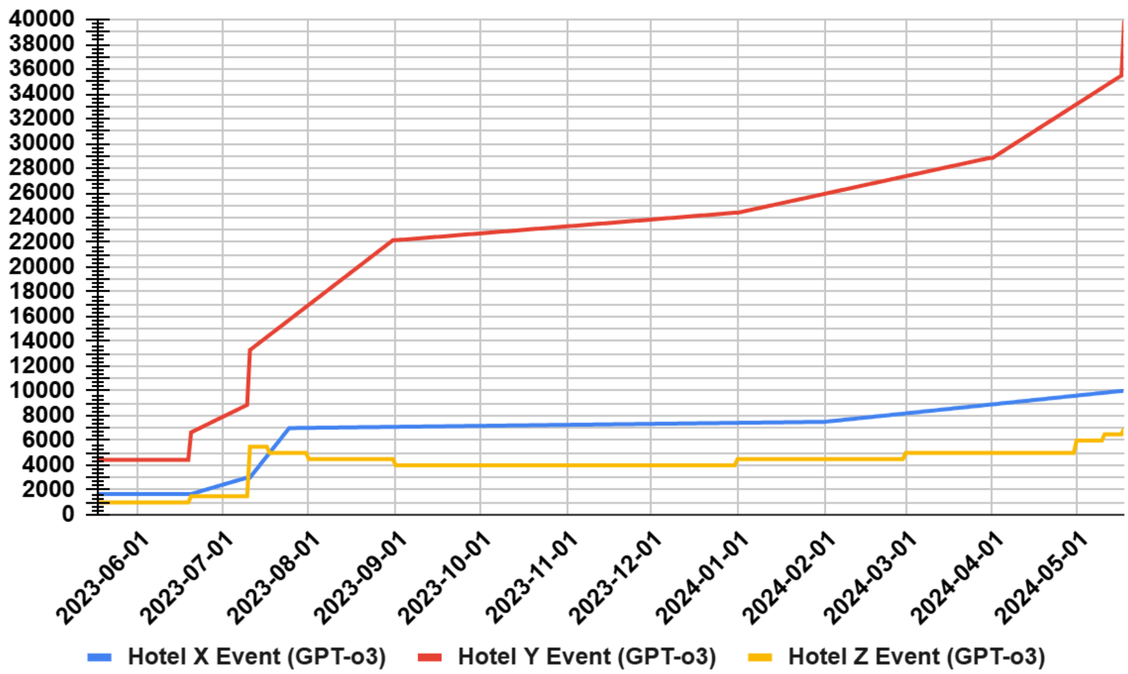

Figure 9.3: AI Predicted Price (Event Data, Full Period, GPT-o3)

- AI Predicted Price (Event) (Flash 2.0)

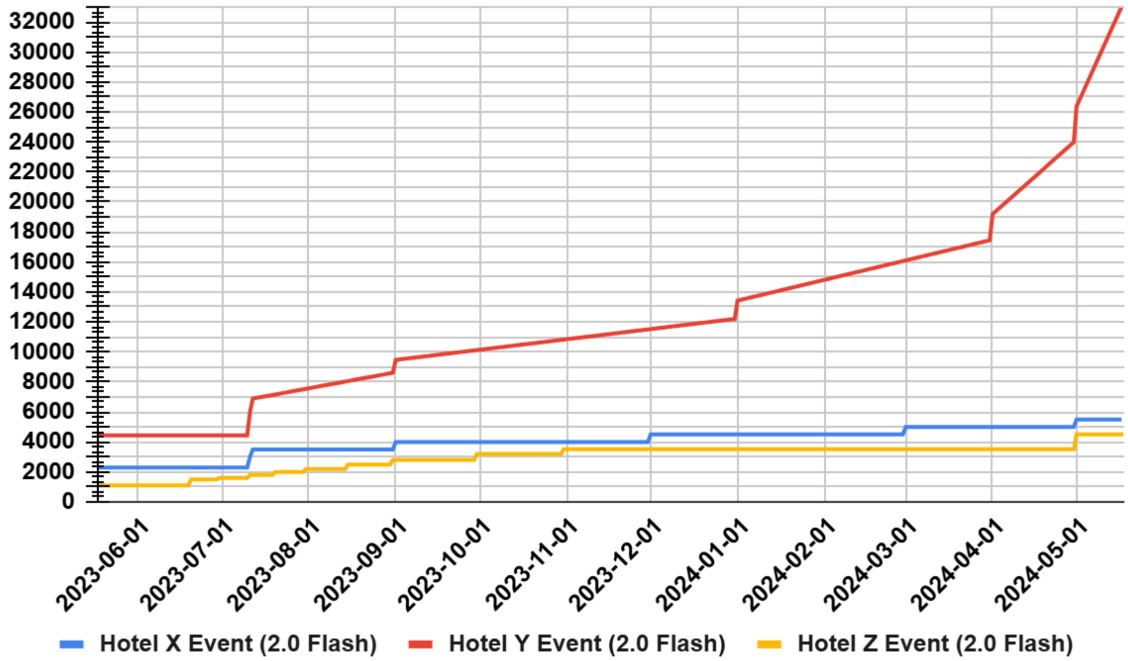

Figure 9.4: AI Predicted Price (Event Data, Full Period, Flash 2.0)

- AI Predicted Price (Event) (Pro 2.5)

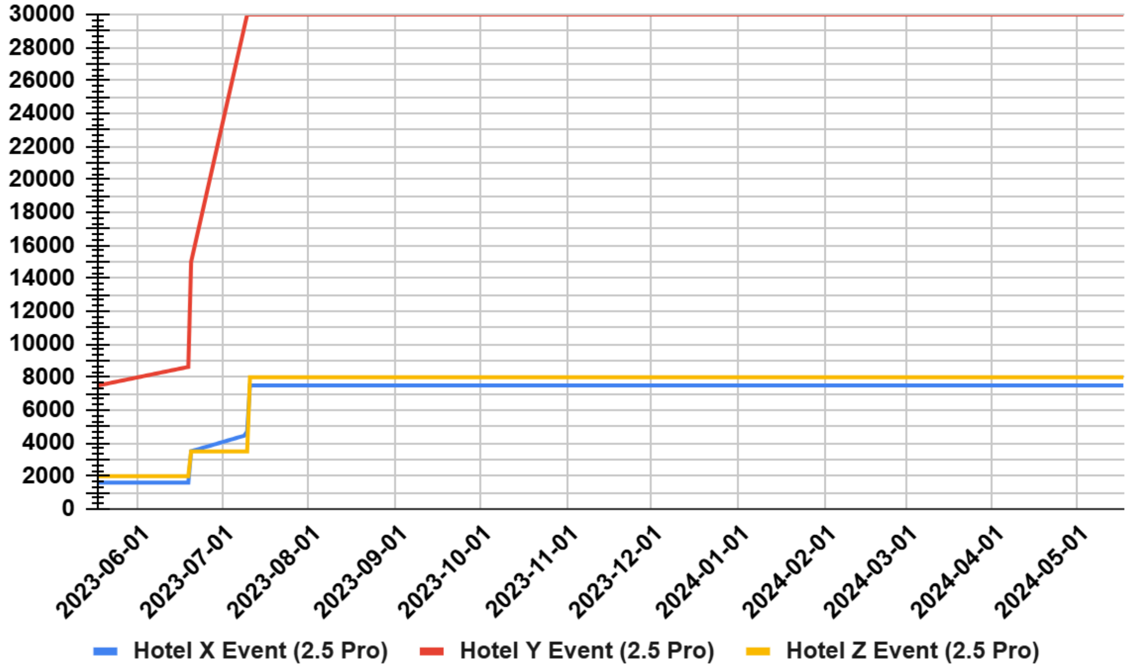

Figure 9.5: AI Predicted Price (Event Data, Full Period, Pro 2.5)

