Big data usage in transient hotel room pricing: deconstructing a black box

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Abstract

This research explains the use of big data in transient hotel room price decision-making, where transient prices are those charged to individuals rather than groups or those with specially negotiated corporate rates (Hayes & Miller, 2011; Ideas, 2018). From a practice-based viewpoint, this issue had not been fully explored in the literature and the links between big data and pricing in the hospitality literature appeared particularly blurred. It was also directly suggested that more empirical research was needed into big data "issues" (Raguseo, 2018, p.187). Crucially, it was felt that the complexities and realities of the use of big data in transient hotel room price decision-making, in particular at the individual property level, were situated within a black box that required deconstruction.

To achieve this, Straussian grounded theory was utilised. The speed of development of the literature on big data and the many gaps in the literature in this area of hotel pricing made it a challenge to develop hypotheses to test. Instead, this approach allowed for the successful deconstruction of the black box by generating a substantive theoretical framework that could explain the use of big data on the transient hotel room price decision-making process. This resulted in three main contributions to knowledge.

The first was that big data was not the only input into the price decision-making process. In fact, through various discussion processes the general manager and revenue specialists, where present, interacted to reinterpret the big data with small data, which was characterised by customer insights locally generated in the hotel property. This formed a new type of hybridised data. The discovery of this hybridised data also meant it was possible to reconstruct the Vs framework, commonly used to define big data. This resulted in the contribution of a new typology of pricing data within the hotel context.

The second contribution was uncovered whilst observing the use of hybridised data within the price decision-making process. Here the countervailing forces of local market dynamics, characterised by the stability and predictability of demand factors, resulted in a simplified interpretation of the hybridised data. General Managers felt a pressure to make a decision that often, given the unpredictability of the market, became a decision made using trial and error, short-term, tactical approaches that did not incorporate the full range of hybridised data available to them. Observing these processes also allowed for a more general contribution by allowing fresh insights into the role of the general manager to bring up-to-date the existing literature on the role.

Ultimately it discovered that the impacts of big data on price decision-making were not as significant as the hype around big data would suggest. Market forces proved more powerful than the data. This suggests not only that economics should become a greater part of revenue education but also that although the technology is capable of making constant, instantaneous price changes the process of decision-making should be slowed down. This would, in turn, make decision-making less reactive as there would be time to factor in all the hybridised data that has been generated as overall fewer decisions would be made.

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Glossary of Technical and Methodological Terms

TERM	DEFINITION
ARI (Average Rate Index)	A performance metric that compares a hotels daily revenue share against its competitor set.
ARPAR (Adjusted Revenue Per Available Room)	A performance metric that takes into account the costs per available room in the RevPAR calculation, calculated by dividing the net revenues of a property by the total available rooms for sale.
Automated revenue management systems	A data-driven system that using algorithms can make revenue management decisions, such as setting prices, technically without human intervention.
Axial Coding	Axial coding is an analytical process where, once the theoretical categories are delineated in terms of properties and dimensions, they can be viewed in terms of the relationships they have with each other (Strauss & Corbin, 1998).
Black box	A term existing in both technical and social science that describes a device, system or process solely in terms of its inputs and outputs without describing and explaining its structures or workings (Winner, 1993).
Classic grounded theory	The strand of grounded theory developed by Barner Glaser, often characterised by its assertion that researchers could obtain objective data by adopting a passive role in data creation (Glaser, 1978, 1992).
Coding Paradigm	The data analysis tool suggested for use in Straussian grounded theory. Strauss and Corbin (1998, p.128) describe the paradigm as a “perspective towards the data” that helps order the data in a way that both structure and process are understood.
Competitor Set	A group of competitor hotels that a hotel can benchmark itself against using a variety of performance metrics. This aggregated data is usually supplied by STR Global.
Constructivist grounded theory	The strand of grounded theory developed by Kathy Charmaz (2006, 2014) which takes a postmodernist approach to grounded theory.
Dynamic pricing	Real-time adjustments to transient room prices on the basis of supply and demand.
GOPPAR (Gross Operating Profit	A performance metric that allows for the

Per Available Room)	measurement of the profit impact of revenue and pricing strategies and is calculated by taking the total rooms revenue of the hotel less expenses incurred earning that revenue, divided by the number of available rooms for sale.
Hotel property level	An individual hotel unit.
MPI (Market Penetration Index)	A performance metric that compares the market share of a hotel against its competitor set based on occupancy.
Open Coding	Open coding is an analytical process that allows for the identification of concepts and ultimately theoretical categories in the data that has been collected.
Process	An element of the coding paradigm from Straussian grounded theory that focuses the analysis on how things occur, looking at the consequences that denote action/interaction over time of persons, organisations and communities in response to certain problems and issues.
RevPAR (Revenue Per Available Room)	A performance metric that incorporates both room rates and occupancy and therefore provides a snapshot of revenue performance based on how well the hotel is filling its rooms, as well as how much it is able to charge for those rooms. It is calculated by dividing total room revenue by the total number of available rooms in the period being measured.
RGI (Revenue Generation Index)	A performance metric that compares RevPAR performance against its competitive set.
Selective Coding	Selective coding is an analytical process where the core theoretical category is identified. It is reached once theoretical saturation has occurred and no new theoretical categories can be found emerging from the data.
Shadowing	An observation technique used in the research to allow for direct and focused observations of actions and behaviours in a real-life setting to uncover the realities of phenomena.
STR Global	The renowned hotel competitor and market benchmarking data provider headquartered in the USA but operating globally.
Straussian grounded theory	The strand of grounded theory developed by Anselm Strauss and later Juliet Corbin,

	informed by pragmatism and characterised by the use of the coding paradigm.
Structure	An element of the coding paradigm from Straussian grounded theory that looks at why things occur and conditions that denote the circumstances in which problems, issues, happenings or events pertaining to a phenomenon are situated or arise.
Theoretical Sampling	A sampling technique that is directed by the concepts and theoretical categories emerging from the data. Strauss and Corbin (1998) assert that theoretical sampling is directed by asking questions and making comparisons, which means following up on new data and comparing responses to better develop and understand the variety of properties and dimensions found in the emerging concepts and theoretical categories.
Transient Room Prices	Prices charged to individuals rather than groups or those with specially negotiated corporate rates (Hayes & Miller, 2011; Ideas, 2018).

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1. Introduction

Big data usage in transient hotel room pricing: deconstructing a black box

This first chapter addresses the question of why researching the use of big data on hotel transient room pricing is of value to both the academic world and the hospitality industry, where transient room prices are classed as being those booked by individuals rather than groups or those with specially negotiated corporate rates (Hayes & Miller, 2011; Ideas, 2018). It will also serve to place the research and the remaining thesis into context. The chapter is divided into three main sections. The first section will outline the focus of the research and highlight why it is a valuable area of research interest, given the current gaps in knowledge that exist in the literature. This section will serve to demonstrate that a black box exists around what is currently known about the realities of the use of big data on hotel transient room pricing at the hotel property level. It is the complexities and realities of the impact of big data on price decision-making processes that from a practice-based viewpoint are not fully explored in the literature and therefore exists in a black box that requires deconstruction. A black box is a term existing in both technical and social science that describes a device, system or process solely in terms of its inputs and outputs without describing and explaining its structures or workings (Winner, 1993). The theory surrounding black boxes in relation to this research will be explained further, later in this chapter. The second section of the chapter will introduce the aims, objectives and the methodological approach that will be used to deconstruct the black box. Finally, a chapter-by-chapter outline of the thesis will conclude the chapter, providing a guide for the reader.

1.1 Research focus, value and key gaps in existing knowledge

"In God we trust: all others must bring data". (William Edwards Deming, 1993)

This quotation from William Edwards Deming, an American engineer, statistician, academic and management consultant presents data as a kind of panacea and stresses his belief in the importance of data in management decision-making and his deep faith in its ability to provide a solution to a range of problems. However, Deming was born in 1900 and died in 1993 and so perhaps, he could not have anticipated the hype that would grow up around the concept of big data in the

modern business world. Today the levels of hype surrounding the positive impacts of big data have reached what has been described in the literature as “fever pitch” by Ransbotham, Kiron and Prentice (2016, p.3) and confirmed in other papers (Weinberg, Davis & Berger, 2013; Barnes, 2013; Constantiou & Kallinikos, 2015). Now, despite this hype, questions are beginning to arise as to whether big data is the cure-all some suggest it to be. Reading articles that extolled the virtues of big data sparked a strong interest in pursuing a big data research project that would help tackle the question of the level of impact big data has in a practical business context. A need to explore the realities of big data was uncovered, a need widely supported in the academic literature from several quarters. In the general big data literature Kitchin (2013, p.266) took a critical approach to big data studies, stating “as we enter the age of big data, it is clear that we need critical reflection and research.” This was later supported by Gandomi and Haider (2015, p.137) who also claimed there was “not enough fundamental discourse in academic journals” about big data. In more specific terms and more recently, the literature has agreed on the need for applying a practical focus to empirical research into big data. Günther, Mehrizi, Huysman and Feldberg (2017) called for future research to look at how different actors within organisations worked with big data and Raguseo (2018, p.187) agreed that currently the “literature has provided very little empirical evidence on [big data] issues.” He also stated that it should focus more heavily on the dynamics of the adoption of big data in companies. Mazzei and Noble (2017, p. 25) also believed “scholars are not exploring big data as a firm-level phenomenon with the potential to shift organizational decision-making and leadership”. Specifically in the hospitality trade press this has also been highlighted by Butler (2016, p.1), who argued that,

> “everyone in the hospitality industry has, by now, been inundated with the hype, the potential, the trend toward empowering hoteliers with big, big, big, DATA…but questions for the average hotel director remain: Where is the proof? Is there any tangible evidence a universe of data has helped any hotel owner?”

This demonstrates the importance to both the hotel industry and to the academic world of investigating the true impact of big data.

Alongside these questions about big data from industry, there are also suggestions that within the hospitality literature pricing research “is still in infancy” and remains “understudied” (Mattila and Gao, 2016, p.182) and that the best ways

of implementing revenue management strategies have not been addressed by the academic literature (Altin, Schwartz & Uysal, 2017), in which pricing is a key element. The links between big data and pricing in the hospitality literature remain particularly blurred in the academic literature. This issue adds further value to this thesis, which looks to consider the two elements in combination with each other. On a practice-based level the research will add fresh insights into the role of big data in the increasingly complex world of hotel room pricing models (Kimes, 2011, 2017). Where research has been carried out into big data in the academic hospitality focused literature the focus has been on the impact of analytics on casino hotel operations (Garrow & Ferguson, 2008; Ferguson, 2013), electronic data exchange in hotels (Leung & Law, 2013) and data-mining (Ha & Park, 1998), but not specifically on pricing decisions. In addition, where the academic hospitality literature looks at pricing behaviour, the role of big data has been neglected. The literature is either outdated (Riley & Jauncey, 1990; Gore, 1995; Gibson, 1998) or focused on environmental decision-making (Bonilla Priego, Najera & Font, 2011) or investment and financial accounting (Newell & Seabrook, 2006; Zounta & Bekiaris, 2009; Ivankovic & Jerman, 2010, Jawabreh & Alrabei, 2012). There have been some advances in this literature in more recent years, but it has still not provided a complete picture, and it is interesting to note that recent studies on hotel revenue management often do not even mention big data as a term, for example, Erdem and Jiang (2016).

Lee (2016) did look at the role of the general manager in hotel pricing decisions but only focused on the discounting of leisure rates and he did not specifically mention how big data impacted on price decision-making. Korzh and Onyshchuk (2018) attempted to draw up a decision-making model for the optimal set of analytical tools for revenue forecasting in hotels but it was only based on the researcher's personal experience rather than empirical research and did not deconstruct any of the complexity of the decision-making process. The focus was purely on the type and source of data used in the forecasting rather than on manager interactions with the data and impacts on behaviours in the price decision-making process. Saxena and Lamest (2018, p.287) did look at information overload caused by data using the hospitality sector as a case, although their paper focused mainly on general customer opinion data from digital

sources rather than on price. However, they did agree that “there is very little empirical evidence on how managers and organisations deal with this information overload”. These gaps in the literature are where the interest in this research area began to develop further and gain a sharper focus. As already touched upon, this interest also grew from a desire to challenge the hype surrounding big data and from recognising the importance of reaching an understanding of the practical implications of big data on hotel pricing within the field of revenue management.

However, why make transient room pricing the focus and why research the use of big data on pricing decisions purely at hotel property level? These interesting questions might be arising in the mind of readers but to answer them requires further development of the context. Crucially, it is important to recognise that the focus on transient pricing and the individual hotel properties go hand in hand; where, as already mentioned, transient room prices are classed as those booked by individuals rather than groups or those with specially negotiated corporate rates (Hayes & Miller, 2011; Ideas, 2018). Even with modern developments in the centralisation of hotel revenue management, individual hotel properties still have significant control over setting room prices, especially for transient room prices. Transient room prices were chosen as the focus for the investigation as they were considered most likely to be controlled at the hotel property level rather than by the area, national or even global sales teams negotiating corporate discounts for multiple properties.

The hotel sector has gone through a revolution in the last two decades with increasing competition and consumer power driving extensive development in revenue management techniques (Noone, 2016; Abrate & Viglia, 2016). In addition, due to the increase in the popularity over recent years of the management contract and franchise model of ownership and operation in the hotel industry, the general manager in individual hotel properties has had an increasing amount of autonomy over the implementation of the price decision at property level (Ivankovič & Jerman, 2010), as has traditionally been the case in independent hotels. Possibly against expectation, the centralisation of revenue managers has not necessarily led to the centralisation of decision-making. Whilst revenue strategy may be guided at a corporate level (Hodari & Sturman, 2014) the implementation and final decision on daily price setting, most likely for transient

customers, is done at a property level, often overseen, if not led by, general managers. Hotel managers need to be able to demonstrate to a wide range of stakeholders their ability to deliver accurate and reliable revenue decision-making that brings profits (Mauri, 2013).

Alongside these hotel specific trends has been the growth in the availability of data, which has impacted on hotel organisations. From previous research conducted into a working definition of big data in the hospitality sector it was found that the definitions of big data offered by participants were context and role specific in terms of what they felt constituted big data, for example revenue managers identified forecast data as big data and human resource managers identified it as including guest satisfaction data. However, in general big data was considered to be made up of large datasets which were highly variable, required computer analysis and could be numeric or more unstructured in nature (Haynes and Egan, 2015). General managers also face complexity and time pressure (Yan, Hong & Gu, 2013) when implementing daily changes to prices, due to the perishable nature of the hotel product. Hotel managers do not get a second chance to sell rooms and neither can they react quickly to changes in demand due to fixed supply. They are also inundated with unusually high levels of pricing data as compared to other industries, especially competitor data, gathered and disseminated to managers daily by industry specialists such as STR Global, third party distributions channels and companies such as Revinate, who put together summaries of user generated content. All these factors combine to demonstrate the value of focusing research on the use of big data on transient hotel price decision-making at the individual hotel level.

There is a lack of practical knowledge of the impact of big data generally and within the hotel industry, particularly in pricing, and the specific complexities and unique data sets available in hospitality make it an interesting case. However, the proposed status of the general manager as a vital decision-maker also suggests the importance of looking at the involvement of general managers in the decision-making process and at their interaction with big data when they set prices. This again is not a widely examined area in the current academic literature. Garrigós-Simón, Palacios-Marqués and Narangajavana (2008, p.361) express surprise that little research has focused on what they call "managers' individual knowledge, and

on the accuracy of their perceptions, especially in the hotel sector". More recently, Cetin, Demirçiftçi and Bilgihan (2016) agree that research on revenue management decision-making has neglected the people element and for big data, Phillips-Wren et al (2015, p. 466) point to the need for the literature to investigate the role of human behaviour in big data access and usage, arguing that "on the usage side of the spectrum, behavioural research questions abound". Josephi, Stierand and van Mourik (2016, p.255) confirm that "future avenues for research should explore the role of automation and human judgement in revenue management decision-making in line with the shifting balance between the art and science of revenue management". Therefore, not only is this research valuable in terms of uncovering the use of big data on transient hotel room pricing processes at the individual hotel property level, but it will also prove significant in understanding more clearly the impacts of big data specifically on general manager led decision-making approaches in hotel pricing.

Essentially these early explorations into the unanswered questions in the literature uncovered a black box that required deconstruction in order to uncover the realities of the use of big data at hotel property level on general manager involvement in transient price decision-making. There are many more specific gaps, themes, contradictions and incomplete conclusions that exist in the literature surrounding big data, hotel pricing and manager decision-making and the linkages between them that make up this black box, and these will be more widely explored in the literature review chapter. However, before this, it is important to be clear about the perspective this research takes on what a black box actually is. This requires an examination of a range of literature from the social sciences that together help to reach a consensus on a definition of a black box and the reasons why it might be created. In essence, there are gaps in the literature which leave the realities of the process of using big data in transient hotel room pricing unexplained and the unexplained is at the heart of black box theory. So how closely does the existing state of knowledge fit with the thinking on black boxes? Winner (1993, p.365) defined the term black box,

"in both technical and social science parlance as a device or system that, for convenience, is described solely in terms of its inputs and outputs…while neglecting any comprehensive account of their structures, workings and social origins".

Jacobs, Cairns and Strebel (2007) also assert that the stability and persistence of black boxes exist where a technological artefact is obscure enough to resist counter-claims and shed controversy but “beneath the surface of any black box is uncertainty, competition and controversy” (p. 616). This is one of the key drivers of this research; to deconstruct the black box, to make the uncertain, certain. We know that hotels have access to big data and that they set transient prices daily but we know little about the complexities of how big data interacts with managers and how it is used to set prices in practice. This is further exemplified by the publication of white papers by consultants specialising in big data analytics (Gantz & Reinsel, 2011; Manyika et al., 2011; Baker, Kiewell & Winkler, 2014; Laney et al., 2014; Duetto, 2015) which, in order to sell their services, potentially over-stress the positive benefits of big data (Weinberg et al., 2013; Gandomi & Haider, 2015). This therefore supports the perpetuation of the black box. MacKenzie (2005) and Jacobs, Cairns and Strebel (2007) suggest that in black box theory the contents may be kept deliberately opaque by parties who benefit from its mystery, agreeing with the comments made by Winter (1993) and suggesting that the hype around big data may have been built-up by consultants who can profit from offering big data solutions. Fox and Do (2013, p.741) agree the term big data has been “promulgated by international management consultancies.”

MacKenzie (2005) explained further that the term black box originated in the field of engineering to describe a device whose internal structure could be disregarded since all the engineer considered important was that the device transformed given inputs into predictable outputs. How this was achieved was considered less relevant as the focus was on the outcome. In this way the internal process could be treated as opaque, creating a black box where its contents could not be seen. This research questions whether in the increasingly complex and competitive world of hotel pricing it is any longer appropriate to ignore the importance of gaining a deeper understanding of the impacts of big data on transient room pricing. It argues instead that it is too relevant to the success of hotel transient room pricing to ignore and that there is a strong need to uncover the intricacies and complexities of the impact of big data on hotel transient price decision-making given increasing competition and the amount of available data. This means opening the black box, deconstructing it, and making it clear rather than opaque

by researching the realities and minutiae of the process. Peña Garcia Pardo, del Valle and Moreno (2009) confirm that opening black boxes is about exploring the intricacies of a process. It means moving beyond the superficial, cutting through the hype and looking at what Boxall, Ang and Bartram (2011, p.1505) call, in their discussion of black boxes, "the critical human interactions inside the opaque and complex realm of organisations that account for performance outcomes". Jiang, Takeuchi and Lepak (2013) also describe this as uncovering the mediating mechanisms in a process. Ultimately, this is summed up by Ragueso (2018, p.195) who argued that future studies into big data must be conducted "among companies that use big data technologies in order to enter into the black box of the dynamics of their adoption."

1.2 Closing the gap in knowledge

The opening of this thesis has already served to demonstrate the existence of a black box surrounding the practical use of big data in hotel transient price decision-making at the individual hotel property level. This research is designed to deconstruct that black box using the following aims, objectives and methodological approach to uncover the realities of the process or processes occurring within that black box.

***Aims*:** To develop a substantive theoretical framework that explains the impact of big data on the way transient hotel room prices are decided upon at the individual hotel property level and within this framework to fully identify and deconstruct the processes that currently exist within the black box.

