APPLICATION OF HEURISTICS TO REVENUE MANAGEMENT SYSTEMS OVERRIDE DECISION-MAKING

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Abstract

Although revenue management studies suggest heuristics are applied when overriding revenue management system (RMS) recommendations, research has yet to explore the frequently used heuristics and their effects on hotel performance. This study first employed qualitative techniques to ascertain the frequently used heuristics – anchoring and overconfidence – in RMS overrides and the reasons behind their prevalence. It then applied quantitative techniques to examine the effects of these heuristics on hotel performance, leveraging the insights from the qualitative findings to offer a nuanced understanding of the relationships. The qualitative insights reveal that anchoring is frequently used mainly because of the belief that the system can learn from the overrides. In contrast, overconfidence's frequent use arises from the lack of transparency and trust in the RMSs' algorithms. The quantitative results indicate that overconfidence has a significant negative direct effect on performance, while anchoring's positive relationship with performance is mediated by RMS override effectiveness.

Keywords*:* revenue management, human-system interaction, system overrides, judgemental decision-making, behavioural economics

1. Introduction

Over the past four to five decades, hospitality and tourism businesses have embraced revenue management (RM) as the science and art of selling the right quantity of a product to the right customer at the right time for the right price and through the right channel (Kimes, 1989). This practice has sparked an ongoing interest in how RM decisions are made. As a science, operations researchers, data scientists and economists have provided decision-theoretic models and computational algorithms (or rules) to explain, for example, how the right price is determined using optimisation techniques and economic principles and theories (Vinod, 2022). These computational models have evolved from basic yield management systems to advanced revenue management systems (RMSs), which analyse large volumes of data to forecast demand and optimise price-inventory allocations (Egan & Haynes, 2019). Prior to the development of these systems, RM decision-making focused more on the art of human judgement, relying on simple techniques, informal data, gut feelings or intuition (Kiely, 2008).

However, with the evolution of RMSs and the emergence of big data, RM decision-making has become more complicated and strategic. The RMSs rely heavily on historical data and sophisticated machine learning algorithms, which operate as "black boxes" (i.e., lacking transparency and interpretability) and lead to mistrust or distrust (Yeoman, 2019). In some cases, RMS outputs have been rendered valueless due to the lack of reliable and quality historical data (e.g., during COVID-19). In other instances, RMSs have gone rogue because of special events, incomplete data, rapidly changing market conditions, uncertainties and tragic happenings. For example, during a 2016 bombing in New York and a terror attack at

London Bridge in 2017, Uber's pricing algorithms increased fares astronomically by 500% and 200%, respectively (Bertini & Koenigsberg, 2021). Similarly, Air New Zealand's RM algorithm surged regional fares that typically sold for US$89-102 to about US$534 during the 2019 Christchurch Mosque shooting (Yeoman, 2019).

All the aforementioned cases highlight RMS pitfalls, particularly their inability to account for human intuition, experience, and compassion, which are crucial for RM decision-making in hospitality and tourism. In light of these, recent studies have noted that hotel RM executives use a hybrid price decision-making process (i.e., human judgement and automated systems) (Haynes & Egan, 2024; Ivanov & Webster, 2024). In this hybrid process, the RM executives evaluate their systems' output and recommendations and decide whether to push them through or override them. When making override decisions, RM executives often apply heuristics (Mohammed & Denizci Guillet, 2024) – mental or cognitive shortcuts to quick decision-making or problem-solving under uncertainty (Hillier & Lieberman, 2001). Such heuristics are suited to hotel RMS override decision-making because of the perishability of room nights, intense competition, risk and uncertainty, time pressure, limited information, bounded rationality and computational complexity of algorithms (Bearden et al., 2008; Kiely, 2008).

Decision science theories and studies have shown that some heuristics can forecast future trends as accurately as sophisticated forecasting models (Goldstein & Gigerenzer, 2009), while others may introduce errors and biased judgements that do not predict the future equally well (Dale, 2015). This ambivalence implies that empirical studies must provide insights into which heuristics best suit a problem (Goldstein & Gigerenzer, 2009). In hotel RMS override decision-making, this imperative is yet to be fulfilled. The few studies confirming the use of heuristics in RM decision-making (e.g., Mohammed & Denizci Guillet, 2024; Bearden et al., 2008; Kiely, 2008) provide a limited understanding of the frequently used heuristics and their impact on performance. Due to this lacuna, it is unknown which heuristics are frequently applied to override RMS pricing decisions, the reasons behind their frequent use or preference over others and their effects on hotel performance. Meanwhile, understanding these insights and relationships can lead to awareness of personal biases and better RMSs override decision-making.

To fill these voids, this study used exploratory sequential mixed methods to a) investigate the common heuristics used in RMS override decision-making to identify the two frequently used ones and the underlying reasons for their frequent use and b) examine the direct and indirect effects of the two frequently used heuristics in RMS override decision-making on hotel performance through the mediating effect of RMS override effectiveness (i.e., the extent to which RMS overrides are believed to achieve their goals, e.g., forecasting accuracy). The findings offer insights into the realities of a hybrid price decision-making process in the hotel industry, which contribute to knowledge and practice in three significant ways. First, it explored the numerous heuristics in cognitive psychology to identify the two most frequently used ones in RMSs override decision-making. The 'overconfidence heuristic', in which RM executives often believe they have superior knowledge or market insights than the RMSs, and the 'anchoring heuristic', where revenue managers base their decisions on predetermined values or reference points, topped the list.

Second, the study uncovered the reasons behind the two most frequently used heuristics in making RMS override decisions. For the overconfidence heuristic, the lack of transparency and trust in the RMSs' algorithms were the main reasons; they generated an acute understanding of the systems' recommendations and low confidence in their outputs. In contrast, the reasons for using the anchoring heuristic were mainly for compliance with company policy and belief in the system's ability to learn from historical data (the 'anchors'). Third, the study examined how the two frequently used heuristics affect hotel performance in algorithmic environments, providing a better understanding of the theoretical mechanisms of the effects and practical ways to enhance their effectiveness in a hybrid price decision-making process. Understanding these insights and relationships can promote RM executives' awareness of their biases and lead to better override decision-making.

2. Literature Review

2.1.Hotel revenue management in an era of automation

Contemporary hotel RM traces its roots to the airline industry, where it started as yield management and was defined as the art and science of selling the right seat to the right customer at the right price at the right time to maximise revenues (Anderson & Wilson, 2003). In its early stages of adoption, hotel managers relied on simple techniques, informal data, gut feelings and heuristics to make RM decisions (Kiely, 2008; Bearden et al., 2008). However, as technologies advanced and computerised systems became prominent (Kimes & Wirtz, 2003), RMS evolved to facilitate RM functions. Rising online activities and access to big data have contributed to adopting computerised RMS to process these data in real-time for decision-making (Abbasi-Moud et al., 2021; Ortega, 2016). Subsequently, the literature has shown that using RMS can improve hotel performance (Jain & Bowman, 2005; Rannou & Melli, 2003), especially, increased occupancy rates (Ortega, 2016).