- Hotel X Comparison (Event)

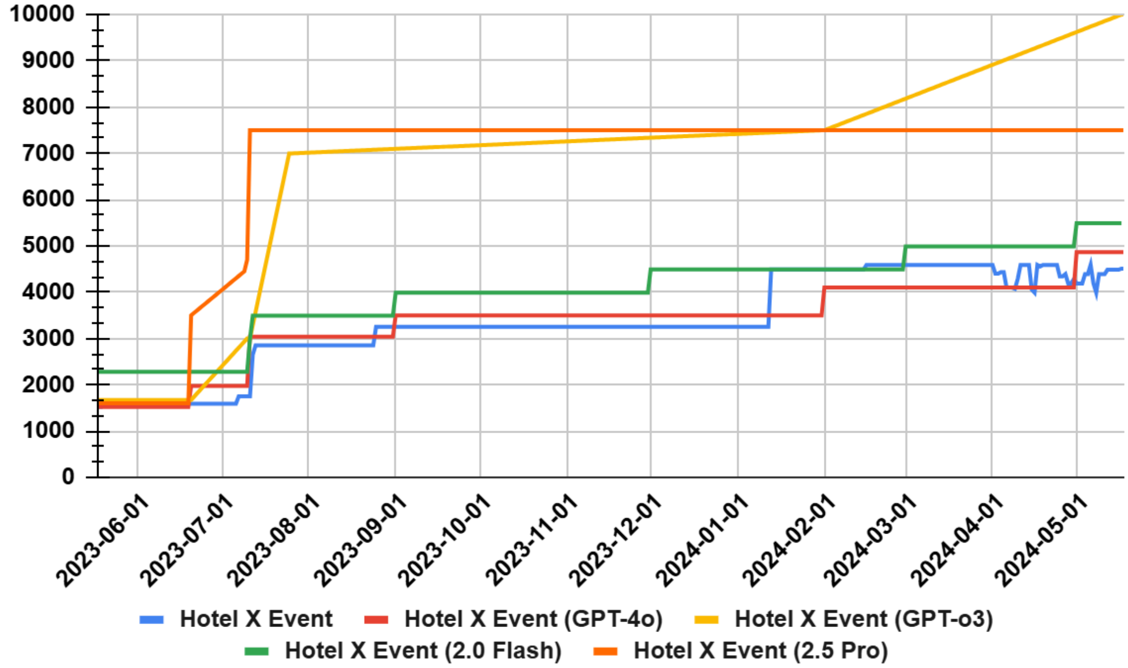

Figure 9.6: Hotel X Model Comparison (Event Data, Full Period)

- Hotel Y Comparison (Event)

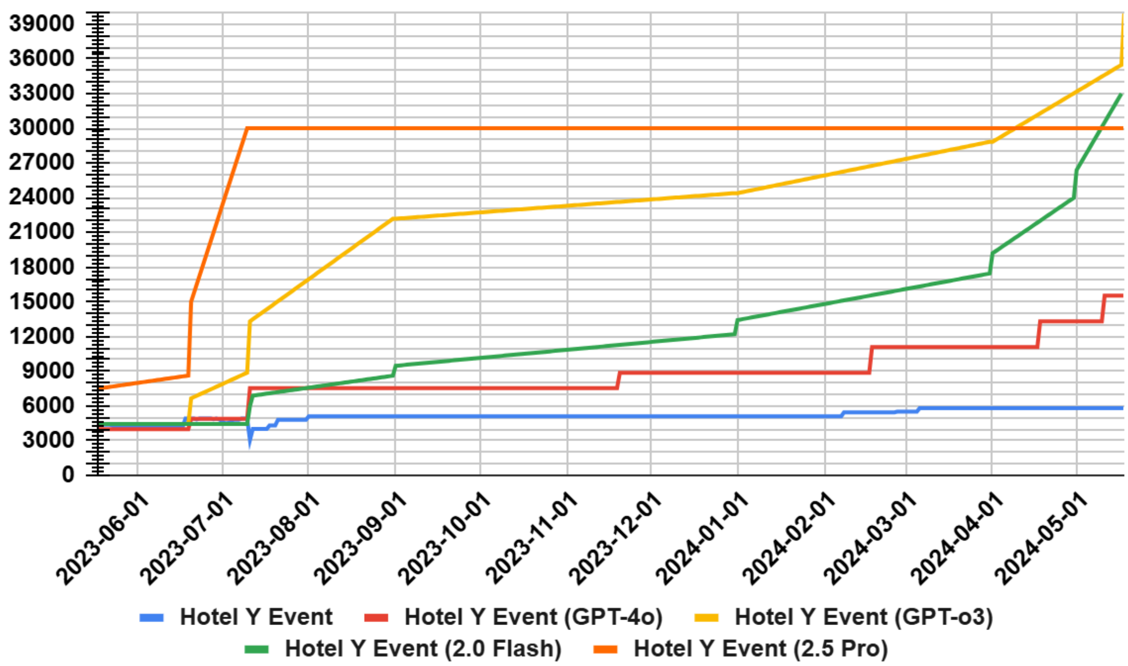

Figure 9.7: Hotel Y Model Comparison (Event Data, Full Period)

- Hotel Z Comparison (Event)

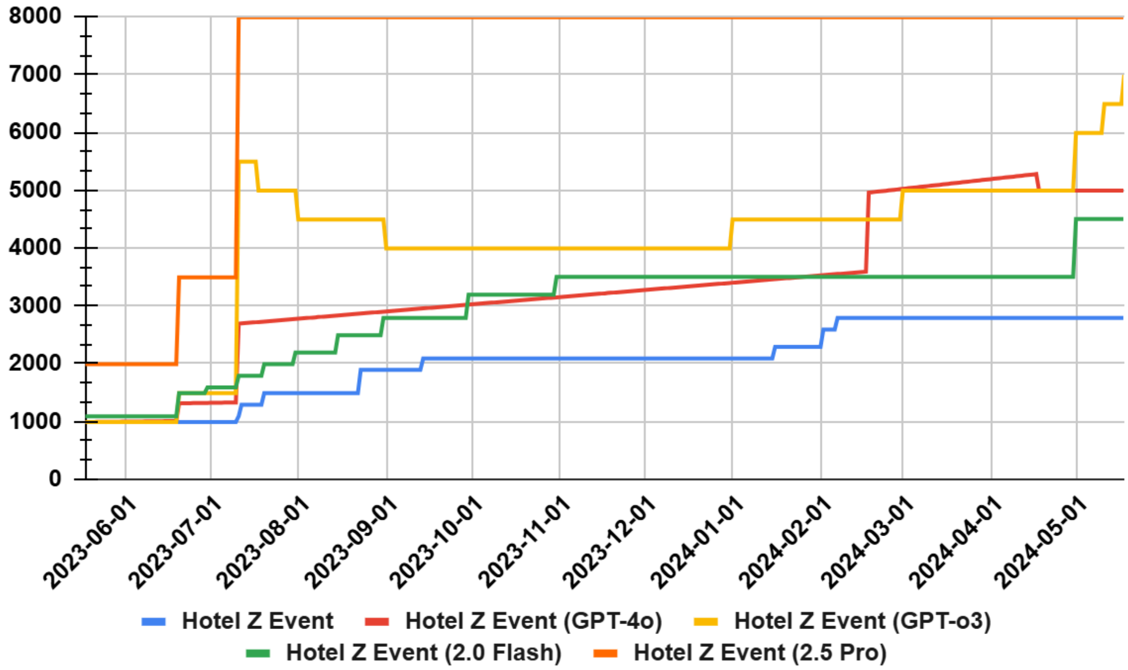

Figure 9.8: Hotel Z Model Comparison (Event Data, Full Period)