Objectives:

- To explore the intricacies of the systems behind the way transient price decisions are made at the individual hotel property level, and to examine the types of data that are used to make those decisions.
- To investigate how general managers of individual hotels interact with and use big data and big data driven-technologies to make transient room price decisions within the context of revenue management strategy.
- To explore the impact of the existence of revenue specialists on the use of big data in the transient price decision-making process at hotel property

level and to uncover how data is exchanged in practice in this collaborative decision-making process.

Methodology: The methodological approach chosen to address these aims and objectives is one of Straussian grounded theory. Although a complete justification of this approach is available in Chapter 3, some of the initial reflections on the literature surrounding big data and its use in the hotel sector sparked thinking for the need for both a qualitative approach using grounded theory and one that allowed for the development of new theories, especially as the gaps in the existing literature were so wide. This was confirmed by recent calls for more qualitative research techniques to be used in big data research, from, for instance, Sivarajah, Kamal, Irani and Weerakkody (2017), and by calls from within the specialist hospitality research for new theories, for example, Zounta and Bekiaris, (2009, p.206) stated that due to "the peculiarities and special circumstances of hotels require more than just a simple adaptation of existing theories". A grounded theory approach fitted perfectly with the need to develop a new theory. This was strengthened by the fact that the speed of development of the literature on big data and the many gaps in the literature in this area of hotel pricing made it a challenge to develop hypotheses to test. Youtie, Porter and Huang (2016, p.2) confirm that "big data is a rapidly emerging area, which, at the time of writing, is in its early stages of emergence". In essence, a methodology was needed that allowed the formation of a substantive theoretical framework that was based on uncovering the realities of the hotel property rather than testing hypotheses based on the existing theory which may be irrelevant as they are either based on corporate level perspectives or become quickly outdated.

1.3 Thesis outline

This section provides a chapter-by-chapter outline of the remaining chapters of the thesis, highlighting the key elements covered in each.

Chapter 2 - The Literature Review: This chapter begins by outlining the positioning and treatment of the literature, within the methodological approach of Straussian grounded theory. It goes on to explore the history and development of hotel revenue management and the concept of big data, and factors that influence decision-making at the individual hotel property level. There is then a more

specific focus on what is currently known about hotel pricing in the era of big data and the impacts of big data on manager decision-making. The chapter concludes with a summary of the major gaps in the existing literature on these topics and highlights where there is also a lack of consensus.

Chapter 3 – Methodology: This chapter explores why Straussian grounded theory was selected as the methodological approach for this research and explains how it was implemented in practice through the data collection and analysis processes. This covers a detailed explanation about how work-shadowing, in-depth interviews and email interviews were used to collect data and how the Straussian coding paradigm was used to analyse the data to develop the findings and the substantive theoretical framework. The chapter ends with a discussion of the research validity, data management, and general ethical issues.

Chapter 4 – Findings: This chapter presents the findings as theoretical categories derived from the grounded theory data collection and analysis processes as described in the methodological approach. The main theoretical categories and their related sub-categories are delineated, and how they relate to each other to form a core category is discussed, entitled the 'hybridisation of transient hotel room pricing'. The core category represents the identification of where the black box exists. Extracts from the field notes and interview transcripts are offered as evidence of the existence of each of the categories.

Chapter 5 – Discussion: The discussion reflects on the findings at a more abstract level and presents a more detailed examination of the key features of the core category, enabling a final deconstruction of the black box that exists around transient hotel room price decision-making processes achieved through the generation of an explanatory and substantive theoretical framework generated from the grounded theory process. The chapter also covers the key contributions to knowledge of the research on big data impacts, hotel transient room pricing and wider hotel revenue management issues.

Chapter 6 – Conclusion: This final chapter provides an overall summary of the thesis but also reflects on the key contributions and directions for future research.

It also pauses to consider the potential future impact of this research on industry practice and hotel revenue management education.

1.4 Chapter Summary

This chapter has provided the background for the research and for the subsequent chapters of the thesis by exploring the focus of the research, why the research is of value and through placing it in the context of some of the existing literature on the topic. It has evidenced the existence of a black box around the true impacts of big data on the transient hotel room price decision-making process from a practical perspective at the individual hotel property level and demonstrates how this will be addressed through a clear aim and set of objectives. The thesis will now turn to a detailed examination of the existing literature, building on the points introduced in this chapter.

2. Literature - Preunderstanding and Historical Background

2.1 Introduction - The Approach to the Literature Review

The literature review is separated into two chapters. This first chapter will initially examine the impact of the methodological choices on the positioning and treatment of the literature, the literature search strategy and the structure and coverage of the literature review. It will then explore the history and development of hotel revenue management and big data as well as providing context on what is already known about decision-making at the individual hotel property level. In terms of grounded theory, this part of the literature review was conducted early in the research to sensitise the researcher to key concepts in advance of the data collection, a process recognised by Strauss (1987) and Strauss and Corbin (1998). A summary is provided at the end to tie the various aspects of the chapter together and highlight key gaps in the literature. However, each individual section will cover the major findings in the reviewed field, the main areas of debate and any outstanding research questions that have not been previously addressed. The second chapter will study in detail the various dynamics of price decision-making considering its place in the wider hotel revenue management context and the impact of big data on hotel pricing and management decision-making. It will culminate in a consideration of the role individual general manager's play in price decision-making within the context of hotel revenue management at an individual hotel level in the era of big data technologies. This second section of literature was forming throughout data collection and analysis as categories emerged, again in line with grounded theory as will be discussed in section 2.11. In this second chapter the links to the main and core categories that make-up the research findings will be made explicit at the end of each section by providing a brief summary of what was known in that specific body of literature prior to this research being conducted, what the gaps in knowledge were interpreted to be and how these gaps were addressed by the research.

2.11 Positioning and treatment of the literature

The methodological approach chosen to address the research aims and objectives was Straussian grounded theory, as will be discussed in more detail in the subsequent methodology chapter. It is important to mention the

methodological approach here in the literature review chapter because the use of grounded theory has implications for the positioning and treatment of the extant literature. Whenever a researcher chooses a grounded theory approach, questions immediately arise as to whether the extant literature should be reviewed before or after the data collection and analysis (Dunne, 2011; Giles, King & de Lacey, 2013; Yarwood-Ross & Jack, 2015). Therefore, the researcher must be clear before commencing the literature review what position it will take in the completed thesis (Dunne, 2011).

Glaser and Strauss's (1967) original development of grounded theory and Glaser's (1978, 1992) subsequent development of classic grounded theory called for the literature to be disregarded prior to the commencement of data collection, so that the findings emerge fully from the data and are not forced. Dunne (2011) confirms that classic grounded theory deliberately privileges what emerges from the data above the extant theoretical concepts in the literature. However, this is not the position taken for this literature review due to the selection of Straussian grounded theory. Strauss (1987) and Strauss and Corbin's (1998) approach to grounded theory, that emerged after a split with Glaser and his classic grounded theory, view the extant literature as playing a valid role in the early stages of grounded theory research. They stress that literature can be used to sensitise researchers to key concepts in advance of the data collection, as long as the researcher is happy to deviate from this should the emerging categories from the data collection and analysis demand it (Corbin & Strauss, 1990; Strauss & Corbin, 1998; Yarwood-Ross & Jack, 2015). This results in literature being reviewed on an on-going basis throughout the data collection and analysis process. They believe that it is impractical to expect researchers to be able to clear their minds of any previous literature read and studied. Giles et al. (2013) describe this approach to the literature as having an open mind but not an empty head.

Also due to the methodological approach these literature review chapters are the product of two distinct stages of engagement with the literature. The first stage was the use of the literature as a collection of sensitising concepts prior to data collection (chapter 2) and the second was the use of additional literature as an analytical tool during data collection and analysis (chapter 3). This means that this completed literature review both revisits the literature that helped place the

research in context, and addresses the literature relevant to the theoretical categories as they emerged from the data, thereby staying true to the Straussian grounded theory approach. Initially, the literature was treated as a collection of sensitising concepts to direct the early stages of question formulation and the direction of data collection, as well as providing context to help understand the voices of the participants. The term sensitising concept actually originates from Blumer (1954) but has been used more recently by Bowen (2006) in grounded theory research. Blumer (1954, p.7) describes a sensitising concept as one

> "that gives the user a general sense of reference and guidance in approaching empirical instances. Whereas definitive concepts provide prescriptions of what to see, sensitizing concepts merely suggest directions along which to look".

Therefore, the sensitising concepts did not force the findings but guided an understanding of what was happening in the data.

In the second stage of the review, the literature was used as an analytical tool in the coding process to help stimulate questions around what was potentially affecting what was seen in the data and to develop further the emerging theoretical categories (Strauss & Corbin, 1998). As the findings still needed to emerge from the data, where new categories arose during the data collection and analysis process, new literature was considered in relation to them. Urquhart and Fernandez (2013) describe this as a non-committal literature review where emerging theories can be related to a combination of fresh data and new literature rather than the extant theories. This is consistent with the views on the treatment of the extant literature in Straussian grounded theory. The literature was used to "enhance, rather than constrain" the development of the main theoretical categories (Strauss & Corbin, 1998, p.49, Thornberg, 2012) and to help highlight the contributions of the emerging theoretical framework to the extant literature on pricing and revenue management. Coffey and Atkinson (1996, p.157) agree that where a researcher has no knowledge of the extant literature there is a danger that they could "rediscover the wheel" in the sense that they end up claiming false originality of their theory as they were unaware that it already existed in the literature. Addressing the literature viewed during data collection and analysis in chapter 3, and relating it to the findings and discussion, helps to demonstrate the

fresh contributions of this research to the hotel price decision-making and wider revenue management literature.

2.12 Literature search strategy

The literature used in this review was sourced predominantly by using Google Scholar and databases, such as EBSCOhost, available through the Sheffield Hallam University library catalogue. For the early literature exploration, the search terms originated from key aspects of the working title of the research, for example, the research aims and objectives. Later in the research, additional search terms were taken directly from the language used by the research participants as the categories emerged as a part of the grounded theory process during data collection and analysis. To help broaden or narrow the searches within these databases, Boolean operators were used and there was careful consideration of synonyms, and American spellings and terms, for example, hotels are often called lodging in American articles. When potentially useful articles were identified the abstracts were carefully reviewed to check their relevance. If the article was found to be important, it was printed, read and critically annotated. A synopsis and the citation for the paper were then saved in an annotated bibliography in MS Word, which was constantly updated as more literature was found. The reference lists of these papers were also reviewed as this often helped uncover new literature or further papers by the same author. The MyLibrary feature of Google Scholar was also used to save papers that needed reading in the future.

The hotel revenue management literature extends beyond pricing into areas of inventory controls and over-booking policies, but following the focus on pricing in the research objectives much of the literature on inventory controls and over-booking was put aside, unless it was found helpful in gaining a sense of the wider context of revenue management, particularly its historical development. This literature was removed from the annotated bibliography but still saved in another file for reference. This ensured the annotated bibliography was always focused on literature that was potentially going to be used in the thesis, but no literature was fully discarded. To keep track of new literature that was reaching publication, Google Scholar Alerts were also used and checked via email on a regular basis. The annotated bibliography was broken down into sections covering key areas such as the history of revenue management, and papers were listed in

chronological order for ease of recall. Again, as new categories emerged from the data, new Google Alert topics were added, and fresh literature explored, and this was added to the annotated bibliography. The types of literature used were varied and covered academic research papers, discussion papers, published literature reviews, industry reports and the business, hotel industry, and management press. Key textbooks were also used as a gateway to understand some of the key theories and researchers in the main topic areas, to guide further literature searches.

2.2 History and background

This section will take a chronological approach to the literature in order to provide background and insights into the historical development of both hotel revenue management and big data, whilst aiming to reach a working definition for each. Taking a chronological approach to the literature was chosen as this made sense when exploring the historical background of a particular subject. This background, contextual literature was explored prior to data collection. Although the focus of the research objectives is on price decision-making, pricing is a key component of revenue management theory and therefore it is important to explore the development of revenue management to place later discussions in context. This section will end with a consideration of changes in managerial decision-making practices within individual hotel units.

2.21 The development of hotel revenue management

In its early incarnations, revenue management was more likely to be known as "yield management" (Relihan III, 1989, p.40). The majority of the literature cites the starting point for modern day hotel revenue management to be the airline industries' development of yield management processes, in particular, American Airlines. This occurred after the airlines were deregulated in 1978 which resulted in more fare flexibility but with it brought increased competitive pressures (Donaghy, McMahon & McDowell, 1995; Cross, Higbie & Cross, 2011; Ferguson & Smith, 2014; Vinod, 2016). Yield management was borne out of a need to maximise revenues to aid airline survival in these increasingly competitive conditions (Jenkins, 1995). However, it has surfaced in the literature that yield management may have been utilised by the airlines earlier than 1978. Yeoman and McMahon-Beattie (2017) claim that the first revenue management models

emerged from British Overseas Airways Corporation (BOAC) when Ken Littlewood, an analyst at BOAC developed an algorithm that could forecast the optimal revenues for a single leg flight with two fare classes utilising the airlines' recently developed computerised reservations systems. Weatherford (2016) confirms that what became known as Littlewood's Rule, was the first static resource-based revenue management model.

Like the airlines, hotels had been applying basic yield management for a while by adjusting room rates to take into account the changing demand patterns over the average year based on seasonality (Donaghy et al., 1995), but more complex yield processes were not adopted until the mid-1980s and not developed extensively until the 1990s. Cross et al. (2011) offer a detailed timeline of the evolution of hotel revenue management, which explains that a chance meeting in the mid-1980s between Bill Marriott and Bob Crandall, Senior Vice President for Marketing for American Airlines was the moment when yield management began to be implemented by the hotel industry. Bill Marriott saw the similarities between the hotel and airline industries in terms of perishable inventory, advance bookings, lower-cost competition and challenges balancing supply and demand but changed the airline's term of yield management to revenue management (Cross, Higbie and Cross, 2011). Marriott Hotels developed their own computerised revenue management system, which by the late 1990s was claimed to have added $150-$200 million in additional annual revenues (Marriott Jr & Cross, 2000). Marriott was closely followed in their adoption of revenue management by other major chains such as Hilton, Sheraton, Starwood and Intercontinental (Schwartz, 1998; Kimes, 2003; Erdem & Jiang, 2016).

Cross et al. (2011) cite the differential pricing strategies used by the airlines as the first yield strategies adopted by hotels, classified as selling the same seat for different prices to different people. Just as with airline seats, the sale of excess hotel rooms was promoted through pricing offers and room prices were maximised during periods of high demand helped by understanding the price sensitivity of different customers in different market segments. However, Ivanov (2014) argued that not all yield management processes were directly transferable from the airlines. He states that although the need to accurately forecast demand and offer targeted discounts to price-sensitive market segments to fill excess supply was the

same for both sectors, hotel revenue management was made more complex due to the length of stay factor (Cross et al., 2011). In essence, the basic economic principles of supply and demand were at work but needed managing in a more structured way given the complexities of hotel bookings, often using emerging computerised technologies (Lieberman, 1993). In this way, Kimes (1989) and Kimes and Wirtz (2003) define revenue management as the application of information systems and pricing strategies to allocate the right capacity to the right customer at the right price at the right time. Yet, during the late 1980s and early 1990s the literature suggests that outside of the major chains the hotel industry was slower to adopt revenue management (Lewis, 1986; Solomon, 1990), perhaps, though not clearly stated in the literature, due to the lack of access to the systems developed by the chains. Relihan III (1989, p. 41) suggested that "traditional pricing practices" still existed here, such as basing room rates on a percentage of construction costs, even with some smaller chains. There remains little literature focused specifically on the adoption and use of revenue management in independent hotels, apart from an older, geographically focused study (Luciani, 1999) and therefore detailed comparisons between the practices of chain and independent hotels in price decision-making remain fully explored.

However, where revenue management had been more widely adopted by the hotels by the late 1990s it continued to evolve, a process that is still continuing. This has led to revenue management being described in current literature as "very complex and dynamic" (Altin, Schwartz & Uysal, 2017, p.2). The literature reflects a continuing trend of increasing complexity in the implementation of revenue management. Historically, these complexities were often driven by technological developments, such as mobile technologies, social media, the development of automated revenue systems (Kimes, 2011; 2017; Guha Thakurta, 2016) and the internet, increasing the transparency of hotel room rates through the rise of online travel agents and price comparison sites. This has resulted in the need to consider the customers' view on the fairness and value communicated by revenue management strategies as customers have become increasingly well informed and have instant access to pricing information (Hayes & Miller, 2011), increasing the range of factors needing to be considered in the decision-making process. From the perspective of the revenue management decision-maker, developments

in technology have also resulted in a rising tension between manual and automated decision-making. This will be explored further in section 2.33 of this chapter.

The revenue management literature also highlights the tensions that exist over achieving the correct balance between tactics and strategies in revenue management decision-making. Some of these tensions can be directly attributed to global events, for example the terrorist attacks in New York in 2001 caused dramatic drops in air travel which reduced demand, and so short-term, tactical price drops were used, if unsuccessfully, to increase demand (Cross, Higbie & Cross, 2009), with longer-term impacts on profitability not being considered. Certainly, shortly after 9/11, the revenue management literature of the time returned to advocating the need for short-term pricing tactics over longer-term strategic attempts to develop revenue management (Lieberman, 2003). In contrast, other more current literature suggests that revenue management has become more strategic (Erdem & Jiang, 2016; Altin, Schwartz & Uysal (2017) and is increasingly led by a focus on the longer-term value of consumers to the business rather than a transactional approach (Cross & Dixit, 2005; Hayes & Miller, 2011). However, there is agreement that the term revenue management has broadened over time to encompass many elements of hotel management strategy, including marketing, profit management, and customer relationship management, culminating in the introduction of the term, total revenue management (Wang, Heo, Schwartz, Legohérel & Specklin, 2015; Josephi et al., 2016) which includes all revenue streams in its strategy, not just rooms. This is now viewed by some as central to the success of a hotel business, as it favours longer-term strategies over tactics (Kimes, 2011; 2017). Cross et al. (2009, p.56) confirm this approach stating, the “era has ended when revenue management can stand alone as a tactical approach to room management” meaning it must include all revenue streams available in the hotel.

However, much of the literature remains divided over whether a totally strategic approach to revenue management is warranted or correct and this debate is on-going it seems. Erdem and Jiang’s (2016) review paper of literature from 2001-2016 highlights that tactical revenue management still contributes to just over twenty percent of the seventy papers reviewed. Some literature appears to

appreciate that within a longer-term revenue management strategy, short-term, targeted pricing tactics might have their place (Noone & Mattilla, 2009; Anderson & Xie, 2010) but are often not fully clear on how that balance can be achieved. Jones and Lockwood (1998) attempted to clarify the situation by dividing revenue management into three strands that separated out strategy and tactics depending on what level those decisions applied to. They argued that strategic revenue management decisions were the domain of head office that would look at the long-term pricing strategies and market segmentation criteria, whereas tactical decisions were linked to the intermediate running of the individual hotel operating units. Finally, at an operations level was the hotel front desk and the sales office that were operating the systems where previously set prices were inputted. Hayes and Miller (2011, p.11) also hint that the balance between tactics and a more strategic approach could be achieved by implementing “a revenue management philosophy that places customer gain ahead of short-term revenue maximisation in revenue decision-making.” Interestingly, there was consideration of the customer in some of the earlier revenue management literature and although it was not widespread, modern academics cannot claim to have invented customer-centric revenue management. Lewis (1986) in his paper on hotel pricing stated that if firms could not keep up with customers' perception of value and their willingness to pay the prices set, they would fail. Slightly later, Donaghy et al. (1995) also called for consideration of the interface between revenue management and customers.

However, the contemporary literature is more certain that the key driver for increasing the strategic nature of revenue management is a move towards both a greater consideration of the longer-term impacts on the customer of tactical price changes and a focus on building total customer contribution over time (Cross et al., 2009; Noone, Enz & Glassmire, 2017). In their most recent paper, Yeoman and McMahon-Beattie (2017, p.69) summarise clearly what they mean by this new “holistic approach” to customer-centric revenue management and cleverly update Kimes’s (1989) originally definition of revenue management at the same time. They state that if the primary aim of revenue management is selling the right/product/service to the right customer, at the right time, for the right price, to generate revenue from perishable capacity, then an understanding of customers

and their behaviour is critical to its effective development and implementation. As already discussed, the reactions of customers to revenue management decisions have served to add yet more complexity to the process. This issue has also potentially brought into focus the importance of how customer feedback, particularly their reactions to prices, should be gathered and has also raised the question of who is best to do this. However, this has not so far been adequately addressed in the literature.