Other scholars have criticised RMSs as "black boxes" lacking transparency and interpretability (Koupriouchina et al., 2023; Webb et al., 2023; Schwartz et al., 2021; Pereira, 2016) and are unable to account for human intuition, experience, and compassion, which are crucial for RM decision-making in hospitality and tourism (Yeoman, 2019). Given these pitfalls, human interventions or "user overrides of machine prediction[s] are a 'must' feature in all of the leading hotel revenue management computerised systems" (Schwartz *et al*., 2021, p. 276). A few studies have also explored how override decisions are made and concluded that heuristics, an approach to decision-making that is quick and takes into account experience (Bearden et al., 2008; Hillier & Lieberman, 2001), are commonly used (Mohammed & Denizci Guillet, 2024; Bearden et al., 2008; Kiely, 2008). However, these studies do not provide insights into how heuristics affect hotel performance. The following section reviews heuristic decision-making as the theoretical underpinning of this study.

2.2. Theoretical literature review

The overarching theory of this study is behavioural decision theory, which explains how individuals make decisions (Burkhard et al., 2018). The predominant view of this theory is heuristics, which is defined as the rules of thumb, mental shortcuts or computationally simple but valuable methods used by individuals in uncertain situations to "quickly [find] good feasible solutions" (Hillier & Lieberman, 2001, p. 624) or solve problems and make decisions (Hertwig & Pachur, 2015). Initially developed by Simon (1956) as part of the theory of bounded rationality, heuristics were further developed by Tversky and Kahneman (1974), who unveiled three main types: representativeness, availability, and adjustment and anchoring. Following this, many other heuristics have been identified and studied. In a systematic literature review, Blumenthal-Barby and Krieger (2015) identified 19 heuristics and biases, including ambiguity aversion, anchoring, availability, bandwagon effect, confirmation, overconfidence or optimism, and default or status quo (see Blumenthal-Barby & Krieger, 2015, p.6 for the comprehensive list and definitions).

Heuristics application to RMS override decision-making can be explained by bounded rationality and dual processing (or system thinking) theory. These theoretical frameworks have also been applied to understand tourist decision-making under conditions of bounded rationality and changing risks and uncertainties (Chen et al., 2024; Hrankai et al., 2024). According to bounded rationality, individuals' decision-making is often convoluted and constrained by uncertainty, limited information, time pressure, and cognitive load or processing capabilities, which make using heuristics attractive (Guercini & Milanesi, 2020; Simon, 1956). In RMS override decision-making, these conditions prevail. The perishability of hotel room nights pressures revenue managers to make quick RMS override decisions to avoid unsold rooms. Also, because of the multiplicity of pricing options and complexity, revenue managers adopt heuristics to lessen the computational efforts. The dual processing also comes into play because it posits that human judgements result from two systems of thinking: a fast, automatic, associative and intuitive process vs a slow, deliberative, reason-based and logical process (Bago & Neys, 2017; Evans, 2003). This dual-system thinking is akin to what Haynes and Egan (2024) describe as a hybrid pricing decision-making process in the hotel industry.

2.3. *Anchoring and overconfidence heuristics in RM decision-making*

RM decisions are made under conditions of uncertainty and, therefore, are inherently risky. Accordingly, decision scientists and revenue management scholars have argued that heuristics can work as well or even better than complex algorithms in such environments (Goldstein & Gigerenzer, 2009; Bearden et al., 2008; Kiely, 2008). The basis of this argument lies in the notion that, under conditions of uncertainty and limited information, complex decision algorithms are more susceptible to errors due to their sensitivity to data variance than heuristic-based decision-making approaches, which are more robust and adaptive to these conditions (Artinger et al., 2014). In managerial decision-making, a plethora of heuristics have been identified and used in different contexts. In RM decision-making and overrides, anchoring and overconfidence are among the frequently applied (Mohammed & Denizci Guillet, 2024; Cleophas & Schüetze, 2022). Other well-known heuristics are loss aversion, confirmation and bandwagon effect.

However, because this study confirmed anchoring and overconfidence are the most frequently used for override decisions, it is essential to explain these further in context. According to Tversky and Kahneman (1974), anchoring is the tendency for decision-makers to excessively rely on a prior piece of information or value, referred to as the anchor, which serves as a reference point leading to insufficient adjustment away from this point or value. In RMS override decision-making, anchoring occurs when RM executives seek to influence the RMS to produce recommendations or outputs that align with expectations. Overconfidence refers to the tendency for decision-makers to believe that they are more likely to make the right decision with a positive outcome than a wrong decision with a negative outcome (Seo & Sharma, 2018; Busenitz & Barney, 1997). In RMS override decision-making, overconfidence manifests when RM executives boast superior knowledge and market insights than the RMSs. They are less trusting of the RMS and override instantaneously and frequently.

2.4. Empirical literature review

Traditionally, heuristics were considered the second-best options for solving problems or making decisions. This implied that they were not widely used until now. However, as evidence of their competitive results accumulates (Goldstein & Gigerenzer, 2009), they have become acceptable and even more desirable and appealing, leading to several studies on the choices and uses of heuristics (Del Campo et al., 2016; Payne et al., 1993). These studies note that the selection of heuristics depends on several factors, including the decision context and task (Payne et al., 1993) and individual decision-maker characteristics, such as personality traits and decision styles (Del Campo et al., 2016). Besides the decision-maker characteristics, some researchers have demonstrated that, under certain conditions, some heuristics may be preferred over others (Hilbig et al., 2012; Hogarth & Karelaia, 2006; Newell et al., 2003). For example, in high uncertainty, the reliance on the take-the-best heuristic increases (Hogarth & Karelaia, 2006). Also, time pressure contributes to using the recognition heuristic (Hilbig et al., 2012).

Apart from the factors influencing the choice of heuristics, empirical studies have examined the effects of selected heuristics on outcomes such as firm performance and investment decisions. Ahmad et al. (2020) examined the mediating effects of risk perception and moderating effects of financial literacy on the impact of the overconfidence heuristic in investment decision-making on performance. Their study findings confirmed that risk perception fully mediates the relationship between the overconfidence heuristic and investment decisions and performance. Further, the results suggested that overconfidence impairs the quality of investment decisions and performance. Exploring the mediation mechanism of heuristics on performance, ul Abdin et al. (2017) tested the indirect effects of heuristics on performance through technical and fundamental anomalies in investment. They found that fundamental anomalies, not technical anomalies, are significant mediators in the heuristic-investment performance relationship.