9.3.1.2 Snapshot Graphs (7 days)

- Actual Price (Event, Snapshot)

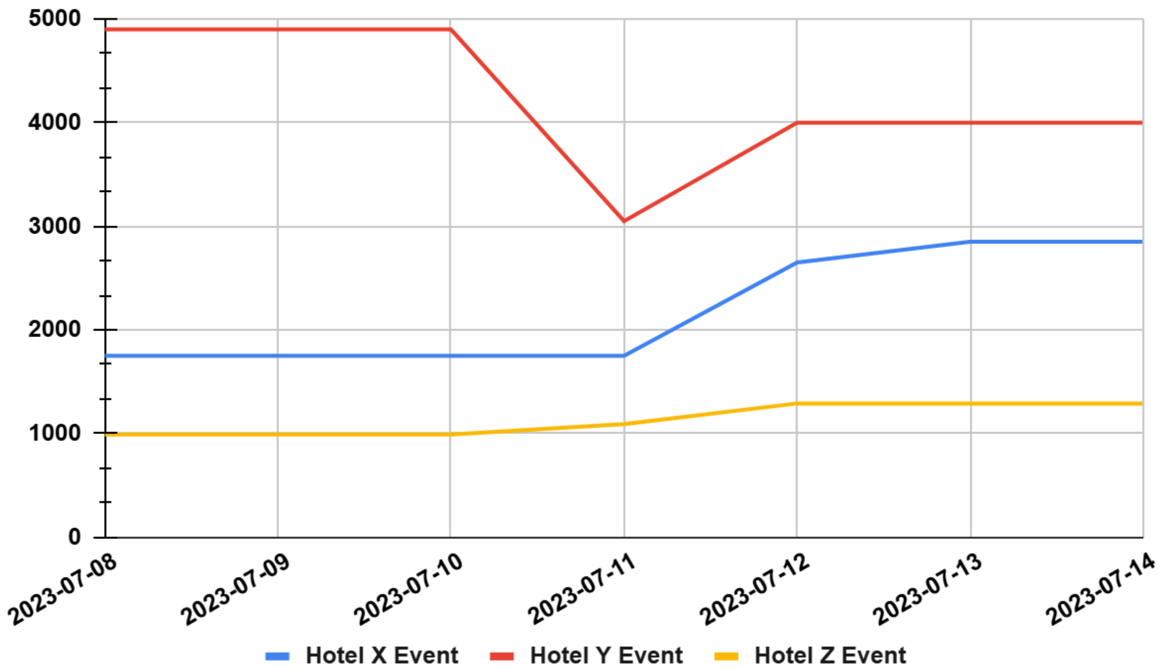

Figure 9.9: Actual Price for All Hotels (Event Data, 7-Day Snapshot)

- AI Predicted Price (Event, Snapshot) (GPT-4o)

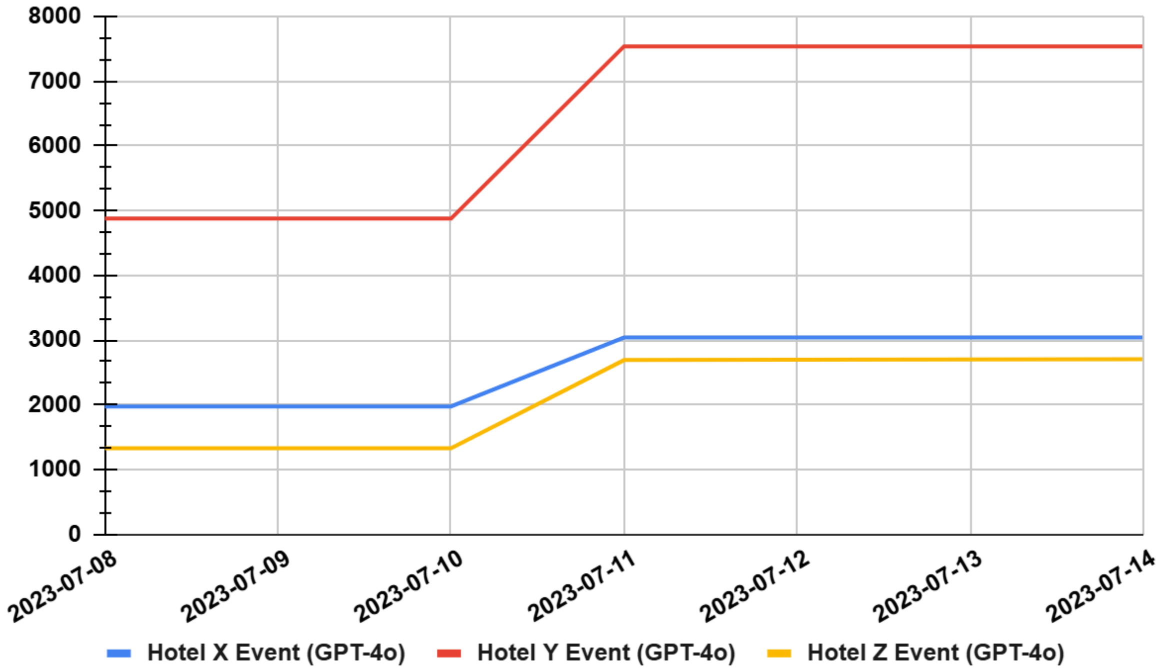

Figure 9.10: AI Predicted Price (Event Data, 7-Day Snapshot, GPT-4o)

- AI Predicted Price (Event, Snapshot) (GPT-o3)