Most recently hotel revenue management literature has turned its attention to the role of profit in revenue management rather than simply top line revenue and it calls for a deeper consideration of costs, especially distribution costs. This is not replacing the customer-centric approach but suggesting that the focus should be on understanding the long-term profitability of a customer and not just how much revenue they will generate. Most notably, Noone, Enz and Glassmire (2017, p.5) suggest revenue management should be renamed strategic profit management and explain that this would include “consideration of multiple revenue sources, a deep understanding of customer value, and a shift from top-line metrics to bottom-line measures to be able to take into consideration operating costs”. This suggests the need to consider more metrics and data points in the decision-making process and therefore again highlights increasing complexity through data. It also highlights tensions that may exist between developing revenue and balancing the cost base, particularly in relation to distribution channel management choices. Less directly, Altin, Schwartz and Uysal (2017) also call for an increased focus on the cost base. This is, however, again not a totally new perspective. In their forward-thinking paper, Donaghy et al. (1995) criticised the absence of a consideration of costs in yield management in some parts of the literature, particularly the work of Orkin (1988), and called for decisions to be made on profit maximisation not revenue maximisation. They even concluded that this would involve looking at the profitability of guests within different market segments, although their understanding of the complexities of modern distribution channel costs would naturally have been lacking.

What is seen through this review of the literature on revenue management is that through its development it has broadened in scope with many more factors now impacting upon the decision-making process. Clearly, the definition of revenue

management is itself even in a state of flux. Although the more contemporary literature has been influenced by the more progressive earlier thinking of some academics, in general what is seen is that the incorporation of many more different elements into the revenue management decision, suggest an overall increase in the complexity of the revenue management decision-making process, yet the practical impact of this on general managers at an individual hotel property level remains unexplored by contemporary academics. This review has also highlighted several key tensions, specifically the balancing of tactics and strategies, growing revenues versus managing costs and understanding the role of general manager decision-making in a growth era of automated revenue systems. These tensions have developed over time and still exist today, but are not fully resolved even by the current literature. Although this chronological review of the literature has highlighted a general trend towards the increasing complexity of revenue management, the question of whether big data is driving this complexity still seems to exist within a black box. There are many indications through this section that data was involved in revenue management from an early stage, for instance in the algorithms developed at BOAC, and the early computerised revenue management systems at Marriott must have been driven by data input. However, the literature does not specifically address this as big data or deconstruct its role in the evolution of modern revenue management. As a result, the question remains over the true degree of shift in industry practice at hotel property level from older, simpler revenue practices to the theory of complex revenue management strategies suggested in more contemporary literature. Again, the realities of industry practice remain within a black box, which requires deconstruction.

2.22 Big data

Interestingly similar tensions as discussed above were also evident when reviewing the literature on the development of big data. These began with the difficulties of defining the term big data which are widely recognised in the literature (Boyd & Crawford, 2012; Weinberg et al., 2013; George, Haas & Pentland, 2014; Gandomi & Haider, 2015). Despite these tensions and to advance any research that investigates big data it is crucial to attempt to draw together the disparate descriptions of the term, so it can be clearly communicated to research participants. This is particularly important when participants' perceptions of big

data may have been influenced by the widely accepted hype that surrounds the use of big data in the management and business press and the potential over-commercialisation of the term caused by its use as a sales tool for companies selling big data services (Weinberg et al., 2013; Pearson & Wegener, 2013). The hype also extends into the hospitality industry press, with big data being heralded as the solution for understanding customers, personalising service and gaining competitive edge (Terrier, 2017; Richard, 2017), as well as enhancing marketing and website design based on machine learning of customer actions (Crozier, 2017) and increasing operational efficiencies through predictive data analytics (Prakash, 2017). The challenge with these types of claims is that they are very general and do not explore in detail the implications of operationalising big data in the real world and many are not based on empirical data and therefore do not represent a clear understanding of the true impact of big data. Take for example Prakash (2017, p.1) who finishes a blog post by stating "unpack your hotel data…and watch the benefits role in". This promises instant results from data with minimal effort but does not address how this "unpacking" can be achieved. This knowledge exists within the black box.

To cut through this hype it is important to dissect the tensions that exist over the definition of the term which appear to begin with disagreements over the origins of the term. Friedman (2012) in his paper exploring the history of big data argues that the term was first used by Michael Cox and David Ellsworth of NASA to describe the large amounts of data generated by NASA's supercomputer in 1997. Yaqoob et al. (2016) confirm that ever since the invention of computers, large amounts of data has been generated in ever greater volumes. This suggests that initially, the focus of the definition was often on volume. To be fair the very fact that the word 'big' appears in the term, suggests that volume is a central element. Puschmann and Burgess (2014) agree that "historical trajectories" of big data are marked by a shift towards even greater computability of volumes of data, meaning that you can gather more data and do more with it. However, outside of NASA and commercial settings, the first academic use of the term is most often attributed to Diebold's (2003) paper entitled "Big Data Dynamic Factor Models for Macroeconomic Measurement and Forecasting", first presented in 2000 and published in 2003 (Lohr, 2013). In reality, however, the definition is thought to have developed from

a combination of “industry and academics, computer science and statistics/econometrics” (Diebold, 2012, pg. 2).

Interestingly the most widely used and comprehensive way of describing big data, the Vs framework, was originally developed by Laney (2001), a consultant not an academic (Chen, Chiang & Storey, 2012; Malik, 2013; Kwon, Lee & Shin, 2014; Phillips-Wren and Hoskisson, 2015). This framework has been extensively developed over time to incorporate a range of big data characteristics, suggesting that like revenue management, big data has also increased in complexity and potentially become more concerned with more than just the volume of data, as can be seen in figure 2.1. Diebold (2012) himself recognised that Douglas Laney had contributed further to the development of big data because his framework recognised big data as more than just high volumes of data. The 3 Vs framework in its original format is still widely referred to in recent literature (Vidgen, Shaw & Grant, 2017; Alharthi, Krotov & Bowman, 2017; Raguseo, 2018) and this is most recently demonstrated in Günther et al.’s (2017) thorough literature review of nearly five hundred big data related papers published since 2000 which demonstrated that it has remained the most widely used framework for understanding big data. Even papers that argue that there is no universal definition of big data still refer back to the Vs framework to help explain what the term means (Jin, Wah, Cheng & Wang, 2015). Laney’s (2001) 3 Vs framework originally signified the increasing volume, velocity, and variety of data in the modern age, which in essence defines big data as large amounts of data, arriving at high-speed, on a constant basis, made up of both structured and unstructured data (Marr, 2015). Bendle and Wang (2016) added that unstructured data needs more treatment than structured data before it could be termed useable.

However, the framework has since been updated to add a further 3 Vs, as highlighted by Gandomi and Haider (2015), reflecting the recognition of big data as being more complex. They state that IBM added the term veracity, highlighting the uncertain and imprecise nature of big data, and showing the continued influence of commercial organisations on developing the definition of big data, although this feature was also supported by the work of Mayer-Schönberger and Cukier (2013) who argued big data would mean accepting imprecision, searching not for causality but for correlation. Gandomi and Haider (2015) also state that

SAS then introduced variability, not to be confused with variety. This term refers to the variability of data flows and suggests big data velocity may not be constant but may follow peaks and troughs. Phillips-Wren et al (2015) term this volatility. Finally, Gandomi and Haider (2015) cite Oracle as introducing the idea of value and state that big data as a raw material only increases in value when data analytics processes are applied, more often than not driven by technology. A seventh V was then added, visualisation, referring to the increased need to summarise and graphically present key information from highly detailed data (Ekbia et al., 2015; Phillips-Wren & Hoskisson, 2015; Sivarajah et al., 2017). Finally, most recently Lee (2017, p.295) suggested that the term decay should be added to the Vs framework, referring to the declining value of data over time if it is not used and that "in a time of high velocity, the timely processing and acting on analysis is all the more important". However, this seems less of an addition to the framework and more of a comment on the conditions and consequences of the existing Vs, in the sense that high velocity can reduce value if data is not analysed in time. These final two additions to the framework also seem less well established in the literature and their significance less recognised. Another recent paper covering past big data literature did not even mention these additional aspects of the framework and only recognised the 6 Vs (Mishra, Luo, Jiang, Papadopoulos & Dubey, 2017). Consequently, the 6 Vs framework was used as the basis of defining big data for research participants in this research, as highlighted in bold in figure 2.1 below.

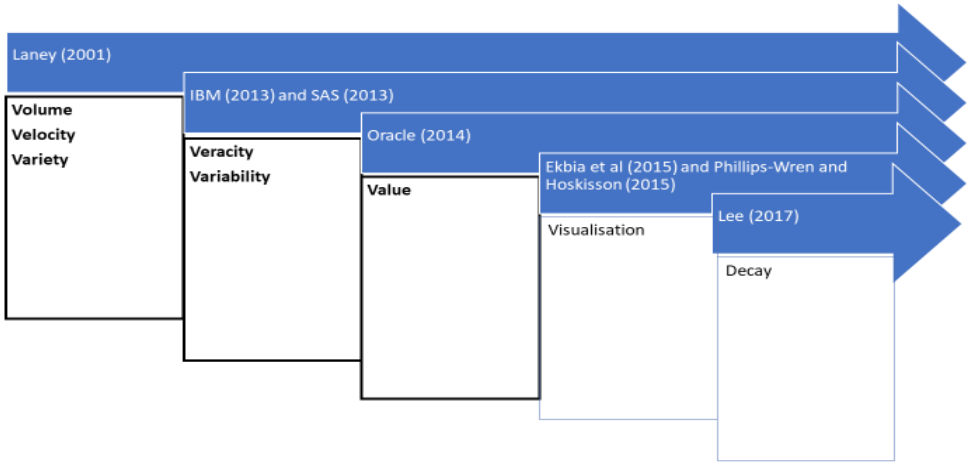


Figure 2.1: A Summary of the Development of the Vs Framework

However, it was recognised that even with common agreement on the six Vs framework even these elements have also been subject to change so these developments must also be taken into account, for example, velocity, that once referred to the high speed of data arriving, has now been extended to mean that big data arrives in real-time (Gillion et al., 2014; Constantiou & Kallinikos, 2015). The term variety has also been further explained in terms of the variety of sources of big data, both internal and external (Phillips-Wren & Hoskisson, 2015; Yaqoob et al., 2016) and big data's ability to describe things in fine detail with exhaustive scope (Kitchin, 2013), described by some as granular data (George, Haas & Pentland, 2014; Yaqoob et al., 2016). All these developments continue the theme of taking the focus of the main characteristic of big data beyond volume. In fact, Boyd and Crawford (2012) suggest the focus should be taken off the word "big" as they feel big data is less about the amount of data and more about the technology used to analyse it. They argue that data has always been characterised as big and use the example of the large amounts of data recorded in the first census. They stress the focus should now be on what we do with the data, which suggests more research is surely needed on how human managers interact with big data and analytics technologies, especially in areas such as hotel revenue management where the number of metrics and consequently data points is increasing.

Even Laney et al. (2014) are critical of definitions of big data that focus on the volume of data rather than on other more meaningful characteristics that explore how the data can be used. George, Haas and Pentland (2014) agree the focus should be on the insights that can be drawn from data through analytics. This suggests a move towards a process driven definition that steps away from describing the qualities of data in its raw state towards how it can be used as a decision-making tool (Youtie et al., 2016; Alharthi, Krotov & Bowman, 2017). Carillo (2017, pg. 33) summarise this clearly in a recent paper stating that "the big data phenomenon is not a matter of size. It is about the central and critical role that data now plays in businesses". However, the problem the extant literature appears to still have is accurately identifying the big data processes as they occur in the reality of a business on a day-to-day basis. Puschmann and Burgess (2014) agree that the real complexity of big data lies in the ways in which it is created and used and Ekbia et al. (2015) add that the process-orientated perspective on big

data is complex but also remains novel. As discussed in the introduction to this thesis, in terms of revenue management, in particular, the realities of these processes at the individual hotel property level still seem to exist in a black box.

As already touched upon, this leads onto another tension that exists in the field of big data that also lacks a clear understanding in the literature, namely the balance between humans and technology. Although it seems widely agreed that more often than not big data is digitally created (Alharthi, Krotov & Bowman, 2017) and stored at low cost within computers for future use (Weinberg et al., 2013; Puschmann & Burgess, 2014), how human managers interact with big data in order to interpret it seems to be particularly under debate in the literature and lacks clarity. Shiffrin (2016, p. 7308) argues that “a hallmark of big data is the fact that it vastly exceeds human comprehension”, which suggests that managers would be unable to interpret data without technology. Bowker (2014) agrees that it is the computer that interprets the big data and humans only act upon those interpretations. Whereas Ekbia et al. (2015, p.1534) suggest that whilst there may be a cognition-oriented approach to big data that suggests it is too large for human understanding without technology, big data does need humans to manage it and help extract value from it, something they refer to as "heteromation". Like Shiffrin (2016) this suggests a blending of human action and technology in big data. This is perhaps particularly important given that Zeng and Lusch (2013) suggest big data may even outstrip current computational capacities, implying there may be limits to its value with or without a combination of human capabilities and technology.

Although the balance between human involvement and technology will be explored in more detail in section 2.33 of this chapter it is relevant to highlight it, as the debate has had a direct impact on the definition of big data and it seems now to have led to the evolution of the term small data. The term appears to have been borne out of a criticism of the absence or reduction of human influence in decision-making in overly computerised approaches to big data (Davenport, 2014). Small data seems most likely to originate from the author, consultant and professional speaker, Michael Lindstrom (2016), who describes it is as data that is small enough for human comprehension. He argues that big data is about machines, but small data is about people. In recent academic literature Pal (2017), although

talking about it in the field of political commentary, looked in more detail at the use of small data in decision-making and suggested that small data is humanising and as a process is the interpretive analysis and commentary of data conducted by humans. Marr (2015, p.28) argues that small data should be used in combination with big data for a positive outcome, stating that it is important to "identify what data you really need and very often that will mean a combination of traditional "small" data or existing data and new data formats, new faster data and Big Data". Boyd and Crawford (2012, p. 670) also talk about small data, stating that "during this computational turn, it is increasingly important to recognise the value of small data". However, the term seems to be used more to provoke debate over the value of big data and the hype that surrounds it, rather than explaining how it might be integrated with big data and there is not a clear definition that has yet emerged to fully explain its core differences with big data, despite a recent attempt at definition in the hospitality literature by Korzh and Onyshchuk (2018). However, this definition is only based on their own personal experiences rather than primary research in hotels. They define big data as "information about what surrounds the hotel business" and small data as "information that is in the hotel system or the sales channel manager" (p. 18). Due to the lack of primary research supporting this definition, caution must be exercised and certainly in the academic literature, the intricacies of small data processes remain to be fully explored. However, if as suggested above by Lindstrom (2016) small data concerns people, and if contemporary revenue management requires more consideration of customers it could have a big impact on revenue management decisions that are increasingly customer-orientated and therefore reliant on customer data.

2.23 Factors influencing decision-making at the individual hotel property level

This next section addresses the question of who at the individual hotel property level is the ultimate decision-maker and the factors that may influence their decision-making control, which is important to consider given that the focus of this research is at the property level. The fact that the role of general manager has been identified as one that holds an over-arching responsibility for managing the effectiveness of employees in delivering customer service, profit and ultimately ensuring the survival of the hotel unit (Arnaldo, 1981; Orkin, 1988; Nebel & Nebel,

1991; Kim, 1994; Jayawardena, 2000), it could be suggested that it may be the general manager who has ultimate decision-making control. In fact, the hospitality literature has consistently highlighted the fact that the general manager has responsibility for making final decisions within the hotel unit. Although reviewing the literature on hotel decision-making has shown there to be a general decline in interest in researching the role of the hotel general manager role since a peak in the 1980s and 1990s, the small amount of contemporary literature available continues to support the centrality of the general manager in decision-making (Bharwani & Talib, 2017). There is agreement that the general manager remains ultimately responsible for the day-to-day decision-making that is vital to the delivery of profit and customer service (Bharwani & Talib, 2017) and that if general managers are allowed this autonomy their hotel units are likely to be more successful than ones where there is less freedom to make decisions (Hodari, Turner & Sturman, 2017). The focus of the role of the general manager on the delivery of profit is also in itself an interesting point to highlight, given the shifting focus of revenue management to contributing to the delivery of the bottom-line. This would suggest a greater need for academics to consider the role of the general manager at property level in revenue management decision-making. However, this research is lacking.

Despite the recognition of both the central role the general manager is supposed to play in delivering profit and of the importance of revenue management in delivering the profitability of a hotel unit, there is scant specific consideration in the contemporary literature of the role the general manager plays in revenue management decision-making. This is despite the increase in revenue management literature focusing on profit delivery as mentioned earlier (Wang et al., 2015; Josephi et al., 2016). Whilst this is perhaps not surprising for the research on general managers conducted before 2000, when revenue management was initially being adopted and developed by the hotel industry, now that revenue management is extensively used, it seems strange that there is not more consideration of the involvement of the general manager in these decisions. Even past research mainly focused on the general manager's role in reservations policies (Williams, 1977) and general financial decision-making, but did not explicitly mention yield or revenue management decision-making (Ley, 1980;

Arnaldo, 1981; Shortt, 1989; Kim, 1994; Woods, Rutherford, Schmidgall & Sciarini, 1998; Jayawardena, 2000). A review of the past literature only found a few exceptions which are worth noting where the focus seems to be on the role of the general manager in the pricing element of revenue management.

Where the existing literature does contribute is by helping us to gain some understanding of what aspects of revenue management general managers may have been involved in historically. However, the lack of contemporary literature means that how this has changed is unclear. More exploration is therefore needed. Relihan III (1989) suggested that the economic element most likely to be able to be controlled by a general manager was price, and Riley and Jauncey's (1990) research, although it only covered a small sample of twenty-one hotels, found that general managers were most likely to make autonomous decisions on price without consulting assistant managers, whereas high levels of consultation happened in other areas such as marketing and sales promotion. The only study that could be sourced that directly studied the impact of yield management on the role of the general manager was conducted by Donaghy and McMahon-Beattie (1998). They wished to address the gap in research on the implications of yield management on hotel managers. They found that initially, the general manager was crucial in gathering relevant information to feed into yield management decisions but that as yield managers increasingly took specialist positions in hotels the yield management system became less dependent on the hotel manager as a source of information. The hotel manager, therefore, had "more time to spend with guests" (p. 226) and to think about strategy. This also suggests that they could potentially become valuable stores of customer data, though this is not explored further in the research. The need for specialists had already been commented upon in a study a year earlier that "the industry was felt to have a greater reliance on specialist managers in personnel, marketing, sales, finance, and computing and increasingly recruits these specialists from outside the sector" (Gilbert & Guerrier, 1997, p.122). They also cautioned over a distraction of the general manager from operations, an issue already supported by Donaghy and McMahon-Beattie (1998) who suggested general managers should be relying on specialists to carry out these duties. Later, Steed and Gu (2005) also confirmed that

conflicting objectives in the hotel unit of the hotel manager could lead to insufficient time being spent on pricing, leading to severe financial impacts.

The very few elements of contemporary literature that do reflect on the general manager's role in revenue management suggest that this reduction in general manager involvement in revenue and reliance on specialists appears not to have been a continuing trend. While caution has to be taken over the size and geographical bias of the study, Ivankovič and Jerman (2010) surveyed the general managers of twenty-six Slovenian hotels and found that these general managers were more likely to take sole responsibility for pricing and profitability-based decisions, and service decisions were actually more likely to be left to department managers. Cross et al. (2011) when reflecting on the historical development of revenue management also commented that individual general managers were responsible for rate and inventory decisions and finally Richard (2017) calls for centralised revenue teams where they do exist to report directly to the general manager who should give the final sign-off on decisions. So, the literature tends towards the conclusion that the general manager is a key decision-maker at the hotel property level, although the degree of autonomy may have the potential to be reduced by the presence of revenue specialists and potentially automated revenue systems. However, the balance of decision-making power between these two parties is not well covered and there remain many questions about what happens in practice in terms of general manager involvement in revenue management and price setting.