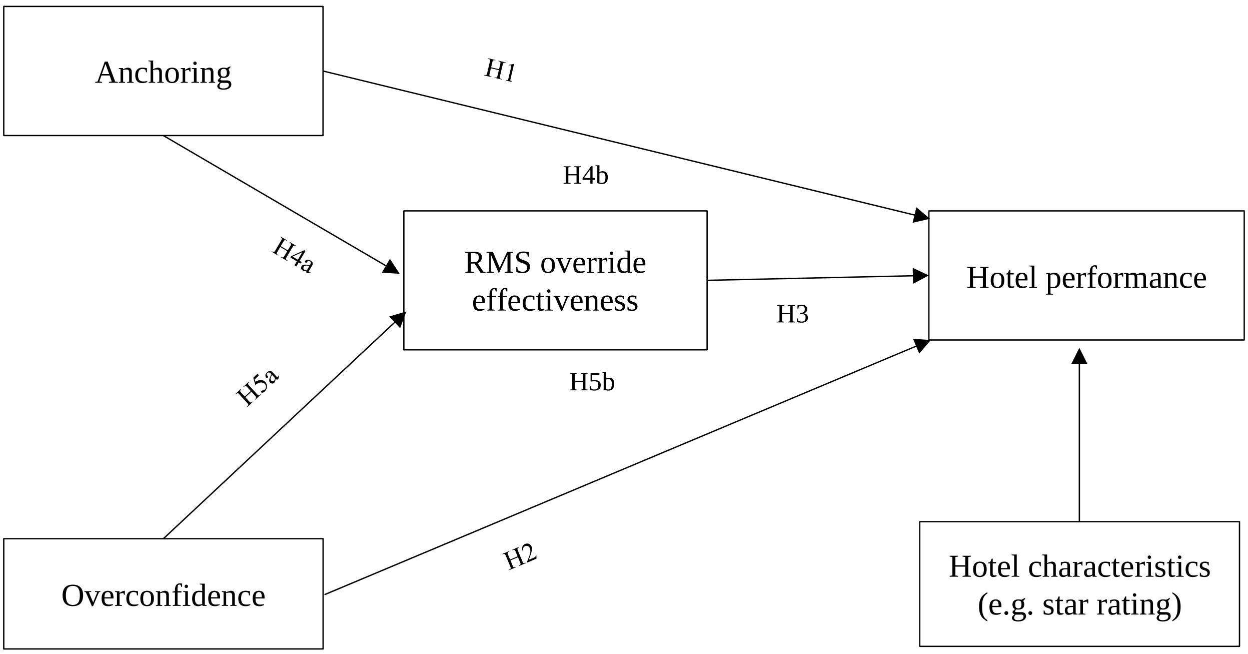
While the empirical literature on heuristics is growing in other contexts, limited studies have been conducted in the RM setting. A few notable studies in this area include those by Mohammed and Denizci Guillet (2024), Cleophas and Schüetze (2022), Lee et al. (2015), Bearden et al. (2008) and Kiely (2008). In Kiely's (2008) study, hotel managers were found to bypass management science decision-making models for decision strategies that emphasise human intervention. However, the study did not identify the types of heuristics used. Using experimental strategies, Bearden et al. (2008) found that RM decision-makers employ heuristics of the same form as the optimal policy. Lee et al. (2015) note that the characteristics of hotel products, such as perishability, make hotel managers amenable to using "quick fix(es)", such as "less-than-35 rule", "80-20 rule", "trial and error", "follow suit", and "habitual decision" to offer discounts on room rates (p.70). According to them, these habitual practices are conveniently chosen based on limited information, experience and belief systems. Although Lee et al.'s (2015) study exposed some habitual management practices or rules of thumb, these were not in the context of override decision-making.

Egan and Haynes (2019) concluded that most hotel managers were not using RMSs because they believed they "have a greater degree of judgement over that of the automated system" (p.34). Mohammed and Denizci Guillet's (2024) study identified several heuristics in human-algorithm interactions. However, they did not provide insights into which heuristics are frequently used to override RMS recommendations and how they affect performance. Thus, the limited studies present two gaps for this study's investigation. First, it is unknown which heuristics are frequently applied to override RMS pricing decisions and the reasons behind their frequent use or preference. This lacuna limits the awareness of personal biases in making override decisions. Second, the effects of the frequently used heuristics and how they affect hotel performance are unknown, limiting the understanding of which heuristics are best suited to address RMS pitfalls and contribute to performance. The following section presents the conceptual framework and hypotheses that address these gaps.

2.5.Conceptual framework and hypotheses development

In a hybrid pricing decision-making, heuristics are applied to change or override RMS outputs (e.g. demand forecast or price recommendations) or input (e.g., data or restrictions) to correct the system's pitfalls, improve its effectiveness (e.g., forecast accuracy) and performance of the hotel ultimately (Mohammed & Denizci Guillet, 2024). However, the chain of effects may differ depending on the heuristics used for overriding decisions. To illustrate these effects, two heuristics – anchoring and overconfidence are chosen because they are closely linked to the two types of overrides – input and output, respectively. They also emerged from this study's interviews and quantitative survey as the topmost frequently used heuristics for overriding RMS decisions (See Figure 2). In light of these, the heuristics-performance relationships in the hotel RMS overrides context are conceptualised as a mediated process in Figure 1, whereby heuristics, directly and indirectly, influence performance through RMS override effectiveness.

Figure 1: Conceptual framework after identifying the two important and applicable heuristics



The anchoring heuristic is operationally defined as the tendency for a revenue manager to emphasize or give too much weight to a piece of information (the 'anchor' or 'reference'), such as historical patterns, without adequately considering current market conditions. When applied to RMS overrides, an example could be a revenue manager using anchoring to play 'trial and error' with the input data to produce outputs that align with the anchor or reference. The overconfidence heuristic is operationally defined as the tendency for a revenue manager to believe they are more capable of making accurate decisions than the RMS because of their experience, knowledge and insights about the local market. In the context of RMS overrides, an example could be a revenue manager changing the system's recommended rate directly because he thinks he is always right.

RMS override effectiveness is operationally defined as the extent to which a revenue manager believes overrides improve the RMS pitfalls and generate more accurate and reliable output. Hotel performance refers to metrics such as the average daily rate, occupancy and revenue per available room. These two constructs, override effectiveness and hotel performance, differ to the extent that override effectiveness is a means to an end while performance is an end. For example, override effectiveness can be seen in improving forecast accuracy, which in turn can lead to improved performance in ADR, occupancy and RevPAR. Given these definitions and the conceptual framework, the following sections develop the accompanying hypotheses. The measurements of the constructs are provided in Section 3.3.

2.5.1 Direct effects of anchoring and overconfidence heuristics on hotel performance

Anchoring heuristic in RMS override decision-making refers to the cognitive bias or inclination to rely on a prior piece of information or value (i.e., the anchor) to adjust the system's recommended value such that it often leads to an inertia or insufficient adjustment away from this prior piece of information or value. Studies in investment decision-making have suggested that investors who use anchoring usually refer to previous stock prices as an initial value or the anchor for the current prices, which strategy may positively or negatively affect investment decisions (Montier, 2002). In RMS override decision-making, similar logic applies. The items used to measure anchoring in RMS overrides indicated that RM executives agreed to adjust the system's recommendations toward a predetermined value based on past or future outcomes. Therefore, when RM executives anchor their price adjustments on a high or low value, hotel performance can be expected to be correspondingly high or low. Thus, the study proposes that:

H1: Anchoring heuristic has a direct, significant positive effect on hotel performance

Regarding overconfidence, it occurs when people see themselves as "better-than-average" (Kim & Jang, 2020, p.276) or overestimate their ability or capability, skills and knowledge and underestimate possible risk (Kim et al., 2022). Studies on CEO overconfidence's impact on firm performance have argued that the effect can be negative or positive (Burkhard et al., 2018). For a negative effect, the argument is that overconfident CEOs tend to make less strategic decisions and engage in strategic persistence and excessive risk-taking (Hiller & Hambrick, 2005). In contrast, the argument for a positive effect is that overconfident CEOs tend to make decisions relatively quickly, and they are associated with innovation and inspiring and stimulating vision (Gigerenzer & Gaissmaier, 2011; Picone et al., 2014). In spite of the theoretical arguments, most empirical studies have found that overconfidence as a bias decreases profit (Kim & Jang, 2020; Burkhard et al., 2018; Jiang et al., 2011; Montier, 2002). In the restaurant industry, Kim and Jang (2020) report a negative impact of overconfidence on profitability. Given the predominance of the negative impacts and the fact that overconfidence is viewed as a bias, we propose that:

H2: Overconfidence heuristic has a direct, significant negative effect on hotel performance.