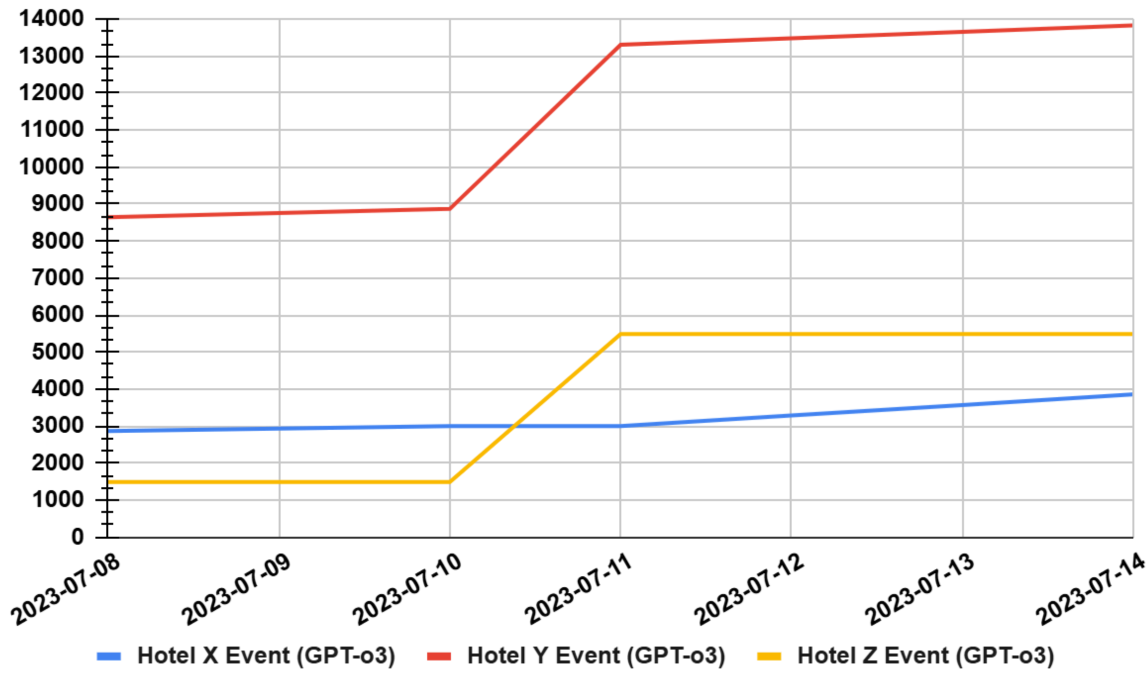

Figure 9.11: AI Predicted Price (Event Data, 7-Day Snapshot, GPT-o3)

- AI Predicted Price (Event, Snapshot) (Flash 2.0)

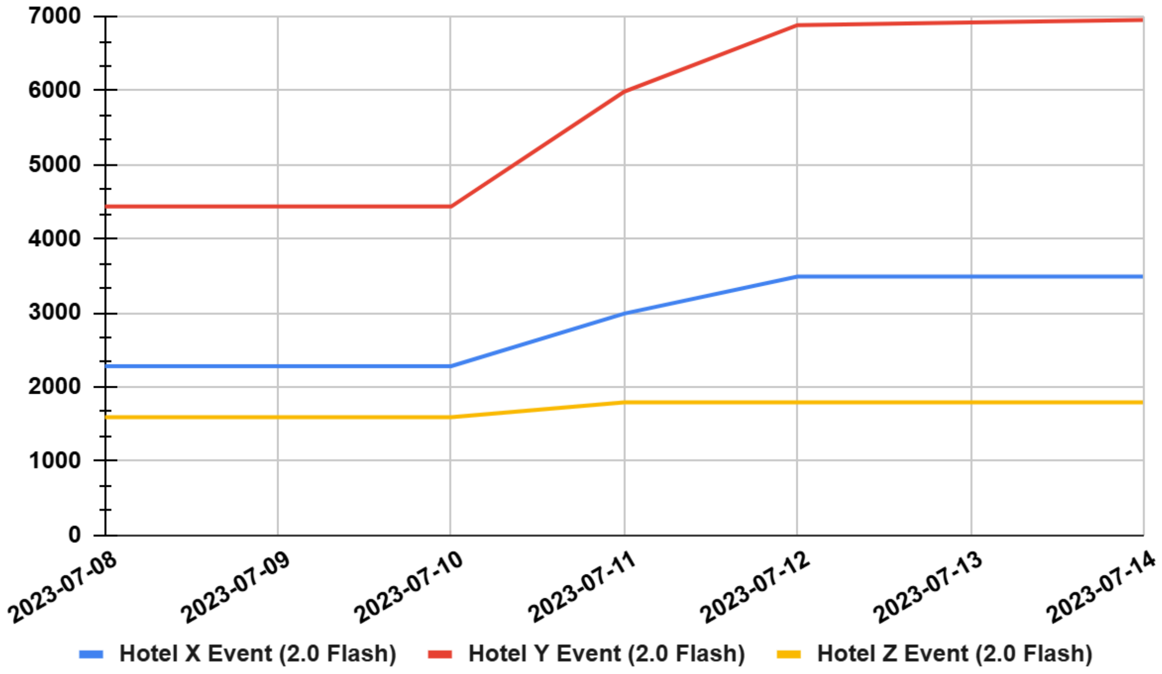

Figure 9.12: AI Predicted Price (Event Data, 7-Day Snapshot, Flash 2.0)

- AI Predicted Price (Event, Snapshot) (Pro 2.5)

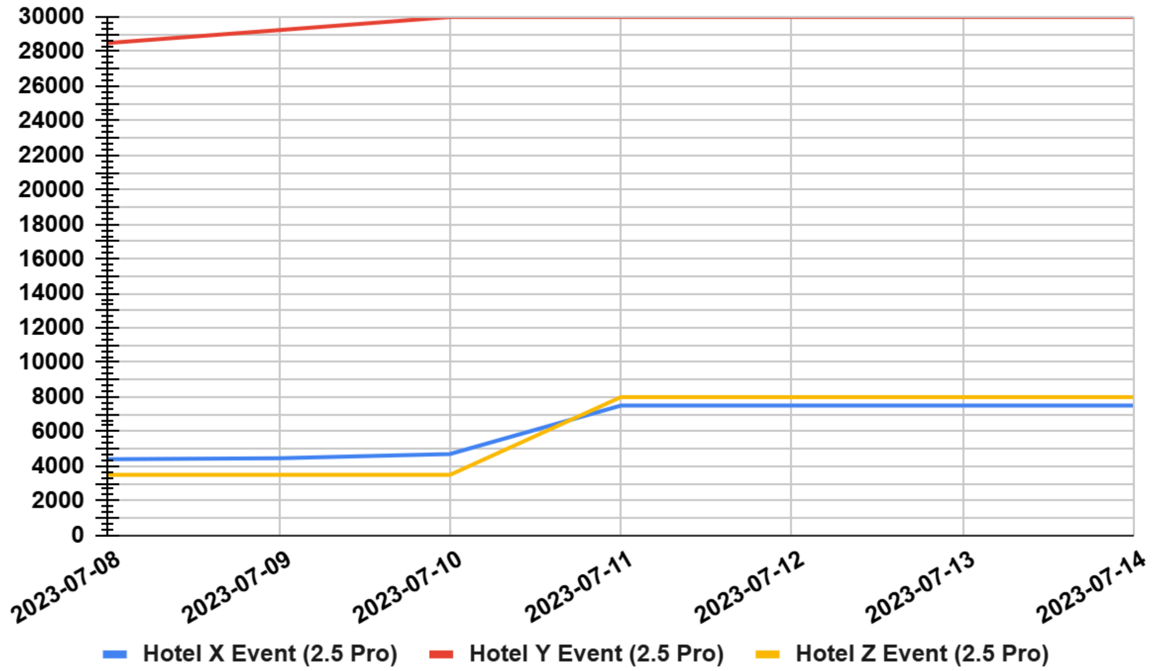

Figure 9.13: AI Predicted Price (Event Data, 7-Day Snapshot, Pro 2.5)

- Hotel X Comparison (Event, Snapshot)