Another key weakness of the literature is that, although little of it is contemporary, it has often only aimed at identifying the different elements of the general manager's job role rather than examining those specific elements of the job role in detail. Largely these insights are based on Mintzberg’s (1973) typology of ten managerial roles, as summarised below in table 2.1, despite the many criticisms of his original research in terms of sample size and the accuracy of managers ability to accurately document how they spend their time (Dann, 1990; Gilbert & Guerrier, 1997; Ladkin, 1999). Focused studies of the hotel manager’s decision-making and information management role are largely missing. However, what is gained from examining this past research is an insight into the general changes in the role over time and the factors that might have driven this.

Category	Role	Activity
Informational	Monitor	Seek and receive information, scan papers and reports, maintain interpersonal contacts
	Disseminator	Forward information to others, send memos, make phone calls
	Spokesperson	Represent the unit to outsiders through speeches or reports
Interpersonal	Figurehead	Perform ceremonial and symbolic duties, receive visitors
	Liaison	Maintain information links in and beyond the organisation
	Leader	Direct and motivate subordinates, train, advise and influence
Decisional	Entrepreneur	Initiate new projects, spot opportunities, identify areas of business development
	Disturbance Handler	Take corrective actions during crises, resolve conflicts between staff, adapt to external changes
	Resource Allocator	Decide who gets resources, schedule, budget, set priorities
	Negotiator	Represent department during negotiations with suppliers, and general defend interests

Table 2.1: Mintzberg's Ten Managerial Roles (adapted from Mintzberg, 1973)

Mintzberg (1973) opposed the classical view of managerial functions (summarised above in table 2.1) where managers were believed to operate in a structured, logical fashion carrying out tasks that centred on planning, organising, coordinating and controlling. Instead, he argued that managers' activities were scattered, short-term attempts at coping, characterised by brevity, variety, and fragmentation. Dann (1990) in his literature review paper on research in this area agreed the general manager role could fit this description, affirming the role to be "reactive, fragmented, subject to many interruptions, involve large numbers of contacts [and] be highly concerned with information gathering and dissemination". Arnaldo's (1981) study of general managers working in American chain hotels identified that the managerial roles they engaged with most were leader, followed by disseminator and monitor but that they also valued time with guests and employees and disliked paperwork, with finance ranking fifth in terms of time spent on different areas of the business. The focus on the disseminator and monitor roles again highlights the importance of general managers collecting information to support decision-making, and this was further supported by a later study (Shortt, 1989) conducted in Northern Ireland. Although it did focus on smaller hotel properties, Shortt (1989, p.122) found that general managers used interpersonal relationships to gather information from a range of different sources both external and internal to enable them to "perform decisional roles", as did Nebel III and Ghei (1993). However, both papers stress a manager's effectiveness in solving

problems in the shorter term is most important. Interestingly, Nebel III and Ghei (1993) place pricing into these short-term decision-making criteria. So, while, decision-making may be strategic, in terms of making decisions to improve performance, it may also be about responding to unanticipated situations and problems, as supported by Baum (1989). Kim (1994) also agrees with the United Kingdom and American studies that the general managers researched in Korea also considered informational roles to be important and to absorb a lot of a time. So, despite there being a range of geographically focused research papers, the general theme that emerged across them is that the general manager played an important role in gathering information for decision-making. However, the research does not make clear the full details of how that information was collected or used and the literature is yet to bring these discussions up to date.

Where contemporary literature does exist on the role of the general manager, the increasing complexity and commercial nature of the role is emphasised, whereas the earlier literature discussed above, focuses on the operational, hands-on nature of the job. Grissemann, Plank and Brunner-Sperdin (2013) stress that the importance of focusing on business performance in hotels stems from increases in the competitive environment. The increasing complexity of the role adds to the question of why more research has not been conducted to examine this role within the hospitality literature in recent years and why there is little consideration of how this increasing commerciality impacts upon the general manager's role in decision-making both in general and specifically for revenue decisions. Bharwani and Talib (2017, p.394) confirm that "hotel management as a process is becoming exceedingly dynamic and highly complex" due to rapid changes in the industry and the complexities of the information-based, knowledge-intensive and service-driven economy, whereas most of the earlier literature had placed the emphasis on the operational nature of the general manager (Baum, 1989; Nebel III & Ghei, 1993; Jayawardena, 2000), Bharwani & Talib (2017) stress the business planning side of the role. They also suggest that data may also have a role to play in driving the complexity of the role. It also highlights the need for more focus on both the changing nature of the decision-making skills needed by managers in a more commercially driven world and their career route to general manager. Ladkin (1999, p.168) had recognised "a slow move towards a business orientation" yet

interestingly still supported the importance of the heavily operational, food and beverage route to general manager, although this is countered by Woods et al. (1998, p.44) who say, “we must conclude that the F&B post is no longer a well-worn path to the top”. Gilbert and Guerrier (1997, p.124) also reported that participants in their research “identified a need to change from being a manager of a hotel to a business manager” and place a new emphasis on the requirement to meet financial targets, save on costs and use technology to reduce labour time. However, the question remains as to the effect of the increasingly commercial nature of the role on the autonomy of decision-making and the use of data in the revenue management decision-making process.

However, the issue of autonomy in decision-making reaches wider than a focus on managers' roles, activities, and skills and extends into the effects of the increasing complexity of hotel ownership structures. Bharwani and Talib (2017) confirm the need for hotel managers to be able to operate hotels that exist within increasingly complex organisational structures. Again there is little research that looks specifically at revenue management decision-making. The debate, which is inconclusive in the literature, is based on whether franchise or management contracts rather than straight owner-operator structures impact on general managers' decision-making processes. Ivankovič and Jerman (2010) argue that under franchise and management contracts, general managers in individual hotel units often have a degree of freedom over the price decision. This issue had been earlier identified by Nebel III and Ghei (1993, p.27) who agreed that the reason general managers could take overall responsibility was that hotels, even if part of a chain, suited themselves to being “treated as a unique profit center”. Other researchers disagree, believing this autonomy may be moderated by the need to report to owners or managers at a corporate level (Hodari & Sturman, 2014), although the focus of the research was only on luxury and upscale hotels. Specifically, they state that “GMs do not have unfettered control of their property, even though they are formally in control of their property… the GM’s autonomy in making decisions for the property is thus subject to the influence of owners or management companies” (p.433). They also argue that centralisation of processes within franchises and management contracts is more likely to reduce general

manager autonomy in making financial decisions than other areas such as operations, marketing, and human resources.

The challenges around decision-making in these types of complex ownership structures are related to agency theory, where conflicts occur between people who have different interests in the same assets (Eisenhardt, 1989). Migdal (2015) confirm that where the ownership, operation, and branding of the hotel, as well as its debt financing and capitalisation are in many hands, each has its own separate and distinct set of interests. Those interests may not be in proper alignment all of the time and owners of hotel assets may not even be interested in the hotel industry. Migdal (2015) cites the example of the ownership of hotels by life insurance companies. Therefore, operators may want to invest in the property to maintain brand standards, but the owner may not be convinced of the return on that investment on the property asset (Guilding, 2003; Davis, 2004; Hodari et al., 2017). Hodari et al. (2017) go on to discuss in more detail the role of the general manager in the agency and goal incongruence problems. They argue that the agent, in this case, the hotel operator, may not always act in the best interest of the principle, the hotel owner. They believe that this often leaves the general manager as a middleman, attempting to negotiate between the two parties and act on behalf of them both. In essence, they conclude that this leads to a tripartite agency problem, which is often made worse by informational asymmetries, in terms of amounts and types of data and priorities of what data to focus on between different parties. Interestingly they conclude that goal incongruence should be avoided, as where it is reduced it “causes greater GM autonomy which in turn causes greater hotel performance” (p.125). The potential interaction between property level managers, owners and brands adds interesting complexities to the research of price decision-making behaviour as it allows for the observation of control and data sharing issues which have not yet been adequately covered in the literature (Hodari & Sturman, 2014) in terms of revenue management decision-making. If the autonomy of the general manager is being moderated in these more complex ownership structures, as suggested by some, it is therefore even more crucial to pay more attention to understanding how hotel revenue management decisions are made where multiple parties may be involved and data is generated from multiple sources. It is especially key, to set this in

contrast to the revenue management decision-making practices that exist in independent hotels where the simpler owner-operator model often still exists.

2.3 Pricing within hotel revenue management in the era of big data

As already noted, the revenue management literature covers a complex number of processes involving not just pricing but also many aspects of inventory control, distribution, and channel management. However, the focus of this research is on pricing and hence the focus of the literature review will now turn to the pricing literature within the hotel revenue management literature. The number of different types of pricing decisions that need to be made at hotel property level are also numerous, but as mentioned in the introduction, the focus of this research is on transient room rates, as they are most likely to be influenced by the hotel property rather than national or global sales negotiations as would be the case for corporate, discounted rates or group rates. Transient rates are those booked by individuals rather than groups or those with specially negotiated corporate rates (Hayes & Miller, 2011; Ideas, 2018). The following sections of the literature review will look in more detail at how price decision-making has evolved in the hotel industry and at what is known about the potential impacts of big data on these developments. It will end with a discussion of contemporary approaches to hotel pricing in the era of big data, considering in detail two central aspects of big data's impact on decision-making. The first is the balance between rational and behavioural decision-making and the second is the influence of data-driven revenue management systems on the level of influence the 'human' manager has over revenue management decision-making. The in-depth study of the literature covering these last two aspects was prompted by the themes emerging from the data collection and analysis.

2.31 Simplistic origins and the introduction of yield management

The past literature was of its time and is based on simplistic and often fairly arbitrary principles with a focus on fixed cost-based pricing, it reflected what appears now to be a rather naïve approach to pricing conducted by the hotel industry. It also echoed the amount of data available in the late 1970s and 1980s, particularly competitor data (Haynes, 2016). Lewis (1986, p.20) describes hotel pricing in the 1980s as "at best, confusing, naïve and unsophisticated" and at worst leading to loses in revenue. This is based on his identification of hotels

basing room rates on charging $1 dollar for every $1000 construction cost, automatic pricing increases based on seasons regardless of demand or business trends, and ultimately on a lack of focus on the customer perception of value (Steed & Gu, 2005). It appears that at this point capital and fixed costs formed the main basis of room prices. Relihan III (1989) confirmed the use of rules of thumb in hotel pricing based on construction costs but added that hotels were also prone to merely following the competition, stating “most often, however, hoteliers determine their prices in relation to the competition, as if the guy down the street somehow knew better”.

Leading on from this, the main shift in the sophistication of hotel room pricing appears to have begun with the introduction of the yield management techniques discussed in section 2.21 and the early development of technologies to measure, if not at this stage to predict, market forces (Lewis, 1986; Relihan III, 1989). Relihan III (1989) and later Steed and Gu (2005) have confirmed it was the introduction of yield management that caused hotels to bring their thinking about pricing in line with actual market forces. In this period, price decision-making became increasingly focused on forecasting market demand, consumer price sensitivity, and responding to more detailed competitive price benchmarking (Vinod, 2004; Collins & Parsa, 2006). It, therefore, became increasingly vital to analyse this information on supply and demand characteristics to maximise revenues (Lee-Ross & Johns, 1997; Upchurch, Ellis & Seo, 2002). This is further reflected in the hotel pricing literature published in the 1990s and early-to-mid 2000s. For instance Baum and Mudambi (1995) linked variances in hotel quality with the prices charged based on consumer perceptions of value, and Desiraju and Shugan (1999) and Yelkur and DaCosta (2001) confirmed that pricing should be based on a deeper understanding of the price sensitivity of different market segments linked to multi-period pricing, which was the idea of adjusting price over time to fill all available room capacity. Therefore, it does appear that overall there was an increasing focus on the economic principles of supply and demand within the workings of the market and that this underpinned pricing during this period, a fact which allowed for more complex pricing structures to appear. What is unclear is whether increases in market data drove the focus on the impacts of the markets on revenue management decision-making or whether it worked the other way

around, in that managers saw the need to focus on market dynamics and hence demanded more data. Donaghy et al. (1995, p.146) stress that in the early to mid-1990s pricing was driven by the increased accuracy of forecasting and segmentation which allowed rises in the "scope and frequency of pricing decisions which more effectively aligned room prices with market forces," but of course both forecasting and segmentation rely on data. Interestingly, as an aside, they also commented that the general manager remained vital in gaining local knowledge of the market. Cross et al. (2009) also suggested that it was the improvement in yield management technologies and systems that drove the increase in forecasting accuracy, through better use of data and more complex algorithms. This perhaps hints at the beginnings of big data being used in pricing from the mid-1990s, although it may not have been termed this at the time. It is interesting to remember that it was in 1997 that Friedman (2012) claims the first use of the term big data by NASA.

Lieberman (1993) and Jones (1999) also highlighted how a better ability to forecast demand and segment markets meant there was a movement away from setting static rack rates to setting rate ranges that only discounted rates where necessary, based on the customers' perception of value. What the literature begins to suggest is that there was a slow emergence of dynamic pricing structures as yield management developed a greater appreciation of market forces. Most importantly, however, Elmaghraby and Keskinocak (2003) cite hotels as early adopters of dynamic pricing but add that to achieve this there was a need for detailed information on customers and the ability to change prices at minimal costs, which they believe was facilitated by new technologies and the availability of decision-support tools for analysing demand data. However what is clear is that the literature suggests that dynamic pricing has led both to price points being changed more frequently and to there being a wider range of prices for the same product, which potentially drives complexity and began to drive the need for real-time data in the decision-making process. Certainly, this view is supported in the wider literature, such as Yelkur and DaCosta (2001) who highlighted how the internet had allowed for much easier adjustments to prices based on greater customisation of prices to react to the price sensitivity of market segments as well as to demand. However, Steed and Gu (2005) although agreeing with the notion

that the internet increases price flexibility and responsiveness, did argue that prices should not be changed too often as consumers would begin to learn and anticipate price changes.

2.32 The importance of STR (Smith Travel Research)

The other major influence on hotel pricing has been from STR Global. It is worth taking time for a detailed consideration of the impact of STR data given the fact that it gave rise to hotels having access to an unprecedented amount of competitor information, unique to the hotel industry (Higley, 2007). During the early stages of the implementation of yield management managers only had a superficial interest in what their competitors were doing, and it was certainly not considered an important part of price decision-making due to lack of data (Williams, 1977). Where competitor occupancy data was collected it occurred manually by way of the daily ring-round, through informal communications between hotel managers at social events or even by the counting of cars in car parks (Higley, 2005a). This shows that there was an appetite for data on the markets but that collecting it was resource and time intensive, inaccurate and subject to bias. Therefore, third-party hotel consultants began to see how they could capitalise on this need, for example, John Lesure, developed a Research, Development and Education Department at Laventhol and Horwath (L&H). However, at this stage industry data was expensive to collect and store and therefore they were limited to tracking broad trends. Randall Smith (2009), who worked at L&H at that time, confirmed that there was “tremendous resistance to some of our work” due to these costs. Even when Randall Smith left L&H to set up his own consultancy, STR Global, in 1985, the company still only concentrated on developing reports that showed industry-wide trends (Smith, 2010). However, at some point in the late 1980s and early 1990s, there was a step change in hotel industry research, with the industry applying pressure to third-party companies, especially STR, to provide competitor data (Haynes, 2016).

Randall Smith from STR (2009) argues it was a combination of factors that drove this change. Firstly, it was once again improvements in information technology that led to the change as they dramatically reduced data processing and storage costs. Secondly, and probably most importantly, the competitive landscape of the hotel industry had changed drastically during that period, suggesting that external

pressures may have an impact on what data is needed for price decision-making. There was a building boom, subsequent increased competition and with it increased pressure on hotel managers to concentrate on competitor room rates to protect their position due to a situation of oversupply (Butler Jr & Benudiz, 1994; Haynes, 2016). At first, the industry pushed for basic market share reports, but it soon moved onto the need for more localised competitor set data. As already discussed, the trend towards the separation of owner and operator, with the wider introduction of management contracts and sale-and-leaseback deals in the early to mid-1990s, has also led to the same brand hotels being owned by different parties (Whitford, 1998; Whittaker, 2008). As a result, trust levels between sister hotels and clusters were broken down and internally data sharing became rarer especially on commercially sensitive data such as performance against budget as hotels within the same brand became viewed virtually as direct competitors (DeRoos, 2010). It appears a situation arose where individual hotels could not meet the level of data originally shared within their brand, as confidentiality issues resulted in data being withheld. So began the move to relying on third-party data suppliers, whose aggregation of data increased trust from hoteliers and increased the supply of data. Higley (2005b) commented that Holiday Inn tried to be sophisticated in terms of their data collection but ultimately could not match the output of STR. Even other hotel consulting firms, such as Ernst and Young and McKinsey and Co, rely on the data supplied by STR (Bloom & Zheng, 2013).

In 1987 STR launched the STAR program which began comparing “a cross-section of competitors that fell within a fairly broad range of groups” (Smith & Zheng, 2011, p.371). However, for the industry, this was not enough as competitive pressures continued to intensify. Westin Hotels were the first to approach STR with the idea of creating specific competitor sets in 1989. Again, the hotel industry, certainly at a corporate level, was driving the need for data. Smith and Zheng (2011) agree that in the late 1980s the industry was desperate for market share analysis due to the building boom. However, STR, even though they are now a major global supplier of competitor set data, was initially cautious about taking up the challenge from Westin. They were concerned that managers would not put together realistic competitor sets but rather create ones that simply made the property look good. Up until this point STR had total control over the

collection and processing of data and there was a big debate over whether they or hotel property managers should select the competitor set, again raising issues of decision-making autonomy. Initially, they asked general managers to gain brand approval of competitor sets but have since left it to the discretion of unit level managers (Smith & Zheng, 2011). Today the STAR report based on specific competitor data that compares one hotel against five or six of its nearest competitors is described by Smith and Zheng (2011, p.371) as “ubiquitous”. The success of the STAR reports has also relied heavily on the industry supplying the data for STR to process into summary reports. The STAR program now benchmarks a hotel against its competitive aggregate and local market data on a daily, weekly and monthly basis, providing up to eighteen months of historical occupancy, ADR and RevPAR data for the whole hotel and individual market segments as well as supply reports, highlighting the importance of the economic forces of the market in hotel pricing (STR Global, 2018). Trust has featured heavily in this process and the use of aggregated data, meaning individually properties cannot be identified in a competitor set, is the major factor for this trust in STR data. Smith (2010) himself highlights that getting industry buy-in was crucial to the success of competitor data sharing in the hotel industry.

However, gathering competitor data was not without its critics in the literature. Lieberman (2003) was critical of using competitor data if it became the sole decision-making tool. They argue that this is because the data can often be distorted by competitor hotels having one-off group bookings, and therefore the statistics are not representative of their normal patterns of business. They add that the driving forces behind the tactics taken by competitor hotels, as evidenced by the data, remain unknown. In essence, they are commenting that the competitors' average daily rate might be known to the decision-maker but not the full details of the strategies and tactics that created the prices charged by the competitor. Smith and Zheng (2011) and Webb and Schwartz (2016) are equally cautious about the use of competitor set data but for a different reason. They believe that due to pressure to outperform the competitor set and the fact that hotels have the freedom to choose the hotels that go into the competitor set there may be a temptation to choose a set that is easy to beat if the payoffs of cheating and the pressure from superiors are high enough. Webb and Schwartz (2016, p. 2) claim

that “sub-optimality” of the competitive set can lead to significant damage if it is used as a performance assessment measure. They add that if that measure is inaccurate, performance might suffer due to inaccurate benchmarking. This also poses questions about the judgement of individual hotel managers in decision-making. Liozu and Hinterhuber (2013) also found that value-based pricing was positively linked to firm performance whereas solely competition-based pricing was negatively linked to performance, although the research did cover both manufacturing and service companies. Later, and specifically for hotels, Enz, Canina and van der Rest (2015, p. 13) found that hotels could actually signal value through setting prices above the competition. They also found that this led to increased occupancies over hotels that followed competitors, although they commented that “it is possible that independent hotel operators do not have the same level of confidence in choosing a higher relative price position than the competition”, perhaps due to the strength of the brand image. Another earlier study had also found that both in weak and strong markets there was no risk to revenues in a hotel maintaining its rates even if competitors were discounting. This was across a sample of just over sixty thousand hotels (Enz, Canina & Lomanno, 2009) based on STR data.