2.5.2 Mediation analysis of heuristics through RMS overrides effectiveness

Studies on RMS in the hotel industry indicate that when they are effectively implemented, hotel performance improves (Ortega, 2016; Jain & Bowman, 2005; Rannou & Melli, 2003). The argument for this positive effect is that effective RMS make more accurate forecasts of future demand, which is then used to allocate the right inventory to the right customer at the right price, thus improving hotel revenue performance (Ortega, 2016). However, RMS can go wrong in practice, leading to dramatic price fluctuations and damaging effects on firm performance (Yeoman, 2019). When RMS go wrong, the immediate solution is to override it using quick fixes or heuristics. Therefore, the extent to which the override fixes the pitfalls (i.e., override effectiveness) impacts the firm performance. Following this reasoning, we propose that:

H3: RMS override effectiveness has a significant positive effect on hotel performance

Since heuristics-based overrides aim to improve RMS effectiveness and performance (Mohammed & Denizci Guillet, 2024), it is reasonable to argue that heuristics may indirectly affect performance through RMS override effectiveness. In AI-enable RMSs, the algorithms use machine-learning techniques, which can learn from overrides to improve their effectiveness (e.g., forecasting accuracy). This advantage has been investigated by Schwartz et al. (2021) in a hotel RMS forecasting setting using experimental strategies and assuming different scenarios for learning across multiple time horizons. They concluded that "in short-term horizons (21 days or less) learning has no impact on the effectiveness of forecast combinations, while in longer forecasting horizons, the impact of learning is positive—the more learning, the more effective the forecast combinations in generating accurate forecasts" (pp. 286-287). Building on this evidence, we argue further that applying anchoring and overconfidence to override RMS can improve RMS effectiveness, which will, in turn, ultimately affect hotel performance. Therefore, it is hypothesised that:

H4: Anchoring heuristic has ***a***) a direct significant positive effect on RMS override effectiveness, which in turn has ***b***) a mediation effect on the relationship between anchoring and performance.

H5: Overconfidence heuristics has ***a***) a significant negative effect on RMS override effectiveness, which in turn has ***b***) a mediation effect on the relationship between overconfidence and performance.

3. Methodology

3.1.Research design and target population

Given the study's dual objectives, an exploratory sequential mixed methods design was adopted, starting with a qualitative study and then a quantitative cross-sectional survey. The choice of these methods was informed by the limited studies on the application of heuristics to RMS override decision-making, which inhibited knowledge and understanding of the heuristics that are frequently applied, the reasons behind their frequent use and how they affect hotel performance. Therefore, neither qualitative nor quantitative alone could address these gaps. For that reason, the qualitative study aimed to provide insights into the two most frequently used heuristics in RMS override decision-making and the underlying reasons behind their frequent use. These insights from the qualitative study informed the conceptual framework tested in the quantitative study. For instance, we focused on anchoring and overconfidence heuristics because of the findings from the qualitative phase, which were cross-validated in the quantitative survey as the most important heuristics. Also, the insights behind the frequent use of anchoring and overconfidence were leveraged to provide a nuanced understanding of how the two heuristics affect hotel performance differently through the mechanism of RMS override effectiveness, noting their associations with the type of overrides (output vs. input). Both studies targeted hotel revenue management professionals across the globe using RMS and making overrides to their systems' recommendations. We defined revenue management professionals as revenue analysts, managers, directors, or sales and marketing executives with RM responsibilities.

3.2.Data collection and sample size

Qualitative data collection phase: The qualitative data were collected through semi-structured interviews conducted online using Microsoft Teams. The interviews were conducted in English, and the sessions were recorded with participants' permission and automatically transcribed for analysis. The principal questions asked are given in Section 3.3. The participants meeting the eligibility criteria of using RMS and making overrides to the systems were recruited using two sampling strategies: convenience, based on postings on LinkedIn and emails to the researchers' network, and snowballing, based on participant referrals. These methods were deemed appropriate because we could confirm participants' professional backgrounds from their LinkedIn to ascertain their experience in RMS. Besides, the methods are appropriate when targeting professionals from different geographical areas. Sample saturation was achieved after the 15th interview, but the final sample size was 20. The interviews lasted 44 minutes on average, with 30 and 59 minutes as the shortest and longest, respectively. Additional information about the background of the participants in terms of gender, position and experience is presented in Table 1 in the results section.

Quantitative data collection phase: The quantitative data were collected through a survey administered online in English and Simplified Chinese using the Qualtrics platform. Expert back-to-back translations were done to ensure data accuracy from the two versions of the instruments. Similar to the qualitative data collection strategy, the survey link was shared on the researchers' LinkedIn to enrol the respondents. In addition to that, the researchers attended conferences and industry talks where the survey links were shared. Two professional associations in revenue, marketing, sales and hospitality technology also assisted the researchers in circulating the survey link widely to their network through publications in their newsletters, LinkedIn, blogs and social media. Thus, the sampling method was convenience since no sampling frame existed for revenue managers who use RMS and make overrides to the system. After 6 months of continuous efforts to enrol more respondents, 501 hotel revenue management professionals responded worldwide. Out of this, 172 met the eligibility criteria and completed the survey. These valid responses were from 30 countries and special administrative regions.

Quantitative sample adequacy for statistical analysis: Given the comprehensive efforts put into the data collection and the extended period the survey link stayed active, it is believed that the eventual sample size indicates that most hotels are still not using RMS or overriding their systems. Other reasons could be the busy schedules of revenue management professionals, which have been acknowledged by other researchers on managers and investors (Ahmad & Shah, 2020). These notwithstanding, the sample size was still large enough to meet the statistical requirement for the partial least square structural equation modelling (PLS-SEM) adopted for this study. According to Reinartz et al. (2009), PLS-SEM achieves acceptable levels of statistical power even when the sample size is relatively small (i.e., 100 observations). As a general rule for SEM, Hussey and Eagan (2007) stated that 5-10 observations are required for each model parameter estimated. Osborne et al. (2008) and other researchers have recommended a ratio of 10 – 15 respondents per item in the model. This stricter criterion yields a minimum of 120 (12 items x 10) responses for this study. In similar studies conducted on heuristics, the sample sizes were generally small: Shah et al. (2018) used a sample of 143, while Ahmad et al.'s (2021) sample was 169. From 29 publications in six leading hospitality management-focused journals, Ali et al. (2018) observed that the sample sizes ranged between 106 and 1,500. Out of this, 7 had sample sizes less than 150.

Samples' generalizability: Although both the qualitative and quantitative data were sampled from RM executives in 30 geographical countries and administrative regions, with some participants having multiple-country experiences or overseeing clusters across different countries, it is important to clarify that samples' generalisability could remain an issue to contend with. Nevertheless, it can be argued that even though the samples may not adequately represent global hotel segments, they reflect that the majority of the hotels covered are large-sized (> 300 rooms is 57.6%), five-star rated (73.3%) and upmarket/luxury category (72.1%) (see Table 2), which is in line with the global trends. According to Dawson (2025), Skift reports that less than 15% of the global hotel market is using revenue management technology, with the majority in the large and luxury segments.

3.3.Measurement

Semi-structured interviews were conducted to ascertain the two frequently used heuristics in RMS overrides and the reasons underlining their frequent use. These interviews were guided by questions from the researchers' knowledge and understanding of the literature and suggestions from three expert industry professionals starting the interviews. The principal questions asked included, "Could you explain how you override your system's recommendations?", "Could you explain why you choose to override the system the way you do? and "What are your reasons for choosing to override the system the way you do? Probing questions, based on the responses, were asked.