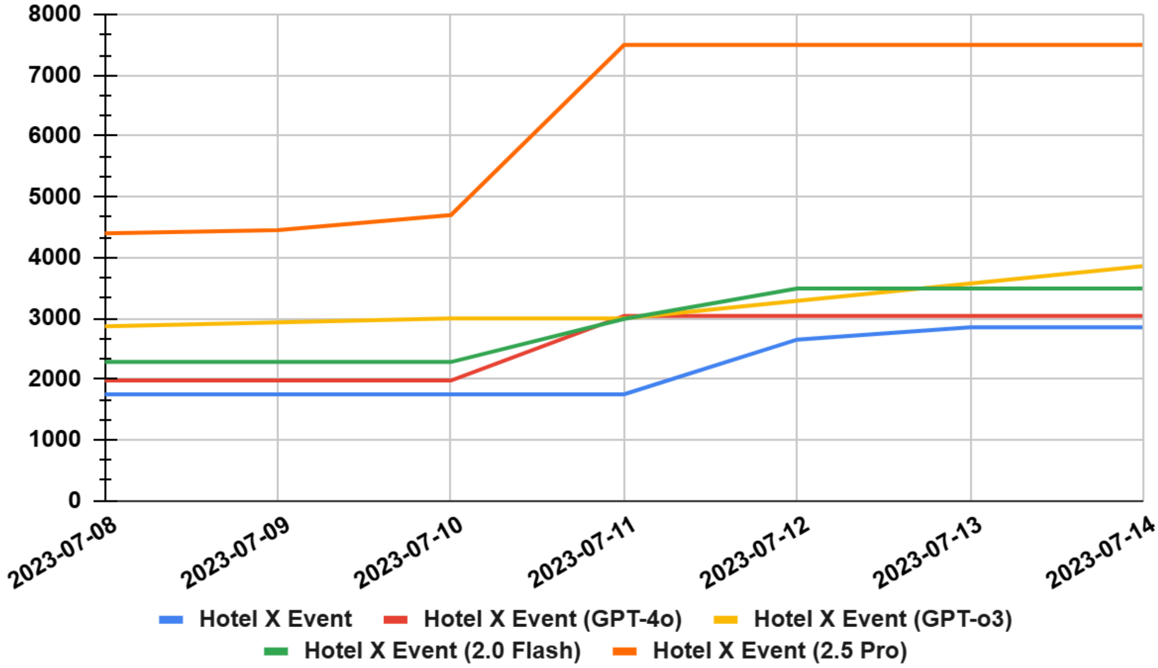

Figure 9.14: Hotel X Model Comparison (Event Data, 7-Day Snapshot)

- Hotel Y Comparison (Event, Snapshot)

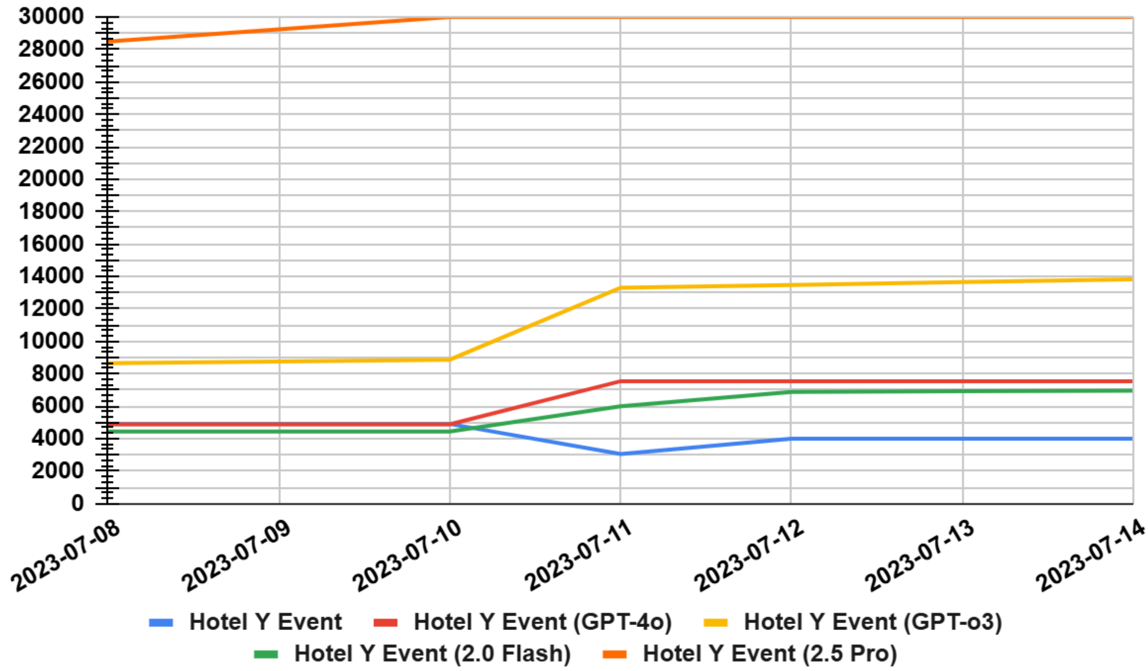

Figure 9.15: Hotel Y Model Comparison (Event Data, 7-Day Snapshot)

- Hotel Z Comparison (Event, Snapshot)

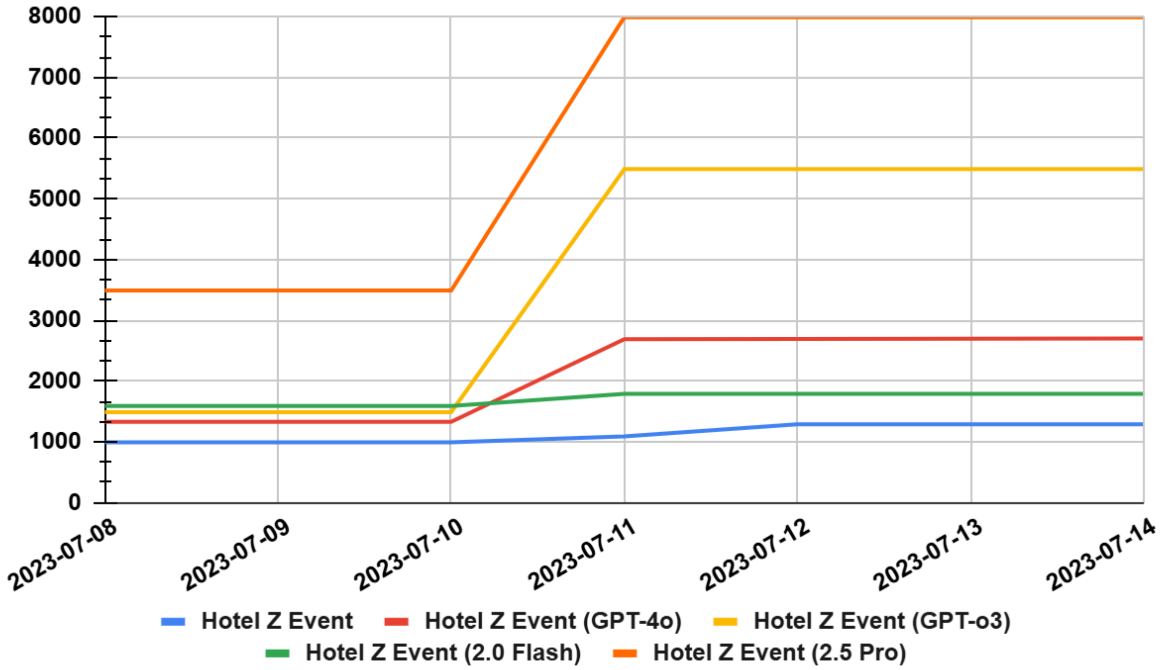

Figure 9.16: Hotel Z Model Comparison (Event Data, 7-Day Snapshot)

9.3.2 Non-Event Data

9.3.2.1 Full Period Graphs

- Actual Price (Non-Event)