2.33 Current trends in hotel room pricing

Charting the development of STR and their competitor data also highlighted the fact that the literature has not recently really addressed questions of whether STR continues to be the primary competitor data source for price decision-making within the setting of contemporary hotel revenue management. In recent times, hotel room pricing has trended towards ever increasing accuracy and granular detail particularly of forecasting (Noone, Enz & Glassmire (2017) and segmentation, supporting the use of dynamic pricing. Naturally, this is matched with developments in technology and further demands for detailed and accurate data. Given the speed of price changes and the rise of automated revenue systems capable of making price predictions, the question remains as to whether STR’s focus on historic data will increasingly become out-dated as the demand shifts to real-time data, for example, internet-based rate shopping tools such as RateGain, OTA Insight, and TravelClick. Perhaps this also reflects the increasing complexity of the definition of big data, which suggests the need is no longer just

for more data but data that allows for the right insights based on the type and frequency of decisions that need to be made. Mattila and Gao (2016) confirm that pricing is now a complex process and Kimes (2017) in her study of the future of revenue management, highlights that technology and data analysis will continue to be the main drivers of change. Academics also stress the use of real-time data in the price decision process (Wang et al., 2015; Guha Thakurta, 2016; Josephi et al., 2016). Vinod (2013), for instance, they comment upon the use of real-time hotel price shopping data and how this can be used to change prices dynamically and automatically on a hotel's website, rather than having to wait for the arrival of daily or monthly competitor reports from STR Global. Abrate and Viglia (2016) more recently confirm that real-time rate changes are enabled by data from the internet and online distribution channels. Therefore it appears pricing has become more immediate and predictive in nature, reacting more quickly to even subtle demand changes in the market.

Pricing is now utilising data from a greater variety of sources and digital channels for capturing customer information. Duetto (2015), a company specialising in revenue analytics also comments that information from the internet such as the number of customers looking at websites can also give insight into unconstrained demand adding another dimension to forecasting. In addition, Mullen (2016, p.41) argues that understanding “outside elements, such as customer reviews” is vital to revenue management as it may in turn influence demand. In this way, Cross, et al. (2009) discuss how revenue systems can now simulate multiple price-demand scenarios and recommend from those the optimal rates to maximise revenue. Koushik, Higbie and Eister (2012) offer the Perform system at Intercontinental Hotels Group as an example of a system that uses competitor rates, forecasted demand and price-sensitivity to make a recommendation for dynamic discounts from the best flexible rates, which would use to have been termed rack rates. The ability to predict the best prices to charge may also originate from the expansion of the number of sources of data that are possible to incorporate in the pricing decision. According to Shafiee and Ghatari (2016) hotels must on the one hand embrace this, but must also transfer this, often unstructured data (Duan & Xiong, 2015), into a format that is analysable.

Davenport (2013) suggests that being able to easily collect predictions on things like the weather and consumer confidence means that ever more real-time pricing decisions can be made. However, Davenport (2013), although arguing from a commercial rather than academic viewpoint, does argue that hotels are much earlier in their big data journeys than the online travel agents and travel distribution companies. He also cites their slow adoption of the use of unstructured data as an example. The use of this unstructured data for understanding consumers is also linked to an increasing focus on achieving profit through pricing. Yang, Cheng, Sung and Withiam (2009) and Zhang, Ye and Law (2011) suggested a pricing strategy that was aware of the services that customers valued and only offering those services within a certain price bracket, so as to maximise customer satisfaction whilst simultaneously controlling costs. This is closely linked to the idea of hedonic pricing (Rosen, 1974), where differentiated products are viewed as a bundle of attributes and characteristics by customers and can be packaged up in different ways to better match the prices charged to the customer's perception of value. This way of pricing is not new but easier to fulfil given greater detail of consumer knowledge, through unstructured data sources such as social media. In addition, van der Rest, Roper and Wang (2018, p.38) recently identified the challenges that hotel property managers have in gathering "credible information on demand and especially customer value" which would allow for the implementation of these more value-based pricing processes and that the setting of prices remains largely competitor-orientated. Earlier, van der Rest and Roper (2013) had stressed the importance of understanding the value perceptions of customers in introducing value-based pricing processes. However, the question still remains as to whether these types of customer information are perceived to be big or small data by managers at the hotel unit level.

Mattila and Gao (2016) also suggest that there are now more novel pricing strategies for hotels to engage with that are also driven by internet technology, such as participative pricing strategies, which covers name-your-own-price (Priceline.com and eBay Travel) and pay-what-you-want, although this seems mainly still related to restaurants, daily deals and flash deals through sites such as Groupon or Living Social. In addition, the increasing use of smartphones to make bookings will make customers less sensitive to slight price increases as it makes

the payment less painful and they compare this to the way credit cards encourage more spending. With this, there is also an increasing need to focus on the customer perception of value and customized pricing (Cross et al., 2011; Wang et al., 2015; Mattilla & Gao, 2016; Butler, 2016; Yeoman & McMahon-Beattie, 2017). This perhaps suggests the use of more unstructured, social media data and user-generated content in gathering information on consumers rather than through more traditional consumer data saved in property management systems. Richard (2017) agrees that micro-segmentation can be achieved by big data analysis of social network profiles and by sentiment data. Interestingly though, the participants in Kimes (2017) study rated the use of individual customer pricing higher than in the study based on 2010 data (Kimes, 2011) but rated prices set through customer relationship management (CRM) and competitive pricing as less popular. Overall the literature seems to be suggesting increased use of user-generated content by decision-makers to guide pricing towards a customer focus. Noone, Enz and Glassmire (2017, p.4) support the need to "balance short-term revenue maximisation with long-term customer development".

Pricing has also followed some of the same emerging trends in revenue management. With the increased focus on total revenue management (Wang et al., 2015) and the delivery of profit, prices must be seen to be driving the bottom line although now there is even greater consideration of marginal and variable costs when setting prices rather than the capital costs used in much earlier hotel pricing models (Altin, Schwartz & Uysal, 2017). Interestingly, these costs, such as commissions payable to distribution channels, may also be viewed as controllable by general managers, adding to their responsibilities within decision-making. The 3D model for hotel pricing developed by Ivanov (2014) reflects this greater focus on costs, as although it considers seasonality it also asks for prices to take into account the costs of selling through different distribution channels and the fact that prices should vary based on different booking terms. The focus on profit is evidenced in the increased sophistication of revenue management metrics which track the success of pricing changes, for example, an article aimed at industry professionals on Hospitality Net cited the many metrics needed to manage hotel room pricing. While the article recognised the common use of occupancy, average daily rate and revenue per available room, they claim these do not offer a detailed

enough view of the hotel's performance. Instead, the list added gross operating profit per available room (GOPPAR); market penetration index (MPI); the comparison of market share against that of the competitor set based on occupancy; average rate index (ARI); the comparison of daily revenue share against the competitive set; revenue generation index (RGI); the comparison of RevPAR against the competitor set; and finally, adjusted revenue per available room (ARPAR), which takes into account the cost per available room in the RevPAR calculation (Vouk, 2016; Starfleet, 2016). Academics, Ivanov (2014) and Kimes (2017) also confirmed that revenue metrics would increasingly focus on profit and consequently take into account costs when setting prices. Although, Noone, Enz and Glassmire (2017) caution that RevPAR from a competitive benchmarking perspective remains a key metric. What we see is a return to the consideration of costs in pricing, although these are marginal and variable costs rather than the fixed capital costs of earlier years. However, there is still a continuing tension between measuring the impact of pricing on top-line revenues and bottom line profit and the literature does not explore adequately which of these many metrics are principally used in practice.

In addition, just as with revenue management in general, a debate rages regarding the balance of tactics and strategies in hotel room pricing, despite Richard's (2017) recent claims that revenue management has evolved from a tactical discipline to a strategic one. Whilst the increased focus on profitability and the customer suggests a more strategic approach, the ability to frequently change prices, often automatically, does suggest that pricing could have the potential to become more tactical and reactive. Despite this, there appears to be no common agreement about how a balance between tactical and strategic pricing can be achieved in practice. Enz et al. (2015, p. 4) argued for a strategic approach to pricing, rather than a strictly tactical approach, as do Altin, Schwartz and Uysal (2017). However, the use of the word 'strictly' is interesting because it suggests an acceptance of some element of tactical pricing. They clarify their position by commenting that "such a strategy would include pricing tactics indicated by revenue management analysis and economic conditions." Therefore, tactics may arise from the unpredictability of market forces, where despite increased forecasting abilities demand still fluctuates and makes it more challenging (Hung,

Shang & Wang, 2010). This means pricing remains heavily influenced by the workings of the market and economic principles. Although, the utilisation of short-term tactics may also have something to do with the role of the general manager and the time pressures they face. Lee (2016, p.70) argues that hotel managers have little to do with strategic pricing and that managers may view room price changes as a "quick fix" that they become accustomed to relying upon over time. This almost suggests that at a unit level there may be an element of habit in making price changes and that under time pressures, longer-term strategies give way to quick, tactical fixes. Of course, there is also a question over whether the ready availability of data also tempts managers to make more short-term, trial and error-based decisions as they can more easily track the outcomes. They can also benchmark many different metrics mentioned above against themselves and competitors, but are they doing this just because they can, or does it actually have value in making future pricing decisions? This question is not clearly answered in the literature.

In summary, what is clear from the literature is that hotel transient room pricing has increased in complexity. These increasing complexities have been driven by corresponding increases in the amount and variety 221-22of data available to decision-makers, often because they themselves, and the competitive nature of the market, have demanded it but because technological improvements have allowed for it (Mullen, 2016). Therefore it still remains somewhat unclear if the big data is increasing the complexity of pricing metrics or whether the need for metrics had resulted in attempts to generate more data. However, what is clear is that for hotel pricing big data has not been the result of a sudden, massive increase in data over a short time period but rather has been a gradual evolution, seemingly tracking similar increases in revenue management strategies from its origins in yield management. One recent paper (Intezari & Gressel, 2017, p. 74) argues that big data is "just a further step in the evolution of data and their applications", rather than being the sudden "disruption" to business decision-making claimed by others (Esteves & Curto, 2013, p.148). The literature consistently fails to address the practicalities and processes involved in how the price decision is made by managers, why some of the highlighted tensions are overcome and some are not and what the impacts of data are in practice. Van der Rest and Roper (2013)

stress the importance of focusing on the pricing process and not just the final outcome of pricing through a resource-based approach. However, the many variables and complexities of these processes have not been fully deconstructed by the literature. This is perhaps particularly concerning given the complexity of pricing and revenue management overall. Mattimoe (2007, p. 137) confirms “the room rate pricing decision, as a time-bound interdependent set of sequential decisions made by the hotelier, faced with an uncertain environment” and Cetin et al. (2016) agree that the complexity of variables involved in pricing now make it harder for decision-makers to reach an optimum price.

2.4 Chapter Summary

This first literature review chapter has examined the history and development of hotel revenue management and big data and provided a definition of big data based around the Vs framework as well as current trends in hotel room pricing. Context was also provided on what was already known about price decision-making at the individual hotel property level, considering the impact of changing hotel ownership structures on how decisions are made at the individual property level. Overall, the key gap that was uncovered was in the understanding of the impact of big data on hotel price decision-making at a practice-based level as highlighted in the following points.

- Big data is hard to define and is surrounded by hype that often clouds the realities of what it can achieve. Clearly, it is more than just about volumes of data and is best defined by describing the transformational processes required to turn it from a raw material into deeper levels of knowledge, understanding, insight and to extract its full value for decision-making purposes. This is reflected in the Vs framework most often used to examine what big data is and how it works. There is also now a move towards small data in the literature, but it is not fully clear how this is defined and or how it may be integrated with big data.

- Both hotel revenue management and transient room pricing have increased in complexity over time through a gradual increase in available data and supporting technologies. Recently there has been a return to a focus on costs in yield management but instead of the capital costs typical of early yield management the focus is on marginal costs and delivering profit based on the long-term profitability of the customer. Yet, the many tensions that exist in the

delivery of revenue management remain unresolved in the literature, particularly over the practicalities of delivery at the individual hotel property level.

- The general manager is still central to decision-making in the hotel property but it is not clear how they are involved in price decisions in practice. There is some suggestion that revenue specialists may be involved in making joint-decisions but there is a lack of focus in the literature on how those relationships might work. The role of general manager has become more commercial and complex, perhaps due to increasing complexities of hotel ownership structures.

To sum up, what is mainly missing from the hospitality revenue management literature is an understanding of the practicalities of what occurs at the hotel property level when general managers, perhaps in partnership with revenue specialists, make pricing decisions with access to big data and increasingly sophisticated technologies. In other words, more insight is needed into the practicalities of how general managers are involved in pricing decisions, how their relationships work with revenue specialists, how and what data they interact with, the extent to which revenue technologies are used and overall how data influences their decision-making behaviours. This chapter has served to prove the point made in the introduction that the complexities of hotel room pricing at the individual hotel property level exist within a black box. To reconfirm, it did not uncover the realities of what was happening in practice. This serves to clearly prove the importance of this research in deconstructing this black box.

3. Literature - New Emerging Theories

3.1 Introduction

As already discussed in the introduction to the first literature review chapter this second literature focused chapter will study in detail the various dynamics of price decision-making considering its place in the wider hotel revenue management context and the impact of big data on hotel pricing and management decision-making. It will culminate in a consideration of the role individual general manager's play in price decision-making within the context of hotel revenue management at an individual hotel level in the era of big data technologies. As a reminder this second section of literature was forming throughout data collection and analysis as categories emerged, again in line with grounded theory. This chapter also links to the research findings in terms how the specific areas of the literature relate to the main categories that emerged from the research data and the gaps in knowledge in they addressed. This is summarised in table 3.1 at the end of the chapter.

3.2 Impacts of big data on manager decision-making

This section examines the conflicting opinions around the impact of big data on management decision-making and places the earlier discussions in further context. It is also important to consider manager decision-making behaviour given their continuing role in setting prices, despite the existence of automated revenue management systems. The balance between automated and human decision-making will be explored further in this section, along with the debates about whether big data alone can be used as a decision-making tool, and whether it causes information overload. Finally, it discusses its overall impact on management decision-making. This exploration of information overload and automated revenue systems again came about as a direct result of the emerging themes coming from the data collection and analysis.

3.21 Big data – a raw material?

The first major question when considering the impact of big data on management decision-making is whether big data can stand alone as a decision-making tool or whether other elements of the decision-making process need to exist alongside it. In general, the academic literature is clear that big data can only effectively be

used in decision-making if it goes through a transformational process, often through analytics, into information and then knowledge, as already highlighted in the definition of big data through the Vs framework. Without these processes, it would remain a raw material from which it would be hard to extract insights and take actions (Puschman & Burgess, 2014; Sivarajah et al., 2017). Gandomi and Haider (2015, p.140) highlight this succinctly by stating that “big data is worthless in a vacuum… [and] organisations need efficient processes to turn high volumes of fast-moving and diverse data into meaningful insights.” Ackoff (1989) in his seminal paper explains that data is simply the symbols that represent the properties of objects and events, whereas information consists of processed data, aimed at increasing its usefulness. Ackoff (1989) went on to state that information is contained in descriptions that provide answers to the key questions that may be asked by managers based on who, what, when, where and how many. Knowledge, he argues, is conveyed by using this information to answer the 'how-to' questions. Finally, understanding is conveyed by explanations, and answers to the 'why' questions.

Ackoff (1989) also believed that understanding could be turned into wisdom although he states that this is rarely achieved. Data, he thought was plentiful, wisdom was not. Interestingly, Batra (2014) defined wisdom as cumulative knowledge tempered by experience. Perhaps wisdom, therefore, could be linked to the distinction between explicit and tacit knowledge made by Nonaka and Takeuchi (1995). In their thinking explicit knowledge is formal, identifiable and easy to capture and transmit but tacit knowledge is informal, tied to the senses and not always possible to transmit clearly. Later Bratton (2016, p. 185) added that tacit knowledge is “embedded in our actions and ways of thinking, and transmitted only through observation and experience”. Most recently, Tian (2017) argued, that actually the speed of big data analytics technology has shortened the tradition data-information-knowledge-wisdom model developed by Ackoff (1989) to big data-knowledge-wisdom. What is clear is that data has to be processed through a number of stages to reach its total value in the decision-making process as summarised in figure 2.2 on the following page. However, little of the hospitality literature has addressed how these stages may be applied in practice in price decision-making, and even Ackoff’s pyramid has undergone criticisms for being a

rather simplistic model, not well-applied in practice (Frické, 2009). Only one article could be sourced, namely that by Liberatore and Luo (2010) who studied the analytics processes at Harrah's casino to come up with a process view of analytics that covered four similar stages of data, analysis, insight, and action. So within hotel revenue management decision-making at an individual hotel level, the transformation process of big data remains unclear.

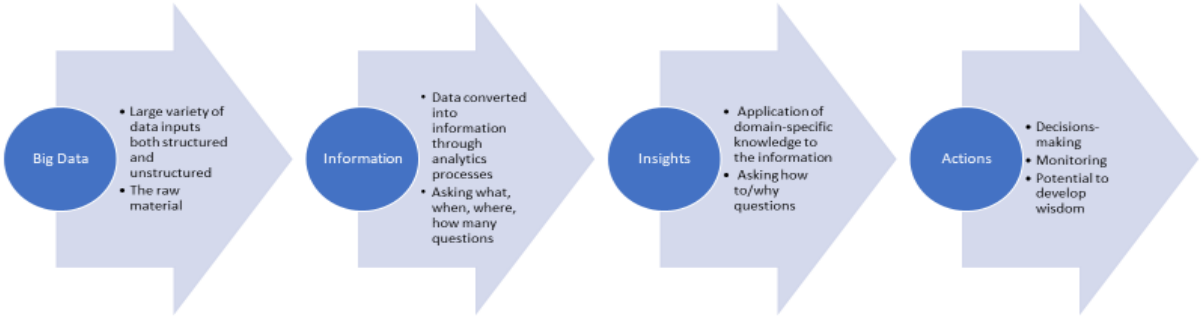


Figure 3.2: A Summary of the Big Data Transformation Process

In fact, the general big data and decision-making literature also seems to suggest that dangers may arise when decision-makers do not follow clear transformational processes that turn big data into a valuable decision-making tool or when big data is collected without a pre-defined purpose, just because it is now cheaper and easier to collect and store (Günther et al., 2017; Constantiou & Kallinikos, 2015; van den Broek & van Veenstra, 2017). Kitchin (2013, p.264) believes this may arise from a "naivety that big data can speak for themselves", whereas they believe that for analysis and interpretation it needs contextual and "domain-specific knowledge" to make sense of it, as highlighted in the figure above. They argue that this contextual knowledge should focus on capturing the complex nature of people's emotions, values, beliefs and opinions that drive the complexities of the way people interact.

There are also further criticisms of big data that cast doubts on its ability to actually develop understanding and answer the "why" questions, as much of the literature suggests that big data has led to a focus on correlation rather than causation (Do, 2013; Ekbia et al., 2015). Perhaps this has resulted in decision-making being unable to move past the knowledge stage of Ackoff's (1989) model. However, Mayer-Schönberger and Cukier (2013) argue that this lack of accuracy

at the micro level is compensated for by the insight gained at the macro level with big data. They confirm that (p.35) “big data transforms figures into something more probabilistic than precise… [and] may require us to change, to become more comfortable with disorder and uncertainty”. However once again, the hospitality literature places little focus on the practicalities of how managers adapt to the changes or manage big data through the transformational process to reach a fully informed pricing decision. Nor does it address to what degree they apply their domain-specific knowledge to the big data they work with. In fact, a thinking point for this research was whether domain-specific knowledge could be considered as a facet of small data and whether its use is an application of managers' wisdom as Ackoff (1989) suggested. As summarised in table 3.1 this body of literature links to the emerging finding from the research that hotel general managers use local customer insights or small data to interpret broader revenue trends from the big data.

3.22 Big data and information overload

There are currently other areas of debate about whether big data causes information overload, what impact this might have on decision-making and whether it adds further challenges to the process of successfully extracting value from big data. The hospitality literature evidences little focus on this area, so it is necessary to turn again to the more general big data literature, although recently Saxena and Larnest (2018) found that in the context of customer digital data, for example, TripAdvisor and Twitter, information overload was present. In simple terms information overload has been described as having too much information, although given that information is borne out of data, it might be more accurate to describe it as too much data. This point was recognised earlier by Meadow and Yuan (1997) and later, based on their work, by Edmunds and Morris (2000). They both argue that for it to be technically termed information overload, the feeling of overload would need to come from the messages that had already been received, understood and appraised as in Ackoff’s (1989) model, whereas actually, the overload comes from the data even before it can be interpreted. Therefore it might be more appropriate, especially in the era of high volumes of big data, for it to termed data overload, although this is not the commonly used term in the literature. The literature on information overload also seems to focus primarily on

the volume of data, but it does not take into account the complexities of big data that have been recognised in other areas of the literature and already discussed. Although an older study by, Speier, Valacich and Vessey (1999) also added that diversity of information could also increase overload, but they did only utilise laboratory research.