For the survey, the items for the constructs were adapted from existing literature and refined from the interviews. The constructs were measured on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Anchoring was measured using three items adapted from Kahneman and Tversky (1979) and Waweru et al. (2018). The three items used to measure overconfidence were adapted from Jain et al. (2020) and Waweru et al. (2008). RMS override effectiveness was subjectively measured with three items adapted from Rodrigues and Hickson (1995). Finally, perceived hotel performance was measured using the average daily rate, occupancy and revenue per available room (Ortega, 2006). These were measured in comparison to the hotel's competition.

3.4.Data analysis method and procedure

The qualitative data were thematically analysed following the process prescribed by Braun and Clarke (2006). With this, open coding was used to categorise the text into emergent themes, while axial coding categorised them into existing themes and sub-themes. Table A2 in the appendix illustrates how the coding process unfolded. The quantitative data were analysed using PLS-SEM, a widely accepted technique for examining complex relationships among several constructs (Hair et al., 2019). Since our conceptual framework had multiple constructs (i.e., four), the PLS-SEM was preferred over other statistical methods, such as the covariance-based SEM or ordinary least square (OLS) regressions, which are inefficient when estimating structural paths and causality without imposing distributional assumptions such as normality (Hair et al. 2019). The other justifications for using the PLS-SEM are the limited studies on the topic and the restricted sample size. According to Hair et al. (2019), the PLS-SEM is suited for small sizes restricted by a small population. Ali et al. (2018) also supplement that the PLS-SEM is most suited when the assumed cause-effect relationships are not sufficiently explored.

In a review of hospitality research, Ali et al. (2018) found a growing use of PLS-SEM and recommended guidelines for using it accurately. Following their guidelines and that of Hair et al. (2019), the analytical process proceeded in three steps: 1) assessment of the measurement model, 2) evaluation of the structural model and path analysis, and 3) assessment of the predictive power of the model. The results of these steps and the statistical thresholds used to draw relevant conclusions on the various tests are provided in sections 4.4.2, 4.4.3 and 4.4.4, respectively.

3.5. Common method bias

Collecting data on a single scale may result in a common method bias (CMB), which, if not checked, can produce unreliable estimates. To overcome this problem, the study followed the techniques Farooq et al. (2018) recommended to not inform the respondents about the study's objectives and assure them of anonymity. It also used the Harman single-factor method to check for the presence of CMB. The exploratory factor analysis was used to generate a single factor using all the dependent and independent variables. The total variance explained for this single factor was 26%, which is less than the benchmark of 50%. Hence, CMB was not a problem in the data (Streukens et al., 2017).

4. Results

4.1. Profile of the qualitative research participants

The 20 participants of the qualitative study comprised 8 (40%) females vs 12 (60%) males who had several years of working experience (averaging 13.7 years with only 4 having less than 10 years) in multiple countries or markets around the globe (23 countries) and conversant with several RMSs, both in-house and third-party developed. All the participants were making overrides to their RMSs. Table 1 lists the details of the participants.

Table 1: Background information on qualitative study participants

Interviewee	Gender	Position	Experience (# years)	Experience (# RMS)
I1	M=male	Revenue Optimiser & Consultant	26	1
I2	F=female	Revenue Management Team Lead	10	2
I3	F	Director of Revenue	15	1
I4	M	Sales Manager	5	1
I5	F	RM Consultant & RMS Co-founder	18	1
I6	M	Revenue Management Voyager	0.5	1
I7	M	Director of Revenue	10	3
I8	F	Revenue Analyst	0.3	1

I9	F	Revenue Optimisation Specialist	25	3
I10	M	Revenue Manager	5	1
I11	F	Director of Revenue	12	3
I12	M	Director of Revenue & Distribution	17	3
I13	M	Director of Revenue Strategy	10	2
I14	M	RM Consultant & RMS Co-founder	17	1
I15	M	Senior Director of Revenue	15	3
I16	F	Revenue Manager	15	1
I17	M	Area Director of Revenue	17	5
I18	F	Director of Revenue & Distribution	15	3
I19	M	Director of Rev. & E-commerce	23	2
I20	M	Revenue Strategist	18	3

4.2. Findings of the qualitative study

The insights gathered from the interviews reveal that anchoring and overconfidence are the two most frequently applied heuristics. Eleven (11) participants frequently used anchoring, while nine (9) participants frequently used overconfidence. Illustrative quotes exemplifying the use of these heuristics are: *Anchoring* – "I mostly rely on my KPIs and adjust the system toward achieving them. (I7)" and *Overconfidence* - "I depend on my superior knowledge of the market to override the system." (I10). Both heuristics were applied to override RMS outputs (i.e., direct overrides) or input (i.e., indirect overrides) to correct the system's pitfalls and improve its effectiveness and performance. However, overconfidence was closely associated with output overrides. By contrast, anchoring was closely associated with input overrides. The reasons underlining the frequent use of these heuristics for the types of overrides were categorised into four (compliance, RMS learning capability, transparency, and experience and knowledge of the local market) and thematically organised into two sub-headings related to anchoring and overconfidence.

4.2.1. Reasons underlining the frequent use of anchoring heuristics

While all the participants of the qualitative study indicated that RMS override was necessary due to the systems' practical inability to capture all relevant information, the decision to use anchoring heuristics was particularly associated with two factors: compliance with company policies and belief in RMS learning capability. For compliance, it was noted that revenue managers used the anchoring heuristic to override RMS because they feel it does not violate established procedures and company policies on overrides but helps to maintain a trail of evidence that can be used to justify the decisions. This viewpoint was expressed by a participant as:

> I have worked with the system for many years and always override the inputs because it is our company policy. We even have a KPI [key performance indicator] restricting the number of overrides, which I don't like but must comply with. (I14)

Another participant stated, "Based on our company policies and standard practices, we are encouraged to override only the inputs." (I11)

The second predominant reason for the frequent use of anchoring heuristic was related to the RMS learning capability, which refers to the design and set-up features that allow the systems to automatically adjust their outputs and recommendations without the need for a reconfiguration. A participant expressed this view: "One of my responsibilities is to keep the system informed about what's happening so that it can learn and adjust to what's happening outside of its parameters". (I1). Due to the machine learning algorithms of RMS, a significant majority of those using the anchoring heuristic believed the systems were intelligent enough to learn from their overrides, so they preferred to use anchoring to teach the systems to adjust themselves rather than override their outputs directly. Highlighting this point, a respondent stated, "Output override is, for me, the least sustainable in the long term. You just put the system on hold and effect the change that you want. The change does not provide any cue to the system to learn from or become more effective". (I15).

4.2.2. Reasons underlying the frequent use of overconfidence heuristics

Invariably, RMSs use computationally difficult-to-understand-and-explain algorithms that lead many revenue management professionals to describe them as black boxes (Webb et al., 2023; Pereira, 2016). In seeking to understand the reasons for the frequent use of overconfidence, one major reason that was mentioned severally by the users of this heuristic was the lack of transparency (i.e., opacity in the processes, data points and weights used by a system to generate outputs and recommendations) and the acute understanding or interpretability (ability to make meaning) of the RMSs' algorithms. In one of the references, a respondent remarked, "That black-box feeling affects my trust in the systems and drives me to override the system with some confidence". (I15). Apart from the lack of transparency, the prospect of automated RMS replacing humans was associated with low trust in RMS and the tendency to overrate the human capacity to make quicker and better decisions. A participant expressed this optimism as:

> There are advancements in revenue management systems, but it's not there yet where they could replace revenue managers. The human brain is more powerful than the computer. It can react to new information quicker than the computer. (I17).