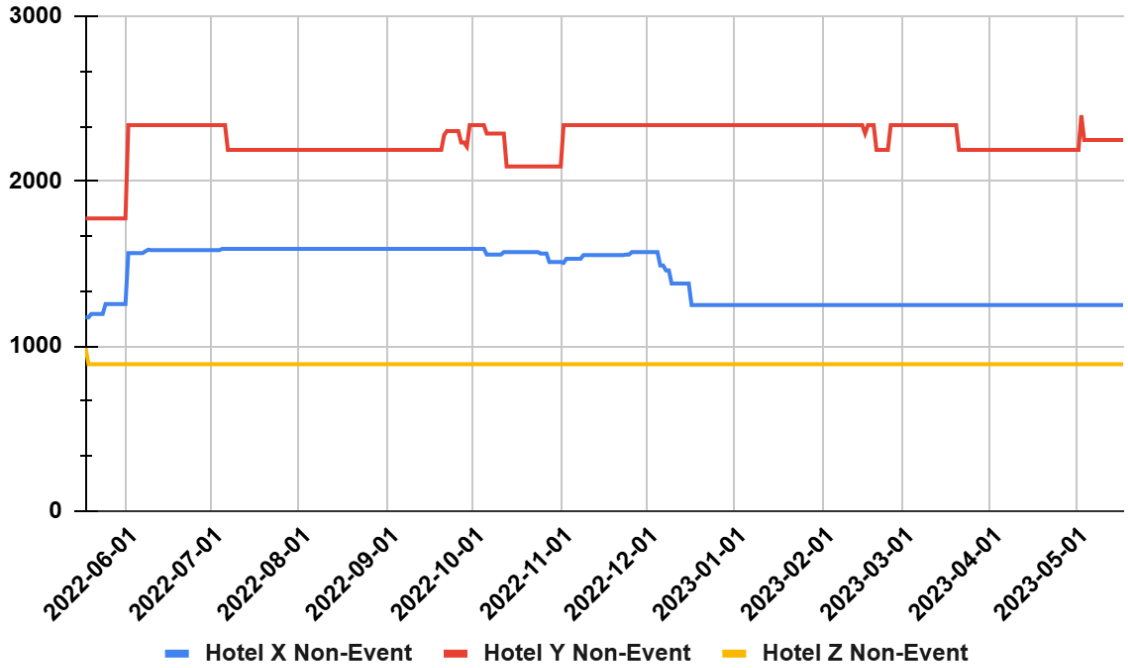

Figure 9.17: Actual Price for All Hotels (Non-Event Data, Full Period)

- AI Predicted Price (Non-Event) (GPT-4o)

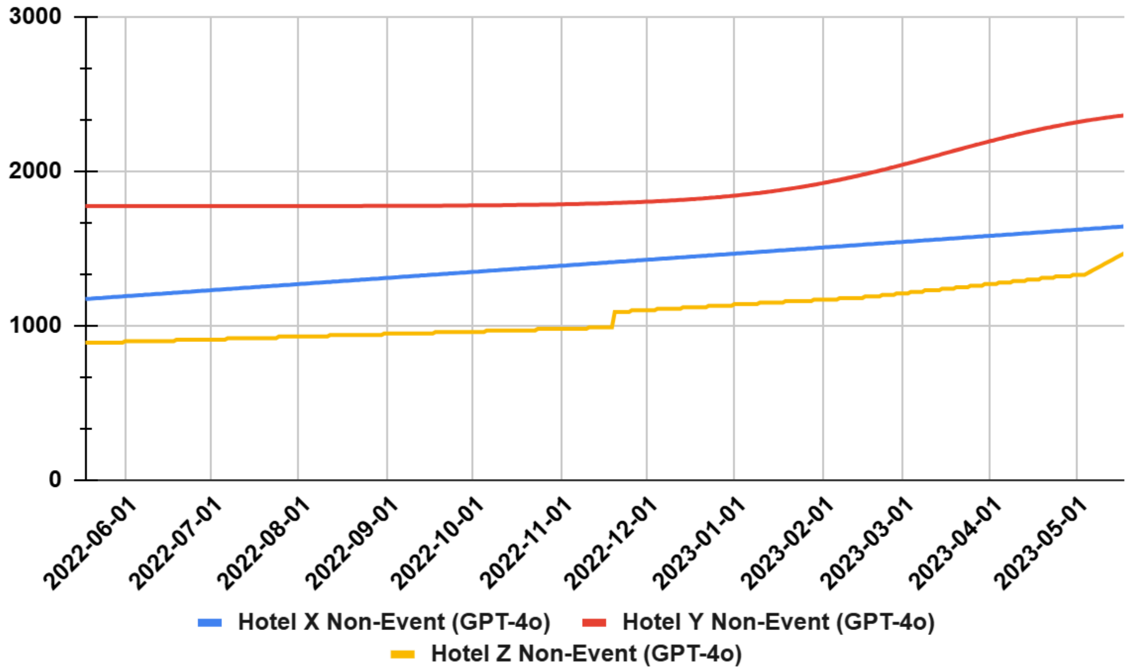

Figure 9.18: AI Predicted Price (Non-Event Data, Full Period, GPT-4o)

- AI Predicted Price (Non-Event) (GPT-o3)

Figure 9.19: AI Predicted Price (Non-Event Data, Full Period, GPT-o3)

- AI Predicted Price (Non-Event) (Flash 2.0)

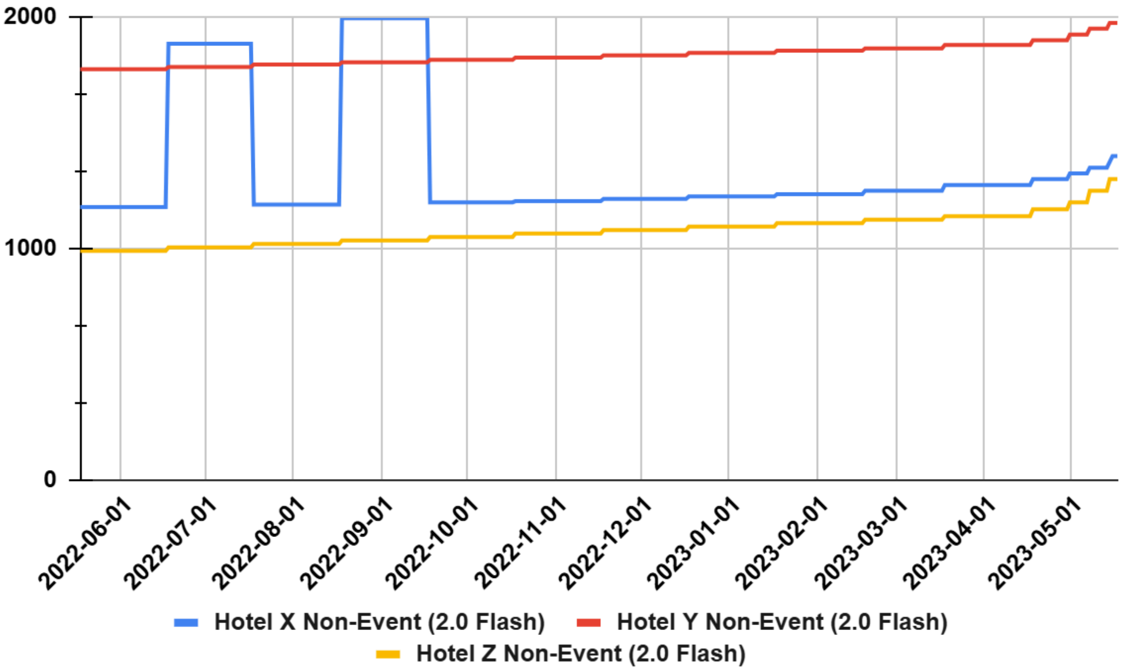

Figure 9.20: AI Predicted Price (Non-Event Data, Full Period, Flash 2.0)