However, despite Edmunds and Morris's (2000, p.26) belief that some people may not explicitly recognise the existence of information overload because they have learned to live with it and it has become an "accepted state", much of the literature does recognise its existence and offers up some explanations for its causes. Eppler and Mengis (2004) comment that researchers across many disciplines have discovered that performance does indeed correlate positively with increases in information but only up to a certain point. After this point when information continues to increase, levels of performance will drop off, which Simon (2013) links to the law of diminishing marginal utility. Although they argue that due to cheaper data storage, even marginally useful data can be gathered and stored for later use, but they say that this may actually add to the sense of overload. The issue seems to be that this point may be reached at different times for different people, based on their individual information-processing capacity and information-processing requirements (Eppler & Mengis, 2004), which links to the information processing view of Tushman and Nadler (1978) and Galbraith (1974). Processing capacity looks at the quantity of information a person can integrate into the decision-making process within a specific time period, and processing requirements look at the amount of information a person has to integrate in order to complete a task. Kock (2000), although utilising a small sample, did also find that the overload was more about the time allowed for completing the task, rather than the volume of information.

Finally, Eppler & Mengis (2004) also argue that overload has a negative impact on decision-making as managers become highly selective and ignore larger amounts of information in the decision-making process, for example Marr (2015, p.47) highlights that the more metrics managers have, the greater the potential for them to "become numb to the dashboard" giving them the data, and consequently they miss data. Later, Van Knippenberg, Dahlander, Hass and George (2015) agreed that too much information is a distraction and may decrease the likelihood that

anyone pays attention. More recently there have been suggestions of how to combat overload. Manyika et al. (2011) argued that technology, especially visualisation techniques, would help to combat information overload, as well as the use of detailed analytics, that may not have been recognised by earlier studies. In addition, Simon (2013, p.162), stressing the importance of organisational culture, says that employees must recognise the benefits of big data and that it is not recognising this, rather than the pure volume of data that may cause them to "regularly ignore or reject information and data" and instead "rely exclusively on hunches, intuition, policy and routine." In summary, what the literature seems to suggest is that information overload, or perhaps more accurately, data overload, does potentially exist but will vary in effect and degree based on a range of factors, which within the hotel pricing literature have not been explored. As summarised in table 3.1 this body of literature links to the emerging finding from the research that information overload is avoided at the hotel property level due to deliberate attempts of the hotel general manager to filter out what they consider to be unimportant data.

3.23 Big data and the way managers make decisions

This section will highlight some of the generic themes and debates that arise from the literature about the way managers make decisions. It will also consider the impact of big data on how managers make decisions, with a focus on price decision-making. At the heart of these debates lie discussions centred on the degree of balance that managers need to achieve between rational decision-making and the utilisation of hunches and intuition. What the literature does not make clear is whether big data influences managers to move further towards rational decision-making or not and under what circumstances this might happen. There is certainly a lack of hospitality literature that considers this in the context of revenue management decision-making, although there is some coverage of it in the pricing and economics literature as will be explored below.

3.231 Do we need human managers to make decisions?

Although this literature review has already hinted that human managers remain involved in decision-making, given the increase in technological based, data-driven analytics and automated pricing technologies within hotel revenue management, it is worth exploring further in terms of manager behaviour. It is also

valuable to consider in more detail the factors influencing the balance between human involvement and automation in revenue management decision-making, in order to demonstrate why it remains important to examine the role of managers in price decision-making later in this literature review. Some of the more commercially driven literature suggests that big data analytics will replace human decision-making with automated algorithms (Manyika et al., 2011), but much of the hospitality and revenue management literature seems to agree that there will always need to be a balance between human decision-making and that driven by technology. This mirrors some of Ackoff's (1989) thinking mentioned earlier, that wisdom, the last and extremely valuable iteration of the data transformation process, can only be reached through human intervention. In fact, he argues that wisdom is the characteristic that differentiates man from machines. However, although the hospitality literature believes the human manager will remain involved it is less clear about what the balance is between pricing made by humans and pricing made by automated systems at the hotel property level and the practical impacts of these two forces working together. The literature is quite general in its approach to human involvement, but whilst it states that there needs to be some human involvement, it does not fully explore the reasons why humans should remain involved or the extent of their involvement (Ekbia et al., 2015; Wang et al., 2015; Shiffrin, 2016; Lee, 2016). The more significant points currently made by the literature are explored below.

The first point in the literature states that automated revenue systems do exist in the hotel industry that are capable of using data and algorithms to predict optimal room prices (Liberatore & Luo, 2010; Pekgün et al., 2013; Davenport, 2013; Butler, 2016; Guha Thakurta, 2016) which are often promoted to potential investors, managers and owners by hotel companies (Intercontinental Hotel Group (IHG), 2017) as being able to integrate local demand forecasting, competitive data and price sensitivity modelling in order to reach optimal pricing decisions for a whole year in advance. Davenport (2014) also highlights that hotels have a long history of successfully applying pricing analytics. However, the degree to which these systems are relied upon by managers will vary due to several factors. In fact, a recent paper claimed that the more data that was available, the greater the need for human judgement in decision-making (Tian, 2017). Phillips-Wren and

Hoskisson (2014) found that it was technological design flaws that were causing issues with the integration of big data analytics in decision-making and argues that this was perhaps resulting in humans not wanting to rely totally on them. Connell and Voola (2007) also stressed the need for integration and co-ordination of big data as did Hayne, Troup, and McComb (2011). Lieberman (2003) had already asserted that revenue management systems could only operate with maximum efficiency when their users understand and capitalise on their strengths, weaknesses and data input needs. Duetto (2015) also placed limitations on revenue technologies by arguing that whilst they can integrate and help correlate a variety of data sets, they are not able to know which ones are most important without human involvement and assessment of the data. This is also supported by an academic paper that stresses the need for humans to interpret data (Steen, van Beurden & de Boer, 2016).

The literature also seems to stress that the type of decision and context may also have an impact on how humans and technology interact. It appears that the strength of the automated technologies may be in performing the tactical, daily price changes made by hotels, for example, Cross et al. (2009) and Guha Thakurta (2016) argue that these systems will support the day to day data crunching, tactical pricing decisions and in matching rate offerings. Cross et al. (2009) maintain that whilst this frees managers to think more strategically they will still have to review and approve those tactical decisions. Another question arises from this, however, as to whether the existence of big data may increase the number of tactical decisions made, potentially distracting from strategic thinking. Butler (2016) also believes it will free general managers to spend more time with guests, which based on the increased importance of the customer in revenue management, might then result in further personalised customer data being collected that could be used to analyse and interpret automated data. Selmi and Dornier (2011) agree that computers will take over the collection, processing, and distribution of data, and the sorting and filtering of information but managers will still need to conduct the analysis-based decision-making, although the literature does not often make it clear how and why this should happen in practice.

Interzari and Gressel (2017) also agree that the type of decision may be an influencing factor, for instance, they argue that structured decisions with

unstructured data may require techniques such as text-mining and content discovery, whereas structured decisions with structured data can be formulated by using advanced analytics for automated and programmed decision-making. Unstructured decisions using unstructured data and even unstructured decisions using structured data may rely mainly on human knowledge, experience, interpretation, and expert insight. What is not examined clearly in this paper is whether pricing is a structured or unstructured decision. In terms of the context of the decision it also appears that some academic papers have found that where there is a lack of revenue support available to hotels there is a greater degree on the reliance on the automated system. Pekgün et al. (2013, p.33) cite the example of the Stay Night Automated System (SNAP) developed by Carlson Rezidor wherein its hotels with no revenue support the hotels were “letting SNAP send the rate recommendations directly to the reservations system without user review, because they believe that SNAP finds more opportunities than they would” and therefore they could use the time saved to tend to customer and operational issues. Ferguson and Smith (2014) also stress that total reliance on automation of revenue management systems may only happen in smaller, limited service hotels rather than larger, full-service hotels.

If there is any suggestion that human involvement is still needed, even with the existence of automated revenue management systems and big data analytics, then the final question would be whether managers involved in pricing decisions for hotels have the required skills to add to, rather than detract from, the insights made by these technological systems, especially as skills are highlighted as a challenge of big data application, as mentioned earlier. Starfleet (2016, p.27) suggests “many revenue decisions today are being made by general managers who may have little or no formal training in the science of demand forecasting and price optimization. Needless to say, the results are bound to be suboptimal”. This is perhaps due to the focus of general manager skills on finance and accounting skills and budget management rather than revenue management, which has been the focus of much of the skills-based general manager research (Suh, West and Shin, 2012; Ruetzler, Baker, Reynolds, Taylor & Allen, 2014; Kim, Schmidgall & Damitio, 2017). Beck, Knutson, Cha and Kim (2011) are also keener to support the revenue manager taking the lead in the decision-making process, when they

state that “the revenue manager must also be able to influence others to accept their recommendations for pricing and inventory management” (p.187). They add that revenue managers must defend their position in a non-emotional way to others. They summarise that “the skill of the revenue manager is to translate market intelligence into revenue management strategy that is convincing for hotel leadership” (p.192). All the literature stresses that the ideal situation may be joint decision-making and collaboration of different approaches (Bhatt & Zaveri, 2002), thereby recognising different skill bases. Within the hospitality literature, Ransbotham et al. (2016) highlight the opinion of the Director of Database Marketing and Analytics at IHG who believes that some of the best analytical results come from collaborations between information technology and traditional decision-makers. This is based on much older literature that suggests that decisions are generally better understood if they are based on shared information (Lindblom, 1959; 1965) but also supported later in terms of a discussion on the importance of silo-busting and sharing information in decision-making (Kiron & Shockley, 2011).

Finally, from the literature on human involvement with automated systems, it emerged that some researchers had noted it was perhaps the manager’s intuition (Mattimoe, 2007) and experience, particularly of the customer, that meant automated revenue systems can be overridden by revenue decision-makers (Davenport, 2013). Tranter, Stuart-Hill and Parker (2014, p. 104) put this succinctly, stating that “consumer behaviour possesses that human element that often eludes the capabilities of technology”. Cetin et al. (2016) and Richard (2017) agree that computers alone would miss nuances in the local market, such as gossip and the needs of specific customers. Coplin (2014) agrees that big data analytics may be helpful at spotting a cluster of insights or the norm but is not so efficient at recognising and incorporating the exception. This is particularly important given that Enz et al. (2009) also earlier agreed that whilst pricing guidelines may be set by brands and corporate strategy, pricing behaviour is led by what is happening in local markets. Phillips-Wren et al (2015) also argue that the human brain is useful for understanding the context in which the data analytics process takes place, within a hospitality context. As summarised in table 3.1 this body of literature links to the emerging finding from the research that where

automated revenue systems exist they are interpreted by humans driven by the involvement of the hotel general manager and the importance of their local customer insights not yet incorporated in these automated systems.

3.232 Collaborative decision-making practices

Leading on from the suggestions made above about the importance of joint decision-making, this is also worth briefly exploring in the context of big data. Most recently, Saxena and Lamest (2018) suggest that information behaviour in organisations should be viewed in the socio-technical context. They cite Tuominen, Savolainen and Talja (2005) who suggest information behaviour is a product of social relationships, technological configurations and the nature of the task. This suggests the need for managers to make decisions in collaboration with other managers and not just technologies. Most recently in the general big data, pricing and decision-making literature there has been further focus on collaboration to strengthen decision-making in order to realise the value from big data (Monino, 2016) and in particular to aid the setting of profitable prices for products and services (Günther et al., 2017), ideally through a hybrid of centralised and decentralised organisational approaches to decision-making. This has also been found to be a suitable structure for revenue management by Altin, Schwartz and Uysal (2017) who found that a mix of in-house and centralised specialist revenue teams was well valued, whereas total outsourcing of the revenue function was discovered to be unpopular. Ivanov (2014) also supports collaboration between revenue specialists and hotel units, arguing that revenue management knowledge should still exist at the unit level. Cross et al. (2009) also suggest that individual hotels make the final call on pricing decisions after listening to recommended guidelines from revenue specialists. However, they are still keen to mention that revenue management may not reach its full potential where all the revenue management decisions are made at a property level due to time restrictions and operational pressures, although this paper lacks empirical strength. Also, in relation to revenue management in hospitality, Wang et al. (2015) talk about information fusions and the merging of information from heterogeneous sources into a new set of information towards consistent, accurate and useful representation to help reduce uncertainty. Phillips-Wren et al (2015) also stress the importance of balancing different skills. They identify two types of

skills users. The first one is business users who have basic skills and domain-based needs, which in this context could be general managers. The second is business analysts who are users that have more complex data skills allowing them to perform deeper analysis to support their decision-making, which could be revenue specialists.

However, what is not so clear in the hospitality literature is how these joint decision-making partnerships work in practice in the hospitality industry, although some general observations have been made across the literature. Manyika et al. (2011) suggest that although at the heart of these collaborations is the sharing of existing knowledge and the creation of new knowledge this requires the breaking down of specific organisational barriers. Zack (2003, p.69) adds that constant interactions are needed, but says that may still involve different teams using different approaches to "gathering and analysing market information, [with each using] a different technology and format to capture and store raw data, [and conduct] analysis, interpretation and final reports." This has been later supported by Little and Deokar (2016) who argued that knowledge-intensive business processes are characterised by a collection of related and often interdependent activities along with sharing knowledge and leveraging existing knowledge. Liozu and Hinterhuber (2014, p.146) confirm that "pricing is a cross-functional activity that involves virtually all decision makers within the firm". Tranter et al. (2014, p.188) agree, stating that,

> "we have stated all along that revenue management is a team process. So, the team coming together to assess information and then review and adjust strategies and tactics is critical to obtaining optimal revenue management success".

This had already been stressed by Garrow and Ferguson (2008) when they called for cross-functional integration in revenue management. Therefore, both the general and hospitality literature agree that pricing decisions using data may not be the remit of just one person, although they do not fully explore the complexities of how this joint decision would work in practice at the hotel property level. As summarised in table 3.1 this body of literature links to the emerging finding from the research that where revenue specialists are present the hotel general manager and the revenue specialist form a co-dependent relationship, blending their own distinct individual data sets and approaches.

3.233 Manager behaviour in the decision-making process and impacts of big data

So, having examined the issues around humans versus automation, data transformation processes, joint decision-making, and information overload, it is important to finally turn the attention to any other literature that comments on the positive or negative impacts of big data on management decision-making and what might be driving these impacts. At the extremes, one recent paper, covering research in the retail, services and manufacturing sectors, claimed that the informational benefits of big data and the ease in which data can be quickly collected and integrated into decision-making meant that it "can be used to improve decision-making in a company" (Raguseo, 2018, p.188). In contrast, Esteves and Curto (2013) argued that the greatest risk of big data was its negative impact on the decision-making process. More recently, Alharthi, Krotov and Bowman (2017) have also been vocal about the barriers to data-driven decision-making caused by outdated technology infrastructures, the inherent complexity and messiness of big data, lack of data science skills and unengaged organisational cultures. However, it is important to place these arguments over the usefulness of big data into the context of decision theory to gain a deeper understanding of the issues driving these different comments and to provide a foundation for uncovering a realistic picture of the value of big data in decision-making that cuts through the hype surrounding the term already mentioned in section 2.22 of this chapter.

If the arguments supporting classic decision theory are to be followed, then managers can be presumed to always be able to select the optimal alternative in any decision-making scenario (Edwards, 1954; Becker, 1976). This is based upon several key assumptions which are that the problem can always be identified, people have access to perfect information and act rationally, using objective criteria to evaluate all options consistently. It links back to the management science model, developed in World War Two, which is based on mathematical and statistical approaches where decisions are made under conditions of little uncertainty. The question that is not really answered in the literature though is whether big data can be classed as perfect information, especially given the need for a data transformation process already discussed. Also, due to the complexity

of factors needed to be considered in the hotel pricing decision, can it ever be described as occurring under conditions of certainty? Perhaps, automated systems driven by big data were originally designed to work on this basis but as already highlighted, human managers are often still involved in the process and human decision-making behaviours have been found to be less rational than classic decision theory suggests Simon (1957, 1983).

Instead, Simon (1957) developed a behavioural model of decision-making based on his concept of bounded rationality. This was based on his beliefs that humans were not rational and that they were more likely to be driven by the idea of satisficing in decision-making rather than by finding the optimal solution. Instead, they were happy to settle for an option that was considered acceptable rather than perfect. Based on research in Irish hotels, Mattimoe (2007) had found this to be the case in hotel pricing practices, although generally, the hospitality literature does not explore this extensively beyond this paper. Simon (1957) linked this satisficing behaviour to the limitations of human cognition and recognised the influence of past experiences and situational factors on the decision-maker. Lindblom (1959) took satisficing behaviours to the extreme with his science of muddling through. This was a short-term approach to control, based on frequent reviews of performance against target, rather than a strategic approach based on the long-term achievement of goals. Similarly, Eisenhardt and Zbaracki (1992) also mentioned the garbage can model, linked to the work of Cohen, March and Olsen (1972). The premise is that decisions are merely the result of a random confluence of people, problems, solutions and choice opportunities, although this model could be criticised for a failure to base this idea on empirical evidence. However, Martin and Fellenz (2014, p. 279) also comment that decision-making is often habitual and follows standard routines rather than being based on “active and reflective consideration”, which had earlier been suggested by Oxenfeldt (1973).

In the same way that general decision theories have developed from rational, classical approaches that accept that human decision-making may be more irrational, so has economics. Over time there has been a conflict between economists who take the neoclassical approach to price and economic theory based on the rationality of human decision-makers and those who accept the

application of psychology to economics and thus the potential irrationality of human economic decisions. Edwards (1954) and Becker (1976) offer a typical account of the neoclassical approach, arguing that *homo economics* or economic man is rational, able to maximise their utility in any given situation using a stable set of preferences, and can accumulate an optimal amount of information to aid these decisions with the goal of human action being to seek pleasure and avoid pain. Bruni and Sugden (2007) highlight changing opinions on this debate over time, from the nineteenth century when key writers such as William Stanley Jevons, Francis Ysidro Edgeworth and Maffeo Panteleoni merely incorporated current psychological thinking into their research without making an obvious distinction between the fields of economics and psychology, to the period between the 1930s and 1980s when psychology was actively stripped out of economics. However, even during this period the application of psychology never really disappeared, for example, as already mentioned, Herbert Simon (1959) had already recognised the increasing complexity of decision-making that would come about and began to look more carefully at how individuals would make economic decisions in a more complex environment through his work on bounded rationality. Howard and Morgenroth (1968) also attempted to recognise the role of intuition in management information processing during this time.

In the neoclassical approach, the importance of the role of information in decision-making is elevated, suggesting that there is an optimal level of information that if reached would lead to the rationalisation of the decision-making process (McQuillin & Sugden, 2012). Becker and Brownson (1964) for instance suggest that information should reduce ignorance, risk, and ambiguity, although this was before the levels of data complexity and volume seen today. Other viewpoints stress the impact of psychology and the fallibility of human decision-making, despite the existence of more data in the modern age, hence the rise of behavioural economics that centres on the “bounds of human behaviour” which restrict the individuals’ ability to make rational decisions. It is also felt that these “draw into question the central ideas of utility maximization, stable preferences, rational expectations and optimal processing of information” of neoclassical economics (Jolls, Sunstein & Thaler. 1998, p. 1471). Particularly important in this research is its challenge to the claim that optimal processing of information in

decision-making can be achieved, although what managers perceive to be optimal processing and what data they would include in this process is not fully uncovered in the literature.