The second primary reason associated with the frequent use of overconfidence was related to accumulated experience and knowledge of the local market, which creates a sense of superior intelligence and overconfidence. A participant stated, "I have a lot of experience in the market and insights on the historical data. Therefore, I have more confidence in myself to make the right output override decision." (I10). Another participant stated that:

> What makes me confident in my override decisions is that I have established a proven track record of making the right decisions where the system has failed. So, my GM [general manager] trusts me on that. (I3).

4.3.Profile of the survey participants

Table 2 presents the valid survey respondents' profiles for the quantitative data analysis. The respondents were from 30 countries comprising the following modal groups: China (47.1%), males (54.1%), aged 27-42 (72.1%), bachelor and master holders (80.8%), 7-9 years of RM experience (26.2%), and Revenue Director position (28.5%). The majority of the hotels the respondents were working in fell into the following categories: five-star, upmarket or luxury segment, 80-90% average occupancy rate and more than US$250 average daily rate.

Table 2: Profile of survey respondents

Characteristics	**Category**	**Frequency (N=172)**	**Per cent**
Gender	Female	79	45.9
	Male	93	54.1

Education	College (no degree)	33	19.2
	Bachelors	89	51.7
	Masters	50	29.1
Age (years)	< 27	8	4.7
	27 – 42	124	72.1
	43 – 58	37	21.5
	59 – 68	3	1.7
RM Experience (years)	1 – 3	19	11.1
	4 – 6	33	19.2
	7 – 9	45	26.2
	> 9	75	43.6
RM Position	Trainee	1	0.6
	Analyst	4	2.3
	Assistant Manager	3	1.7
	Manager	46	26.7
	Senior Manger	27	15.7
	Director -Property	31	18.0
	Director-Area/cluster/group	49	28.5
	Other-Sales and Marketing with RM function	11	6.4
Size of hotel (rooms)	< 100	10	5.8
	101 – 300	63	36.6
	301 – 600	44	25.6
	601 – 1000	17	9.9
	> 1000	38	22.1
Star rating	3 and 4	46	26.7
	5	126	73.3
Classification	Budget/Economy	7	4.1
	Midmarket/Midsegment	41	23.8
	Upmarket/Luxury	124	72.1
Average Occupancy rate (%)	< 50	21	12.2
	30 – 59.99	15	8.7
	60 – 69.99	31	18.0
	70 – 79.99	31	18.0
	80 – 89.99	41	23.8
	90 and above	33	19.2
Average Daily Rate (US$)	< 100	24	13.9
	100 – 149	58	33.7
	150 – 199	28	16.3
	200 – 249	20	11.6
	250 – 299	10	5.8
	300 and above	32	18.6

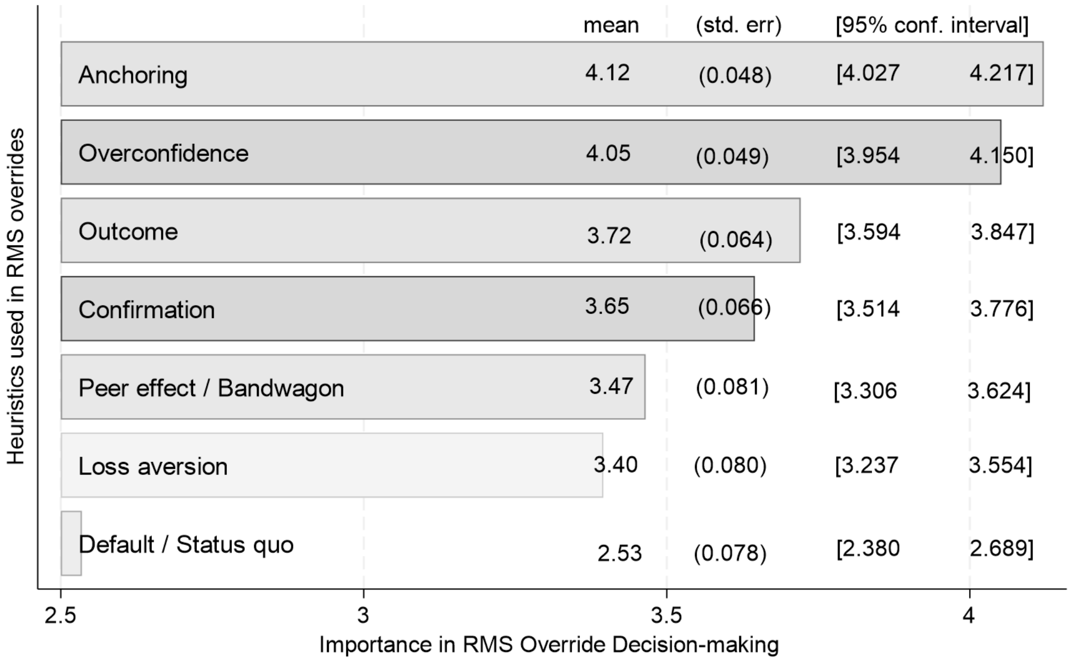
4.4. Findings of the quantitative study

Before the SEM results, the importance of the two frequently used heuristics was evaluated *vis a vis* other heuristics from the literature to provide additional evidence to support the qualitative results on why they are frequently used. This result is presented in the next section.

4.4.1. The importance of anchoring and overconfidence heuristics in RMS overrides

Figure 2 displays how important the revenue management professionals rated the two frequently used heuristics in RMS overrides relative to other heuristics. Anchoring and overconfidence were rated as highly important than the other heuristics, reaffirming why they are frequently used. For each heuristic, a clear definition and practical example were provided to the respondents. These were developed from the literature and interviews and validated through a pilot test. For example, Anchoring heuristic was defined as the "tendency for a revenue manager to emphasize or give too much weight to a piece of information (the 'anchor' or 'reference'), such as historical room rates, past or future performance metric, without adequately considering current market conditions or new data". The example given to illustrate this was "You monitor your hotel's booking pace and pickup for a particular date in the future. After reviewing them against your historical trends and patterns for the same date, you anticipate that your forecast will likely be missed at the current recommended rates by the system. Thus, you make a strategic decision to adjust the recommended rates in line with the previous year's rates to achieve your target".

Figure 2: Importance of anchoring and overconfidence relative to other heuristics



4.4.2. Assessment of the measurement model

Assessment of PLS-SEM results involves two steps: evaluation of the measurement model and assessment of the structural model (Ali et al., 2018; Hair et al., 2017). Table 3 presents the results of the first step, which meets all the criteria for reliability and validity. The indicator loading, Cronbach alphas and composite reliability (CR) are larger than 0.7. The average variances extracted (AVEs) are higher than 0.5, indicating convergent validity. Based on the Fornell-Lacker criterion, the square roots of the AVEs are greater than the bivariate correlations, confirming discriminant validity (Ringle et al., 2015). Also, the HTMT ratios are less than 0.85 for every latent variable, assuring discriminant validity (Henseler et al. (2016).