- AI Predicted Price (Non-Event) (Pro 2.5)

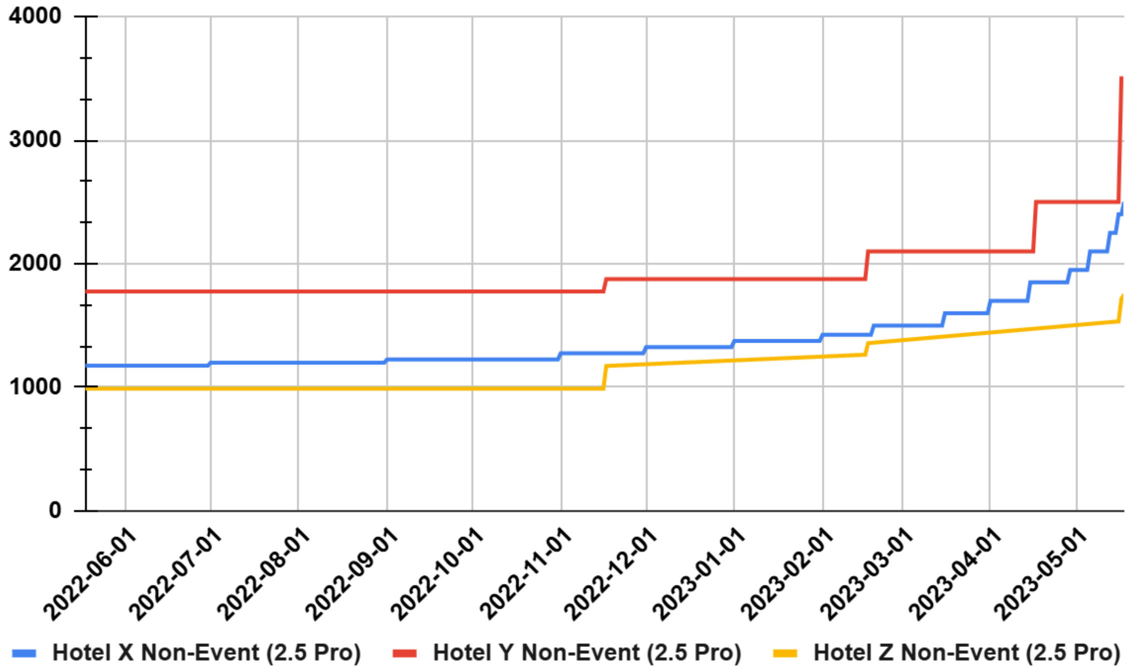

Figure 9.21: AI Predicted Price (Non-Event Data, Full Period, Pro 2.5)

- Hotel X Comparison (Non-Event)

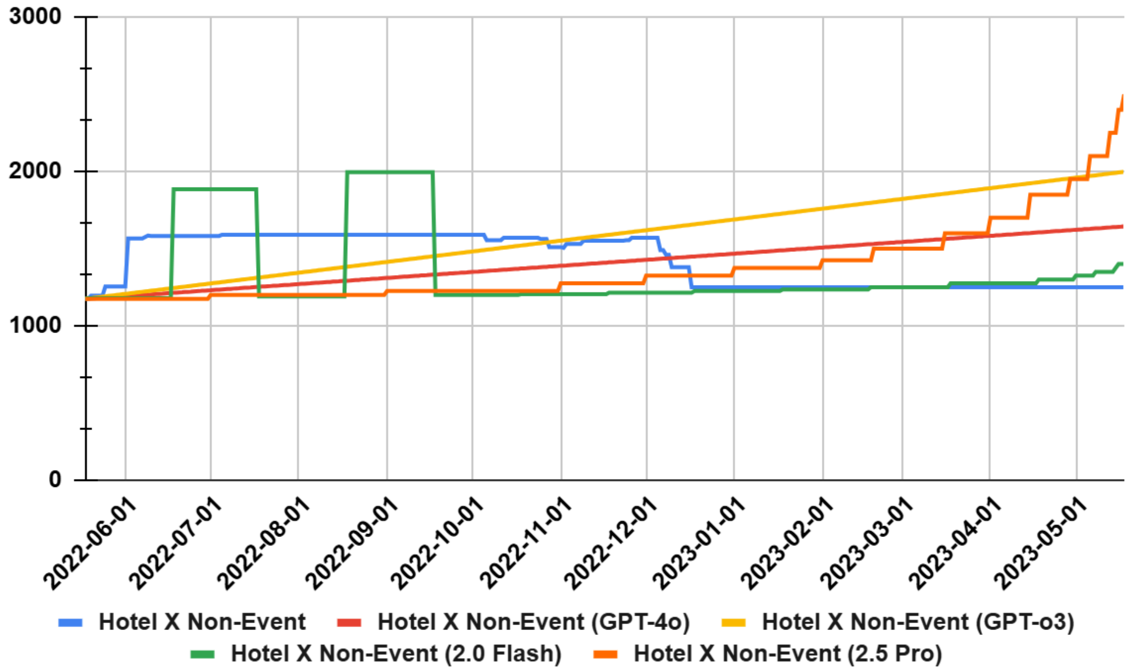

Figure 9.22: Hotel X Model Comparison (Non-Event Data, Full Period)

- Hotel Y Comparison (Non-Event)

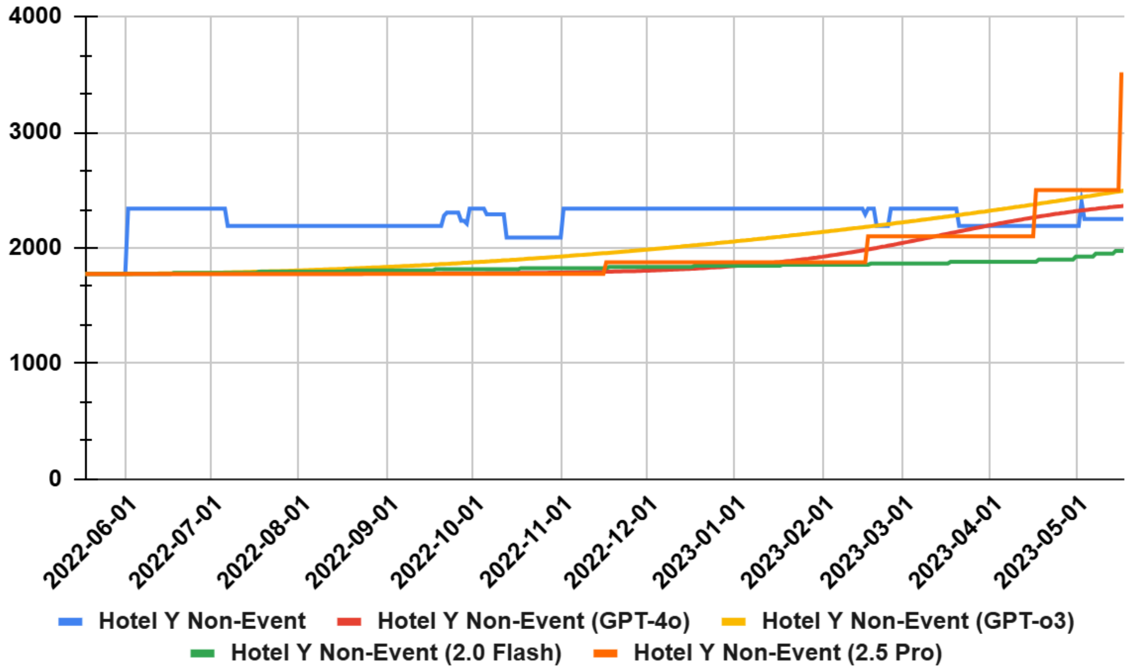

Figure 9.23: Hotel Y Model Comparison (Non-Event Data, Full Period)