Håkonsson and Carroll (2016, p.3) believe that whilst increased access to data should allow for more qualified decisions, it does slow the decision-making process down because managers no longer "have the courage to take decisions fast enough," although Puschmann and Burgess (2014, p. 1701) would argue that making decisions based on real-time data analysis is "framed as being superior to the slow decision-making conducted by subjective individuals". Managers may delay making decisions because they believe that gathering more data may reduce uncertainty. Hereby, aiming for rationality, managers may appear to be acting irrationally, by making no decision at all. Lunn (2008) had already commented that trying to incorporate too much information into the decision-making process can distract focus from the most important aspects of the situation. In a similar vein, Wills and Wycherley (2017) argue that people become so absorbed in analytics that they are guilty of not realising how much they know and how little other people know about a subject and therefore are unaware of the different approaches made towards the same decision by people within an organisation. In this way again, decision-makers may be using rational analytics but acting irrationally by not incorporating all available insights into the decision-making process.

Big data could be seen in the view of some in the literature to be driving a return to classical decision-making theory but perhaps what the literature is more likely to be suggesting is that some elements of decision-making are rational and based on data and others are more based on intuition and may be better that way. Wills and Wycherley (2017, p.16) are critical of assumptions around rational decision-making and believe that "people like to think that organisations employ evidence-based decision-making processes, and that faced with the same evidence, any decision-maker would make the same decision, but this is simply not true". In contrast, Sadler-Smith and Shefy (2004) are supportive of the idea that if intuition is added to the decision-making process it can actually add valuable information that a purely rational approach based on analytics, might miss, such as past experiences, knowledge, perceptions, and feelings held tacitly. They add that

given the existence of information overload “bypassing in-depth conscious attempts at analysis, intuition enables executives to move rapidly to a plausible and credible solution” (p. 83).

Eisenhardt and Zbaracki (1992) also agree that the debate over whether decision-making is totally rational or totally irrational is no longer controversial as there is empirical research that clearly supports the existence of cognitive limits to the rational model. Despite this, there is evidence that decision-makers have been proved to be rational about some things and not about others. Although the following research is old it does supports some of the thoughts above on the use of big data in decision-making. Isenberg (1986) found that managers developed contingency plans based on a rational strategy but acted on incomplete information, which is more irrational. Eisenhardt (1989) found that managers considered many alternatives, which is rational, but then only thinly analysed them, which is less rational. Al-Najjar, Baliga and Besanko (2008) also confirm that in terms of pricing an organisation may choose to change its price multiple times but then may neglect to adjust the budget or the methodology used to determine it, so what may look like a rational price change, is not, because the bigger picture has not been considered or adapted to take into account the price changes. Simon (1959, p. 269) had already commented that “information, says price theory, should be gathered up to the point where the incremental cost of additional information is equal to the incremental profit that can be earned by having it”.

This section of the literature poses more questions than it answers and highlights the lack of research that considers whether the increasing amounts and complexity of hotel pricing and revenue data lead to better decision-making approaches. It proves further that the impact of big data in manager decision-making exists within a black box. The question that remains unanswered is whether within hotel revenue management, big data does increase the accuracy of decision-making or whether more behavioural-led approaches to decision-making may also work, even if used in combination with data. This is especially important as there is a range of behavioural and external factors that may also influence manager decision-making as is discussed further below. As summarised in table 3.1 this body of literature links to the emerging finding from the research

that the value of big data in decision-making is enhanced through blending it with micro, local small data in the form of local customer insights to create a form of hybridised data.

3.234 Other factors influencing manager decision-making

Firstly, human decision-makers utilise a range of mental short-cuts and heuristics to simplify the decision-making process if needed, perhaps in response to some of the information overload issues already discussed. The concept of bounded rationality returns to the work of Simon (1955) who recognised that human cognitive abilities were not infinite and that individuals have limited computational skills and flawed memories. This applies to managers in the same way as the average human. Tversky and Kahneman (1974), often widely credited with the birth of contemporary behavioural economics (Bruni & Sugden, 2007), suggest these lead individuals to use rules of thumb and heuristics, which may be useful in simplifying the decision-making process when the time is short but may lead to non-rational decision-making. They stress the likelihood that not all the available information would be used.

Secondly, regarding risk-seeking and loss aversion behaviours in decision-making, Kahneman and Tversky (1979) and Tversky and Kahneman (1992) also found this led to irrationally formed asymmetries between the way gains and losses were considered in the decision-making process. They say that people are more concerned about suffering losses than they are about achieving gains and that this may lead to unnecessary caution where risk is perceived. Jolls et al. (1998) extended Simon's (1955) bounded rationality to add in bounded willpower and bounded self-interest. Bounded willpower refers to the fact that human beings often take actions that they know to be in conflict with their own long-term interests, and bounded self-interest refers to the fact that people either care or act as is if they care about others when making decisions, even if they are strangers. Simon (1955) also added that bounded self-interest may mean the rational decision, particularly in a business context is not made. Later, Sunstein (1999, p.122) added that bounded willpower was a type of what he called "myopia". This causes short-termism as individuals are willing to make decisions that conflict with their longer-term interests in favour of shorter-term gains, again potentially impacting on the balance of tactics versus strategies in decision-making.

Cyert and March (1992) extended Simon's (1957) ideas and whilst agreeing with the idea of satisficing added that decision-making could also be a political process based on the inner workings of the organisation, confirmed by Martin and Fellenz (2014). Eisenhardt and Zbaracki (1992) summarised the political perspective on decision-making based on certain characteristics of an organisation. They state that they are comprised of people with partially conflicting preferences, (known to be likely in hotels due to complex ownership models), that strategic decision making is ultimately political in the sense that powerful people get what they want, and finally that people engage in political tactics such as co-optation, coalition formation, using information to enhance their power. Martin and Fellenz (2014) also looked at decision-making from an organisational behaviour viewpoint. They view decision-making as a process which can be broken down into stages, which is useful for understanding what may add complexity, and the importance of different decisions at a practical, organisational level. The first area is decision structure that refers to the complexity of the decision and whether it is novel or routine. The second is decision content which covers the magnitude of the decision. This covers the range of different aspects of the organisation affected by the decision, the timeframes in terms of how long the decision will have an impact on the organisation and the centrality of the decision to the organisation's objectives. Decision context covers areas of time pressure, agreement among organisational actors, the presence of established and legitimised decision-making approaches to certain types of decisions and social/group dynamics.

Sunstein (1999) also explores the idea of preference reversals, referred to in Barberis and Thaler's (2003) survey of behavioural economics, that proved individuals make different decisions under different circumstances given the same data, as in a different context they view the information differently when rationally it should be regarded as giving an identical message. This is because different framing effects may be applied to the same information in different decision-making contexts. This has interesting implications for this research suggesting a manager's reaction to the format and presentation of data, as well as the decision-making context, should be observed, as already mentioned by Martin and Fellenz (2014). More recently the importance of context was reasserted by Etzioni (2011) who stressed the impact of social norms and culture on decision-making. This is in

direct contrast to neoclassical economics that McQuillin and Sugden, (2012) suggest would highlight that consistent decisions would always be made across any alternative scenario or context.

The final factor of Martin and Fellenz's (2014) four-stage approach to decision-making highlights the importance of the individual characteristics of the decision-maker, including relevant knowledge and experience, analytical and cognitive abilities, individual preferences, biases, and interactions between decision-makers. The theory of planned behaviour also sheds further light on the individualistic nature of human decision-making. Ajzen (1991) has demonstrated its suitability for examining individual decision-making processes (Lee, Won & Bang, 2014) and also its ability to expose underlying behaviours (Ajzen, 1991, 2012; Zoellner et al., 2012). Although there is significant use of the theory of planned behaviour (TPB) to predict human behaviour in general (Roberts & Barrett, 2011; Lee et al., 2014) and even specifically hotel manager behaviour (Wang & Ritchie, 2012), by utilising the three central tenets of the model it can also be used as an explanatory tool to explain individual behaviours (Ajzen, 1991). The three central tenets of TPB are attitudes toward the behaviour, subjective norms and perceived behavioural control, although in more recent utilisations of the model, experience has also been seen to have an impact (King & Dennis, 2006). Simplistically, perceived behavioural control refers to the ease or difficulty with which individuals perceive the behaviour to be performed, attitudes refer to the degree to which a person has a favourable or unfavourable opinion of the behaviour and the subjective norm is the perceived social or external pressure to carry out a behaviour (Ajzen, 1991).

3.235 Manager decision-making behaviours in pricing

It is also important to note that there is a significant lack of literature that examines the role of information directly within the context of individual manager behaviours in price decision-making, apart from a very old study using a small manufacturing sample that seemed to make some early attempts to link price theory and business behaviour (Hall & Hitch, 1939). Primarily it has either taken a macro-economic perspective, such as Nimark's (2008) research into the role of imperfect knowledge in inflation or it has focused on the impact of information on consumer economic behaviour (Mankiw & Reis, 2002; Ho, Lim & Camerer, 2006). Even the

behavioural finance literature is of little help as it focuses on higher level corporate decision-making (Subrahmanyam, 2007) such as investment, diversification, capital structures and dividends (Barberis & Thaler, 2003) and corporate strategy (Powell, Lovallo and Fox, 2011). This is despite some areas of the behavioural economics literature stressing the importance of understanding real-life decision-making behaviour, taking into account not just psychology but human nature (Simon, 1959; De Bondt & Thaler, 1994; Jolls et al., 1998). These discussions however, do not take place in the hospitality literature.

This gap has, in a limited way, now started to be recognised by some academics. Woodside (2015) has been instrumental in driving this with his recent research into the identification of a theory of behavioural pricing, although at the current time he describes it as a general theory. Although the theory does currently consider the role of information, especially in terms of the fact that managers do not utilise all the information available to them, it doesn't specifically look at big data. Woodside (2015, p.39) describes the theory as a "useful blending of cognitive science, complexity theory, economics, marketing, psychology, and implemented practices in explicit contexts". In comparison to behavioural economics and behavioural finance, the key additions are the attention on practical implementations of price decision-making and complexity theory, which is interesting and relevant given the complexity of hotel pricing. The addition of complexity theory (Urry, 2005) highlights the heterogeneity of price decision-making and that there can be sudden changes in the process and that the same causes can result in different effects in different circumstances. Cyert and March (1992) also commented upon the fragmented nature of pricing information which could potentially add to these complexities. Woodside (2015) also suggested that feedback loops are often present in price decision-making within an organisation and allow for pricing to be improved over time creating a learning process. Later, he argued that decisions are reached by combining factors rather than looking at them in isolation, which links back to the ideas of complexity theory (Woodside, 2017).

Although Woodside's (2015) paper was written from the business-to-business context, some of the key aspects of the theory are worth highlighting in further detail. The theory confirms the concept of bounded rationality in that it stresses

decision-makers rarely use all the information available to them based on a consideration of real-life cognitive processes. They claim the use of simple heuristics is more beneficial than using all the available information and statistical multivariate procedures, as has already been suggested. They state that (p.43) “while individuals are limited in their cognitive capacity, the available evidence does not support a conclusion of lower competence by decision makers from not using all the information available”. Importantly the theory also comments that decision-makers learn from their mistakes and that they use tacit information. This is defined as personal knowledge that is not written down but gained through personal experience of working in an organisation.

Finally, another key piece of literature worth highlighting is by Liozu (2013, p.13) who examined irrational pricing behaviours in organisations. Although his conclusions are not based on empirical research, Liozu found that many factors might be involved in “influencing, shaping, and disrupting decision-making processes in firms”. He does; however, appear to take a more negative view of behavioural decision-making than some of the behavioural economists (Tversky & Kahneman, 1974; Woodside, 2015). He identified eight irrational price decision-making behaviours. The first was termed routines, rules, and recipes and referred to the use of routines, standard operating procedures, industry traditions and practices, information-handling rules, and risk-avoiding agreements to reduce uncertainty when faced with conflicting signals and irrational behavioural temptations. The second was called institutional isomorphism, which highlighted the tendency for decision-makers to copy other widely accepted pricing strategies. Thirdly and more obviously, were the conflicts and power struggles within organisations and decision-makers. This was followed by competitive irrationality, where decision-makers feel overwhelmed by increases in competitor information. The next four behaviours covered the predominance of intuition and gut feeling, irrational behaviours by leaders, breakdowns in information and communications systems and finally uncertainty and complexity. Again, the work of Liozu (2013) and its critique of some of the elements such as routines and rules that Tversky and Kahneman (1974) and later Woodside (2015) suggested may be useful to decision-making highlights the black box that exists around the reality of manager decision-making practices in pricing and the benefits or not of behavioural

approaches to price decision-making that may not be totally reliant on big data. As summarised in table 3.1 these last two bodies of literature link to the emerging finding from the research that due to manager responses to market conditions and pressures there is a simplified focus on a limited amount of revenue metrics, typically average room rate, occupancy percentage and RevPAR.

3.3 Chapter Summary

The focus of the literature in this chapter evolved through the data collection and analysis process in line with grounded theory and the main categories that resulted from this grounded theory process addressed the gaps in knowledge reflected in this chapter. To make this evolving approach to the literature is reflected in table 3.1 below. The table identifies the key bodies of literature covered in this chapter and what was known about these various themes before the research was conducted. It then goes on to show how for each area of the literature what the gap in knowledge was interpreted to be and finally directs the reader to the corresponding categories in chapter 5 where the findings of the research can be found that address these gaps in knowledge.

Key Body of Literature from Chapter 3	What is known?	What was the gap in knowledge interpreted to be?	What are the key corresponding main categories in the research findings where these gaps in knowledge are addressed (see figure 5.1)?
Data transformation processes (see section 3.21)	• Big data can only effectively be used in decision-making if it goes through a process, often driven by analytics, that transforms it from a raw material to information and then to knowledge/insights and then actions. • Analysis and interpretation of big data may require the application of contextual or domain-specific knowledge.	• The practicalities of how managers transform big data to reach a fully informed decision at the hotel property level are not addressed in the literature. • The degree to which managers use domain-specific knowledge to interpret big data to make pricing decisions is not made clear.	• General Manager Involvement • Thinking Local • Decision Negotiation *Key finding - Hotel general managers use local customer insights or small data to interpret broader revenue trends from the big data.*
Big data and information overload (see section 3.22)	• The literature recognises the existence of information overload based on the large volumes often available. • The degree of information overload and its effect may vary based on a range of factors such as organisation culture and individual information-processing capacity.	• The hotel pricing literature does not agree on the degree of information overload faced by managers and the factors that may effect whether information overload is felt.	• Avoiding Information Overload • Balancing Defence and Attack *Key finding - Information overload is avoided at the hotel property level due to deliberate attempts of the hotel general manager to filter out what they consider to be unimportant data.*
Balance between human and automated decision-making in revenue management (see section 3.231)	• Automated revenue systems do exist in the hotel industry that are capable of using data and algorithms to predict optimal room prices. • The type and context of the decision may impact upon the degree of human involvement in decision-making where these systems exist as well as the skills of managers.	• There is no definitive agreement on what the balance is between pricing decisions made by humans and those made by automated revenue management systems for making room price decisions in practical context.	• General Manager Involvement • Thinking Local • Decision Negotiation *Key finding - Where automated revenue systems exist they are interpreted by humans driven by the general manager involvement and importance of local customer insights not yet incorporated into the systems.*
Collaborative decision-making (see section 3.232)	• Collaborative decision-making between revenue specialists and hotel units is encouraged. • Pricing decisions made using data may not be the remit of just one person.	• The complexities of how joint decision-making works in practice at the hotel property level are not fully explored in the literature.	• General Management Involvement • Decision Negotiation *Key finding - Where revenue specialists are present the general manager and the revenue specialist form a co-dependent relationship, blending their own distinct individual data sets and approaches.*
Big data as a decision-making tool (see section 3.233)	• The literature is not clear on the issue of whether big data increases the rationality of decision-making in general and leads to better decision-making. • Varying approaches draw on either classic decision theory which elevates the importance of information in reducing the irrationality of decision-making and those that follow the concept of bounded rationality that argues humans will exhibit satisficing behaviours in the amount of information they use in decision-making.	• Within the hotel revenue management literature it is unclear whether big data increases the accuracy of decision-making or whether more behavioural-led approaches to decision-making may also work, even if used in combination with data.	• General Manager Involvement • Avoiding Information Overload • Thinking Local • Balancing Defence and Attack *Key finding - The value of big data in decision-making is enhanced through blending it with micro, local small data in the form of local customer insights to create a form of hybridised data.*
Manager approaches to using data in hotel room price decision-making (see section 3.234 and 3.235)	• Due to the concept of bounded rationality mentioned above human managers do not have infinite cognitive abilities and have limited computational skills. • To cope with this human managers may apply a range of rules of thumbs and heuristics when they make decisions and that approaches to decision-making may vary on organisational processes, loss aversion behaviours, context and individual characteristics and behaviours.	• The hospitality literature has not explored the behaviours of managers within the context of price decision-making. • In general there is a significant lack of literature that examines the role of information directly within in the context of individual manager behaviours in price decision-making.	• General Manager Involvement • Avoiding Information Overload • Thinking Local • Balancing Defence and Attack *Key finding - Due to manager responses to market conditions there is a simplified focus on a limited amount of revenue metrics, typically average room rate, occupancy and RevPAR.*

Table 3.1 - Summary of chapter 3 literature, gaps in knowledge and corresponding research findings

4. Methodology

4.1 Introduction

This chapter will explore the methodological approaches used to collect and analyse the research data. It will also demonstrate how the findings were reached and ultimately developed into a substantive theoretical framework that could effectively explain the use of big data in the price decision-making process at the individual hotel property level, deconstructing the identified black box. The chapter will begin by exploring a justification for why Straussian grounded theory was chosen as the methodological approach and considered to be suitable for answering the questions the research posed. This will be discussed from a philosophical and a practical viewpoint. The data collection process will also be explained in full detail, covering the techniques of shadowing, in-depth interviews and email interviews. This will lead to the data analysis techniques that were used to scope the findings of the study. How the validity and reliability of the research were judged will also be discussed. The chapter will end with a summary of the data management techniques used and the key ethical considerations of the research. The full data management plan can be found in Appendix 1.

4.2 The methodological approach

4.21 Why grounded theory?

A qualitative approach was chosen based on the focus of the aims and objectives of the research. These research aims and objectives raised questions around how managers interacted with big data and how that impacted upon their behaviour in the price decision-making process. Although studies of big data may be presumed to and often do suit themselves to quantitative studies (Jin et al., 2015), the research objectives for this study required the chosen research methodology to be capable of uncovering the complexities of human behaviours and decision-making dynamics under the influence of big data. This led naturally to the need for a methodological approach that was sensitive to human feelings, behaviours, emotions, interactions, and processes. Strauss and Corbin (1998) stressed that qualitative methods can be used to successfully develop an understanding of these areas. Researchers looking at the role of behaviours in price decision-making have also recently called for future research on price decision-making to

be conducted in real-life settings (Woodside, 2015) so the importance of collecting data in this way was also considered. In fact, Strauss (1987) and Strauss and Corbin (1998) both suggested that grounded theory could be used to uncover the realities of the circumstances being researched. Therefore, as the objectives of the study were centred on the need to deconstruct a black box by uncovering the realities currently hidden within it, grounded theory emerged as a strong methodological approach for this research. Naturally, a range of qualitative approaches were considered in the early stages of the research, for example, a case study approach, but ultimately grounded theory was selected as the best approach to answer the research question for the following reasons.

Firstly, grounded theory was chosen because the methodological approach needed to be adaptable to the ever-changing and high-speed development of big data and revenue management topics. The development of big data and data analytics technologies are moving so fast that literature is often already out of date by the time of publication. George, Hass and Pentland (2014), Phillips-Wren and Hoskisson (2015) as well as Gandomi and Haider (2015, p. 137) highlight that "the fast evolution of Big Data technologies…has left little time for the discourse to develop and mature in the academic domain". Altin, Uysal and Schwartz (2017, p.2) also describe revenue management as a "dynamic area" that operates within a rapidly changing business environment. This, combined with the lack of literature on the behavioural aspects of price decision-making in the real world (Woodside, 2015), would make using a purely deductive approach challenging because as soon as hypotheses had been devised utilising the extant literature they would most likely be out of date or there would be insufficient literature on which to base them, as mentioned in the introduction. With grounded theory, the findings emerge from the data and not from pre-conceived ideas from the literature, although the literature can be used to sensitise the researcher to topics needing to be explored in the early stages of the research. Strauss and Corbin (1998) believe that new literature relating to the emerging findings from the data can be added in as the data collection and analysis develops. Therefore, using this approach for this research meant the findings that emerged from the data could more easily keep pace with changes in the dynamic hotel environments and revenue management practices since it would record the phenomena happening in closer to real-time.