Table 3: Properties of the measurement model

A: Reliability of items

Construct	Indicator	Loadings	Cronbach α	CR	AVE
Hotel performance	PERF1	0.944	0.916	0.934	0.856
	PERF2	0.901			
	PERF3	0.931			
Anchoring	ANCH1	0.843	0.735	0.850	0.654
	ANCH2	0.796			
	ANCH3	0.786			
Overconfidence	OCON1	0.867	0.836	0.853	0.750
	OCON2	0.895			
	OCON3	0.835			
RMS override effectiveness	OEFF1	0.699	0.827	0.931	0.728
	OEFF2	0.930			
	OEFF3	0.912			

B. Fornell-Lacker Criterion				
	1	**2**	**3**	**4**
1. Anchoring	**0.809**			
2. Overconfidence	-0.334	**0.866**		
3. Performance	0.216	-0.202	**0.925**	
4. RMS override effectiveness	-0.185	-0.008	0.133	**0.854**

C. Heterotrait-Monotrait (HTMT) ratios				
	1	**2**	**3**	**4**
1. Anchoring				
2. Overconfidence	0.413			
3. Performance	0.259	0.220		
4. RMS override effectiveness	0.217	0.060	0.157	

4.4.3. Evaluation of the structural model and path analysis

Since all the measurement model items were reliable and valid, we proceeded with the second step to evaluate the structural model. Table 4 presents the results obtained from the bootstrapping technique with 5000 subsamples. First, we check for collinearity among the predictors by examining the variance inflation factors (VIFs) of less than 5, indicating no collinearity problem (Henseler et al., 2016). Second, we examine the model fit indices (SRMR, d_ULS and d_G), which indicate that the estimated model fits the data well. Finally, we evaluate the signs and significance of the coefficients to test the hypothesised relationships using a 5% significance level. These results imply that the direct effects hypothesised by H1, H2, H3 and H4a are supported.

Table 4: Path coefficients

Hypothesis	Hypothesized path	Coef.	t-statistic	p-value	VIF	VAF (%)	Decision
H1	ANCH -> PERF	0.205	2.704	0.007	1.172		Supported
H2	OCON -> PERF	-0.154	2.096	0.036	1.152		Supported
H3	OEFF -> PERF	0.160	2.116	0.036	1.045		Supported
H4a	ANCH -> OEFF	-0.213	2.459	0.014	1.125		Supported
H4b	ANCH -> OEFF -> PERF	-0.034	2.064	0.042		19.88	Supported
H5a	OCON -> OEFF	-0.080	0.807	0.420	1.125		Unsupported

H5b	OCON -> OEFF -> PERF	-0.013	0.676	0.250		7.83	Unsupported

Note: ANCH = Anchoring heuristic, OCON= Overconfidence heuristic and OEFF = RMS Override effectiveness
Total effects: ANCH -> PERF): β= 0.171, t-value = 2.186, p-value = 0.014
OCON -> PERF): β= -0.166, t-value = 2.234, p-value = 0.013
VAF (variance accounted for) = indirect effect/total effect

When RMS override effectiveness is considered a mediator, the results (β = -0.034, p-value = 0.042, VAF = 0.1999) support H4b, indicating that the relationship between anchoring and hotel performance is partially mediated by RMS override effectiveness. However, RMS override effectiveness does not mediate the relationship between overconfidence and performance.

4.4.4. Assessment of the predictive power of the model

Although the study's aim was not to use the structural model for prediction, methodological researchers recommend that due to limitations of the R^2 to in-sample variation, assessment of the model's predictive power allows capturing of the out-of-sample predictive performance, hence, relevant to the model validation. The results, as displayed in Table 5, show that the PLS-SEM_RMSE (or PLS-SEM_MAE) are less than LM_RMSE (or LM_MAE), indicating a good predictive power (Shmueli et al., 2019). For the PLS Q^2 predict, the values are greater than 0, indicating good predictive power.

Table 5: Results of PLS Predict Analysis

Indicator	PLS Q^2 predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	IA_RMSE	IA_MAE
PERF1	0.080	1.183	0.940	1.208	0.952	1.234	0.982
PERF2	0.024	1.029	0.884	1.057	0.907	1.042	0.886
PERF3	0.024	1.089	0.881	1.118	0.901	1.103	0.888
OEFF1	0.030	1.908	1.506	1.948	1.524	1.880	1.459
OEFF2	0.010	1.920	1.492	1.975	1.550	1.929	1.525
OEFF3	0.022	1.958	1.577	1.996	1.624	1.980	1.633

4.4.5. Robustness checks of the results

Given that performance was subjectively assessed by the respondents as the extent to which they believed their hotels' metrics (i.e., average daily rate (ADR), occupancy (occ) and revenue per available room (RevPAR)) improved due to their heuristic-based decisions, it was crucial to cross-validate these findings with objective measures of ADR and occupancy reported in the survey. The results of these checks, presented in Tables 6 and 7, are consistent with the findings in Tables 4 and 5, respectively, reinforcing their reliability and credibility.

Table 6: Path coefficients

Hypothesis	Hypothesized path	Coef.	t-statistic	p-value	VIF	VAF (%)	Decision
H1	ANCH -> PERF	0.196	2.194	0.028	1.180		Supported
H2	OCON -> PERF	-0.178	2.241	0.025	1.131		Supported
H3	OEFF -> PERF	0.010	2.114	0.039	1.050		Supported
H4	ANCH -> OEFF	-0.232	2.787	0.005	1.124		Supported
H4a	ANCH -> OEFF -> PERF	-0.002	2.064	0.036		1.01	Supported
H5	OCON -> OEFF	-0.081	0.789	0.430	1.124		Unsupported
H5a	OCON -> OEFF -> PERF	-0.001	0.676	0.210		0.57	Unsupported

Note: ANCH = Anchoring heuristic, OCON= Overconfidence heuristic and OEFF = RMS Override effectiveness
Total effects: ANCH -> PERF): β= 0.198, t-value = 2.212, p-value = 0.027
OCON -> PERF): β= -0.177, t-value = 2.270, p-value = 0.023
VAF (variance accounted for) = indirect effect/total effect

Table 7: Results of PLS Predict Analysis

Indicator	PLS Q^2 predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	IA_RMSE	IA_MAE
ADR	0.037	1.677	1.403	1.714	1.425	1.710	1.463
OCC	0.007	1.813	1.473	1.826	1.409	1.820	1.486
OEFF1	0.027	1.905	1.505	1.938	1.517	1.880	1.459
OEFF2	0.014	1.915	1.489	1.964	1.538	1.929	1.525
OEFF3	0.025	1.954	1.572	1.988	1.607	1.980	1.633

It is instructive to note that the consistencies in the results are not mere coincidences. They reflect the reliability of alternative methods adopted for evaluating hotel performance in the study. However, the correlation between the subjective and objective performance measures is strong and positive (r=0.89, p=0.001).

5. Discussion and implications

This study has unveiled several insights into heuristic decision-making within the context of automated systems (i.e. RMS). First, it has exposed that when overriding RMS, revenue management professionals tend to heavily weight their decision on recent past outcomes achieved (i.e., anchoring), which supports the argument that recent occurrences are more attention-grabbing (Odean, 1998). It also supports Payne et al.'s (1993) effort accuracy framework, which posits that decision-makers consider the cognitive effort needed to make a decision. They often easily weigh their decisions toward more recent information and outcomes (Del Campo et al., 2016). Second, the study has confirmed that revenue managers tend to overestimate their knowledge and abilities to make the right decisions, which is why overconfidence emerged as the second most important heuristic. Chen et al. (2007) found that one of the reasons why Chinese investors make poor trading is overconfidence. Rationalising the current study's findings with the interview insights, it is noted that the revenue managers' overconfidence stems from two angles: the lack of transparency in the RMS algorithms, which lowers their trust and confidence, and the belief that they are more knowledgeable about the local market based on several years' accumulated experience.