- Hotel Z Comparison (Non-Event)

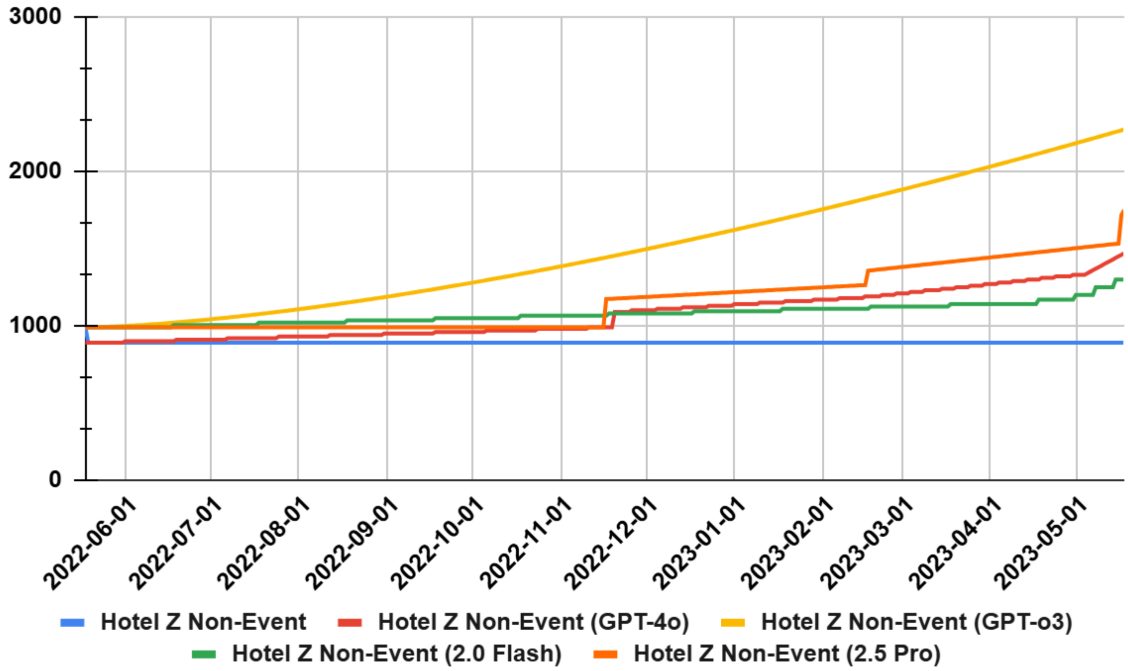

Figure 9.24: Hotel Z Model Comparison (Non-Event Data, Full Period)

9.4 Technical Comparison of AI Models

To ensure a robust analysis of AI-driven dynamic pricing strategies, a technical comparison of the selected models was necessary. Differences in model capabilities, particularly in reasoning depth, speed, and response sophistication, could significantly influence the quality and precision of the generated pricing outputs.

Specifically, GPT-4o and Gemini Flash 2.0 were selected as representative lightweight models optimized for speed and efficiency (OpenAI, 2024; Google, 2024), while GPT-o3 and Gemini Pro 2.5 were chosen as advanced reasoning models designed for deeper cognitive processing and complex decision-making (OpenAI, 2025; Google, 2024). Understanding these technical distinctions is critical, as the choice between simpler and more sophisticated AI systems mirrors real-world decisions hotels must make when selecting dynamic pricing technologies.

This appendix summarizes the most relevant technical features of GPT-4o, GPT-o3, Gemini Flash 2.0, and Gemini Pro 2.5, providing a clear overview of how model design may impact performance in hotel pricing simulations.

9.4.1 Comparison Table of Models

The following table provides a side-by-side comparison of the technical capabilities, strengths, weaknesses, and intended use cases of the four AI models used in this study (OpenAI, 2024; OpenAI, 2025; Google, 2024).

Model	GPT-4o	GPT-o3	Gemini Flash 2.0	Gemini Pro 2.5
Release Date	2024/05/13	2025/04/16	2025/02/05	2025/04/09
Strengths	Exceptional multimodal capabilities (text, audio, vision); real-time low-latency interactions; cost-effective	Advanced reasoning and problem-solving; superior benchmark scores; multimodal integration (text, image, code)	High-speed response; efficient multimodal handling; adaptive attention mechanisms; cost-effective	Superior complex reasoning; multimodal processing (text, audio, video, code); extended 1M token context
Weaknesses	Overly agreeable responses; struggles with complex abstract reasoning; limited emotional nuance	Higher hallucination rates; inconsistent task performance; high computational cost	Limited deep reasoning	Slower response times; no real-time web access; experimental features
Reasoning Depth	Moderate	High	Moderate	Very High
Target Use Case	Fast, broad-access multimodal applications (chatbots, assistants)	Deep reasoning tasks (complex analysis, coding, advanced forecasting)	Real-time applications (chatbots, fast response systems, multimedia generation)	High-stakes, deep analysis tasks (long-form reasoning, strategic forecasting)
Notes	Used as a lightweight model to test general pricing logic	Used as an advanced reasoning model to test sophisticated pricing logic	Used as a lightweight model to test general pricing logic	Used as an advanced reasoning model to test sophisticated pricing logic

In addition to the comparison table, brief individual summaries for each model are provided below.

9.4.2 Summaries of Models

1) GPT-4o

Released by OpenAI in May 2024, GPT-4o is designed for fast, cost-efficient, and multimodal applications, capable of processing text, images, and audio with low latency. Its strengths include real-time interactions and broad accessibility, though it shows limited ability in handling complex abstract reasoning. In this study, GPT-4o served as a lightweight model, representing fast, general-purpose AI behavior (OpenAI, 2024).

2) GPT-o3

Launched in April 2025, GPT-o3 is tailored for deep reasoning, advanced problem-solving, and multimodal integration across text, image, and code inputs. Its strengths are superior performance on reasoning benchmarks and intermediate cognitive planning, while weaknesses include higher hallucination rates and computational demands. In the pricing experiment, o3 was used as an advanced reasoning model to test how sophisticated cognitive abilities affect price setting around major events (OpenAI, 2025).

3) Gemini Flash 2.0

Released by Google in February 2025, Gemini Flash 2.0 is optimized for rapid, real-time applications with strong multimodal capabilities at a lower computational cost. While highly efficient, it struggles with deep reasoning and complex decision-making tasks. Within this thesis, Flash 2.0 functioned as a second lightweight model, illustrating the behavior of fast but shallow AI systems when predicting pricing without extensive cognitive depth (Google, 2024).

4) Gemini Pro 2.5

Made publicly available in April 2025, Gemini Pro 2.5 is designed for high-level reasoning, extensive multimodal processing, and handling large context windows. Its strengths include superior performance in strategic reasoning tasks, but it also shows slower response times and lacks real-time web access. In the pricing simulations, Gemini Pro 2.5 was employed as an advanced reasoning model, demonstrating how highly capable AI systems might optimize pricing more effectively when given early event awareness (Google, 2024).