Third, the findings revealed that the direct effects of anchoring and overconfidence on performance are positive and negative, respectively, consistent with the literature and the hypotheses developed (Burkhard et al., 2018; Montier, 2002). Additionally, it supports Jiang et al.'s (2011) conclusion that managerial overconfidence decreased firm profitability in China. Although the direct effect of overconfidence on RMS override effectiveness was not significant, this was not surprising, considering that the evidence from the qualitative results indicated that it was associated with direct overrides. To our surprise, anchoring's effect on RMS override effectiveness was negative. However, we can use the patterns observed in the qualitative data to rationalise this. From the qualitative interviews, it was noted that revenue managers use anchoring to comply with their company policies and not necessarily because they believe it is the best thing to do. In some cases, participants stated that they used it as trial and error whenever they were unsure because it allowed a "what if" scenario analysis. These reasons, we believe, could make anchoring heuristics distortionary to the RMS learning instead of enhancing it.

Fourth, the study findings indicate that RMS override effectiveness partially mediates the relationship between anchoring and hotel performance but not the overconfidence-performance relationship. The finding that overconfidence has unmediated negative effects on performance suggests biases in its application to output overrides. However, the partial mediation of anchoring implies that the RMS may be learning from this heuristic to become more effective. Thus, it can be used to enhance RMS effectiveness and performance in a hybrid price decision-making environment (Haynes & Egan, 2024). As noted from the interviews, one of the rationales for using anchoring or overconfidence is related to using RMS overrides to teach the system to adjust itself. This viewpoint aligns with Schwartz et al.'s (2021) observation that the human-system learnings' impact on effectiveness may depend on the time horizons, with no impact within short-term horizons (21 days or less) and a positive impact in longer time horizons.

The uniqueness of the context of this study (i.e., human-RMS interaction) makes novel contributions to heuristic decision-making that are worth highlighting. It recognises that in human-RMS interaction, heuristics can be used to influence RMS effectiveness and models this conceptualisation into a heuristics-performance relationship. Thus, it hypothesised that in addition to directly affecting hotel performance, heuristics can indirectly affect performance through RMS override effectiveness when the systems can take cues or learn from the heuristics. The findings partially supported this hypothesis, highlighting that not all heuristics may affect RMS override effectiveness. For the two frequently used heuristics in RMS override decision-making, the findings showed that whereas anchoring affects RMS override effectiveness, overconfidence does not.

The qualitative insights on the underlying reasons shed light on the differential impacts of anchoring and overconfidence. The interviews elucidated that although both heuristics are appealing, anchoring was preferred to overconfidence when the decision makers believe the system learns from their overrides and are committed to using heuristics to achieve the long-term revenue goals through improving the RMS. On the contrary, overconfident revenue managers were pessimistic about the RMS learning capability, exhibiting intolerance about the no or slow-paced learning of RMS and overriding to achieve the short-term goals and targets. This fundamental difference in beliefs showed that anchoring heuristics was associated with indirect overrides (i.e., adjusting the RMS inputs to yield a desired value), and overconfidence was related to direct overrides (i.e., changing the RMS outputs). This could explain why overconfidence did not significantly affect RMS override effectiveness in mediating the relationship.

Practically, the findings of this study hold several important implications for the application of heuristics in overriding RMS recommendations or automated decision systems in general. Starting with the findings from the qualitative phase, the study has exposed anchoring and overconfidence as the widely used heuristics that revenue management professionals need to pay attention to and be aware of their possible biases in decision-making. The qualitative insights on the reasons for their frequent applications can be used to regulate the frequency or type of overrides. For example, the lack of transparency and acute understanding of the system's decision-making process were the primary reasons for using the overconfidence heuristic. This implies that override decisions based on overconfidence could be minimized if the systems are transparent. For anchoring, appropriate policies or guidelines could regulate its use since compliance was one of the main reasons behind its frequent use.

The quantitative results equally have implications. First, they underscore the significant effects of heuristics on hotel performance, which can guide practitioners in knowing how their choice of heuristics affects the performance of their companies. Second, the findings show that aside from the direct effects of heuristics on performance, there are indirect effects through RMS override effectiveness that need to be acknowledged. Especially when the partial mediating effects are competitive, they can reverse the direct effects. Third, the negative impact of anchoring on RMS override effectiveness, contrary to expectations, indicates that most RM professionals do not fully believe that the RMS algorithms learn from historical data as anchors or at least not as quickly or intelligently as technology providers propagate. This calls for education on how the system learns from overrides to become more effective. As part of the education, RM professionals could be trained to provide the right cues or teaching signals to the RMS to facilitate its effective learning. Also, it may be helpful for users to understand how long it takes for systems to truly learn from human interventions to develop the endurance to wait and see and trust the process.

6. Conclusion

Positive psychology and behavioural economics have identified several heuristics (i.e., mental shortcuts or computationally simple rules) that can be used to quickly solve problems or make decisions under risk, uncertainty or incomplete information as accurately as sophisticated methods. These heuristics have been widely applied to the hotel revenue management decision-making process, involving humans and computerised systems, to override the systems' outputs or input to address its pitfalls, improve its effectiveness and ultimately increase performance. However, research has yet to provide insights into the commonly used heuristics, the reasons behind their frequent use and how they affect hotel performance. This study filled these gaps by applying exploratory sequential mixed methods to interview hotel revenue management professionals (i.e., revenue analysts, managers, directors, or sales and marketing executives with RM responsibilities) and survey them.

The findings have provided empirical evidence to conclude that anchoring and overconfidence are the two most frequently used heuristics to override RMSs' recommendations. The reasons underlining their frequent use included compliance with company policies and the lack of transparency in the systems. The findings also established these heuristics' direct and indirect effects on hotel performance, unveiling the mediating role of RMS override effectiveness. Through the structural analysis, the study demonstrated that RMS override effectiveness mediates the relationship between anchoring heuristics and performance but not overconfidence, highlighting the nuances of heuristics that hotel revenue management professionals can apply to make override decisions without hurting performance. Although the study focused on the application of heuristics to override RMS decisions, its findings have contributed broadly to the understanding and implications of using heuristics to complement automated decision-support systems.

6.1 Limitations and directions for future research

Despite the valuable contributions of this study, some inherent limitations regarding the scope, methodology and theory must be acknowledged and incorporated into future studies. First, due to the study's research gaps and objectives, the study context was limited to hotel revenue management contexts, where heuristics are applied to override RMS recommendations or decisions. This limited scope implies that the two frequently used heuristics may not necessarily hold for other managerial decisions outside this context. Therefore, future studies can evaluate heuristics in other contexts to provide comparable evidence. Second, the sample size was restricted due to the small population of hotels using RMS and performing overrides. Thus, the structural relationships of the two frequently used heuristics could be re-examined with several opportunities to explore the phenomenon in new settings, such as tourism recommendations systems in general, apply new and different methodologies to capture actual impacts, such as field or laboratory experiments, and implement new theoretical frameworks or propose new ones that can advance the boundaries of the current study. With larger samples, multi-group or cross-cultural analysis could also be explored to reveal hidden patterns or differences.

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