Therefore the findings are likely to be more current and represent more accurately the voices of the participants (Strauss, 1987; Strauss & Corbin, 1998). This would in turn help uncover realities allowing the black box to be deconstructed. As literature could be updated as the research progressed, this also meant it was possible to keep up-to-date with the new literature being published throughout data collection and analysis and relate it to the emerging findings if relevant.

The choice of grounded theory was also validated by its use in previous studies into hospitality, tourism, and big data, as these helped to demonstrate its suitability for research in this area. It also helped give an insight into how the methodological approach had been used by previous hospitality researchers, aiding the research design. Matteucci and Gnoth (2017, p. 49) argue that within tourism research the use of grounded theory has been "gaining momentum as a methodological approach among tourism researchers." Earlier, Mehmetoglu and Altinay (2006) also produced a paper examining the need for the development of qualitative research in hospitality research, especially grounded theory, as they believed it allowed the development of new insights but also provided the researcher with an analytical approach to the analysis of qualitative data. It is evident that researchers in hospitality and tourism have embraced the idea of using a grounded theory methodology (Idrees, Vasconcelos & Cox, 2011), for example, McGinley, O'Neill, Damaske and Mattila (2014) used it in their study of career change models in hospitality and earlier Lumsdon and McGrath (2011) used it to develop a conceptual framework for slow travel. Most recently Scerri, Jenkins and Lovell (2017) used a grounded theory model to examine service language in Australian luxury hotels. There is also evidence of it being used in previous studies that investigated big data related topics, for instance Crook and Kumar (1998) used grounded theory to investigate comparisons in electronic data interchange across different industries and more recently Waller and Fawcett (2013) used grounded approaches to look at big data in supply chain design and management. In addition Parks and Thambusamy (2016) used it to study the impacts and successes of business analytics.

4.22 Why Straussian grounded theory?

The term Straussian grounded theory appears to have come from the classification of grounded theory into Glaserian and Straussian (Stern, 1994) but it

continues to be used in a number of more recent academic papers (Heath & Cowley, 2004; Cooney, 2010; Wiesche, Jurisch, Yetton & Krcmar, 2017). Straussian grounded theory is informed by pragmatism and the writings of Charles Peirce, George H. Mead and John Dewey whose key works are presented by Thaler (1982) in his edited book on the classic writings of pragmatism. They placed emphasis on action and the necessity of method in the context of problem-solving. It was selected specifically from several strands of grounded theory that have emerged since Glaser and Strauss (1967) originated the term. The reason it was so important to select a specific strand was due to one of the main criticisms often made of grounded theory that users of the methodology confuse the different strands and consequently do not stay true to one strand of the methodology. This has the potential to dilute and confuse the key elements of the approach and therefore researchers potentially risk being accused of not utilising grounded theory techniques correctly (Corbin & Strauss, 1990; Rennie, 1998; Breckenbridge, Jones, Elliott & Nicol, 2012). This research aimed to avoid this criticism by selecting and following the Straussian strand of grounded theory throughout the process of data collection and analysis. Of course, in reaching this decision, a process of understanding the differences and similarities between the approaches was conducted to ensure that it was clear why the other approaches were not suitable in answering the research question or were not a philosophical fit. This was often challenging as the differences were often subtle and it is common for the exponents of each strand and other researchers to add to the confusion by potentially over-simplifying or not making clear the differences between the different perspectives (Corbin & Strauss, 1990; Breckenbridge et al., 2012).

The origins of grounded theory date back to the work of Barney Glaser and Anselm Strauss who first developed the methodological approach through their work understanding the behaviours of terminally ill patients, which was published in two books called the “Awareness of Dying” (Glaser & Strauss, 1965) and the “Time for Dying” (Glaser & Strauss, 1968). They opened and explained their methodological approach in more detail to scholars and researchers through the book “The Discovery of Grounded Theory: Strategies for Qualitative Research” (Glaser & Strauss, 1967). The original thinking behind grounded theory was

influenced by the very different perspectives of Barney Glaser and Anselm Strauss. Glaser was a positivist, an objectivist and had a grounding in quantitative data analysis. In contrast, Strauss was a pragmatist. In time the two split. Barney Glaser continued to stay true to the original thoughts on grounded theory and this developed into what he now terms classic grounded theory whereas Strauss developed his own thoughts on grounded theory (Strauss, 1970) and later outlined his thoughts for researchers in his book “Qualitative Analysis for Social Scientists (Strauss, 1987). Strauss went on to write with his student Juliet Corbin and together they continued the development of grounded theory through their research in the area of chronic illness, eventually publishing the “Basics of Qualitative Research – Techniques and Procedures for Developing Qualitative Research” (Strauss & Corbin, 1990, 1998).

When Anselm Strauss died in 1996, shortly before the second edition of their book was ready for publication, Juliet Corbin took up the mantle of developing Strauss’s thinking. A third recognisable form of grounded theory was then developed by Kathy Charmaz in her work on postmodernist, constructivist grounded theory (2006, 2014). However, Corbin herself states in later editions of the book that she recognised that her philosophical position had begun to move towards some of the thinking of these constructivists and postmodernist thinkers. She states clearly that “there is no doubt that I have been influenced to some degree by the writings of contemporary feminists, constructionists and postmodernists”, whilst still maintaining the technicalities of “Strauss’s basic approach to doing analysis” (Corbin & Strauss, 2015, p.25). The three strands have emerged over time from the original grounded theory (Glaser & Strauss, 1967) and although they share a basic ontological perspective based on the concepts of realism (Matteucci & Gnoth, 2017) there are some fundamental differences in their epistemological approach and methodological characteristics, which made the Straussian approach most suitable for this research, specifically the earlier work of Strauss (1987) and Strauss and Corbin (1998) before the drift towards constructivism.

The original Straussian approach was chosen firstly due to its compatibility with the researcher's philosophical position. Having had extensive experience working in the hotel industry and teaching revenue management it seemed impossible to claim that the researcher could be totally value-free in the way suggested by

Glaser in classic grounded theory. After the split with Strauss, Glaser returned to what he termed the “pure and orthodox” view of grounded theory and hence the term classic grounded theory was coined (Glaser, 1999, p.837). Glaser claimed that researchers could obtain objective data by adopting a passive role in data creation (Glaser, 1978, 1992), in other words, that the researcher could act as a neutral observer (Matteucci & Gnoth, 2017). Strauss’s pragmatic epistemology recognised that the researcher could not ignore the “immense significance of their own experiences” (Strauss, 1987, p.8). Strauss (1987, p.12) claims “the researcher is able to think effectively – and propositionally because he or she has experiences to draw upon in the thinking about those data”. Therefore, Straussian grounded theory was a philosophical fit with the researcher's desired approach and industry background. The researcher could use their experiences not to influence the participants or as findings in themselves but instead to guide initial lines of investigation and to sensitise them to what was emerging from the data. Memos on the impact of past experience were made in the research diary, to minimise bias and ensure the findings still remained grounded in the data.

In addition to this, Straussian grounded theory recognises the value of the existing academic literature. Having studied and published in the field of revenue management the researcher came to this research with a wide awareness of the revenue management literature and therefore a classic grounded theory that expected the cancelling out or ignoring of this knowledge seemed unrealistic. Glaser and Holton (2004) make it clear that in classic grounded theory any extensive pre-reading of the literature should be avoided so that the researcher does not become overly influenced by it and that if this pre-reading does take place it leads to the forcing rather than the emergence of the theory from the data. In comparison, Strauss is more pragmatic in his consideration of the literature although Strauss and Corbin (1998) do stress a note of caution that the knowledge of the literature should enhance and not constrain the development of the theory as discussed in chapter two. Therefore, the researcher should be flexible and willing to change direction should the data reveal the need and also they should always check the emerging findings back against the data to ensure they remain grounded and not pre-conceived. This meant the literature was used to help inform initial data collection, but then further avenues of the literature were

explored only if they were deemed relevant to what was emerging from the data. It was used finally in the discussion chapter to illustrate how the findings of this research fitted with earlier thinking.

Although Straussian grounded theory is happy to accept the influence of past experiences and knowledge of the literature, it stresses that there still must be an attempt to base the findings on the voices of the participants to uncover the true reality of what is happening with any given phenomena (Strauss, 1987). As very little of the revenue management literature had considered the role of big data at the individual hotel property level the aim of this research was to deconstruct the black box around the impact of big data on price decision-making within individual hotels as a part of revenue management theory (see figure 3.1). The researcher viewed it as an unknown area that needed exploration and explanation. Although Weber and Drori (2011) described black boxes as simply areas of unexplored territory, the idea is actually more complex than this suggests and its relevance to this research more deeply rooted. Both Winner (1993) and Latour (1987, 1999) describe black boxes as systems, that for the sake of convenience, are only thought of in terms of inputs and outputs due to internal complexities. The current literature on big data in decision-making seems to be very conflicted with many differences of opinion on whether more data equals better decisions or not. In this sense, it has become its own black box, especially in terms of behavioural approaches to decision-making, because the added complexities of human decision-making within big data are frequently ignored in favour of rational technological data analytics processes and data as in input, as is illustrated below. Or, in some cases, the literature is unsure of how the two, humans and data, should work together in reality. This can be seen in the research of Liberatore and Luo (2010), Kaisler, Armour, Espinosa and Money (2013), Holsapple, Lee-Post & Pakath (2014), Duan and Xiong (2015), Gandomi and Haider (2015) and Bendle and Wang (2016). It is not so much the lack of literature in this area as its current inability to take a holistic picture of the complex realities of the way managers interact with data in order to make decisions that is truly missing, and hence a black box is in existence. The current literature does not deconstruct the issues but in fact, makes the black box more opaque.

Opening a black box to be able to begin to deconstruct its contents means achieving an understanding of the true reality of a situation, and therefore Strauss's approach to extracting the truth from the voices of the participants was appealing as it was focused on the reality of the participants, rather than on the constructivist approach where the researcher aims to construct their own reality of what was occurring (Charmaz, 2014). The aim was to get as close to the reality of the situation as possible and use the experience of the researcher to understand the reality of the participants.

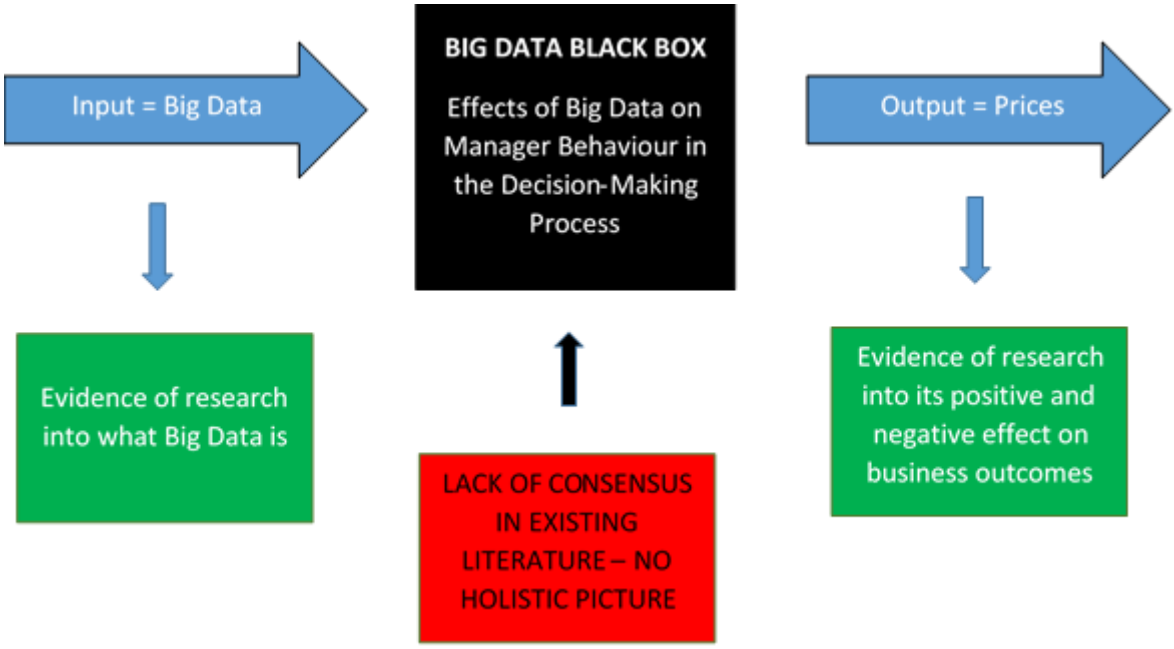


Figure 4.1: A Graphical Representation of the Existing Black Box

MacKenzie (2005, p.570) agrees that "in my experience, opening black boxes can be done only by speaking with those involved…one goal is to learn to see the world as the interviewee sees it". Although Strauss (1987) did not specifically use the term 'black boxes' a clear linkage between his thinking on grounded theory and deconstructing black boxes emerges due to both being focused on uncovering reality. In addition, Matteuci and Gnoth (2017) agree that Straussian grounded theory suits a micro-focus on smaller substantive research contexts, whereas Glaser's (1978, 1992) classical grounded theory aims at more abstract theoretical generalisations. However, the Straussian coding paradigm still allows the findings to emerge from the data, which has been stressed, is crucial to this research. Glaser (1992) contended that the analytical framework proposed by

Strauss forced data and analysis into pre-conceived theoretical categories that were directly opposed to the emergent nature of grounded theory. As has already been highlighted Strauss was not dogmatic about the use of his procedures and encouraged researchers to balance the art and science of data analysis and use their own creativity when using the techniques (Strauss, 1987; Strauss & Corbin, 1998).

Also, Strauss (1987) and Strauss and Corbin (1998) were not suggesting that their coding structure should be followed in a linear fashion or that all their different procedures for analysis should be strictly followed to the letter. They were simply providing a range of tools and techniques to guide researchers in the successful and productive data analysis. They themselves suggest it is a suitable strategy for researchers using grounded theory for the first time (Strauss & Corbin, 1998). In this way, Straussian grounded theory still very much supports the emergence of the findings from the data but this is achieved through the formation of clear theoretical categories. Strauss and Corbin (1998, p.12) stress that Straussian grounded theory is "theory that was derived from data…a researcher does not begin a project with a preconceived theory in mind". The difference between Glaser and Strauss probably appears because Strauss looks at the development of theoretical categories that then form a core theoretical category to develop theory (Strauss, 1987, Strauss & Corbin, 1998), however Glaser maintains a continuous focus on the whole rather than breaking it down into a thematic analysis (Glaser & Holton (2004). However, the Straussian approach achieves the unity of the theoretical categories and also the development of a whole theory through the use of axial and selective coding which seek to develop relationships between the theoretical categories (Strauss, 1987; Strauss & Corbin, 1998). This is why the core category that emerged from the data was then fitted into a wider theoretical framework to ensure the explanations of what was happening in the data could be viewed as a whole. In this research, the theoretical categories discussed in the findings did emerge from the data and the coding paradigm was used as a technique for guiding the extraction of the findings from the data and focusing them on key areas. This was crucial to the development of the theoretical framework that can explain thoroughly what is happening in the data.

Finally, the coding paradigm again fitted the aims and objectives set for the research through its focus on identifying both the processes that are occurring and the reasons why things occur under what conditions. This fits clearly with the topic of this research as the impact of big data on how price decisions are made clearly required an understanding of what was occurring in the price decision-making process, namely how big data impacted it and why. Viewed as a process for deconstructing a black box, a data analysis framework that focuses not just on what happens but on how it happens and why was crucial. The Straussian coding paradigm offered such a framework and allowed for the exploration of the detail of the reality of the phenomena. Strauss and Corbin (1998, p.128) describe the paradigm as a "perspective towards the data" that helps order the data in a way that both structure and process are understood, where structure looks at the context and conditions and why things happen, and the process looks at how participants act and interact and shows how things happen. This coding paradigm also helps focus the data analysis for this research on three key aspects of conditions, actions/interactions and consequences, all of which were thought of as interlinking. Throughout the data collection and analysis, the researcher was sensitive and alert to emerging findings around these three areas and actively coded for those areas during data analysis as well as utilising the research diary (see appendix 3 for example excerpts) to record emerging ideas on the coding paradigm. The specific ways in which this was done and the definitions of the coding paradigm will be discussed further in the section on data analysis.

4.23 Alternative Methodologies

Although the previous sections have provided a detailed justification of why grounded theory and specifically Straussian grounded theory were selected for this research it is worth highlighting that a range of qualitative methodological approaches were considered for the research, particularly as a result of receiving a wide exposure to a range of methodological possibilities whilst studying the research methods modules that supporting the early stages of the research degree programme, covering aspects of ethnography, phenomenology, grounded theory and case study research. However, the only one of these approaches, which was initially considered as possible alternative to grounded theory, was case study research. This was because case study research, in the same way a

grounded theory, was cited as a way to investigate "a contemporary phenomenon in depth and within its real-life context" and "where the boundaries between phenomenon and context are not clearly evident" (Yin, 2009, p.18). This meant it provided a similar fit as grounded theory in being useful in answering "how" and why" questions and potentially in deconstructing the black box that had been identified and researching in a real-life organisation context. However, it was ultimately disregarded due to issues related to access and ethics. Yin (2009) stressed that the key aspect of carrying out case study research correctly was the triangulation of data, including primary data from interviews and observations as well as secondary data. Within hotel pricing research, it was felt that ethical issues may become present if secondary data on hotel performance actually became part of the study, and privacy issues may mean that hotels would be less willing to take part in the study if they felt they had to share competitively sensitive data with the researcher even if anonymity processes were in place. Easterby-Smith, Thorpe and Jackson (2012, p.90) agree that within management research, what they call the "politics of access" are key to success and that for organisations to be willing to be involved in a research project it should not appear to be politically sensitive and that resource requests, such as access to secondary data, should be kept to a minimum.

4.3 Data Collection

The following sections will explore the reasons why each data collection method was chosen within the wider methodological approach of grounded theory and explain how they were employed. There were three main cycles of data collection. Although data analysis was conducted continually through the data collection period in line with Straussian grounded theory this will for clarities sake be treated separately in this chapter. The main method that was utilised was shadowing. This was followed up by in-depth interviews and email interviews, where emerging concepts from the shadowing field notes needed further exploration and investigation to develop them fully and compare them with earlier findings.

4.31 The approach to sampling

The data collection and analysis evolved over four cycles, as illustrated below. The first three cycles were conducted over a period of four months with the final

cycle taking one month due to the theoretical categories becoming more defined by this stage.

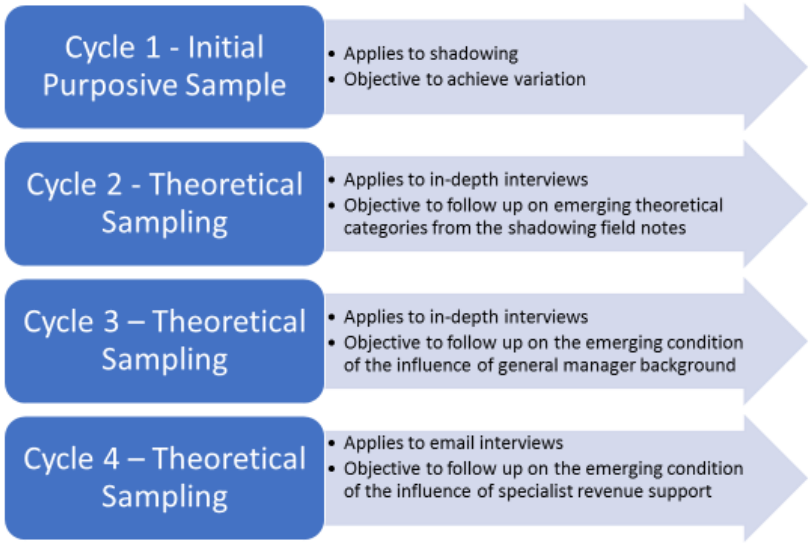


Figure 4.2: The Data Collection and Analysis Cycles

The first cycle was informed by a purposive approach to sampling with the aim of gaining variation in the theoretical categories that emerged from the data. It engaged six different types of hotels for shadowing sessions with a focus on managers who may be involved in making price decisions, which was assessed in pre-shadowing communications (Scerri et al., 2017). The six hotels covered a range of different hotel standards and ownership structures. The standards of the hotels were measured using the STR Global classifications apart from the independent hotels which were approximated using the descriptions of the classifications supplied by STR Global. Achieving variation in the sample is a crucial part of Straussian grounded theory (Strauss & Corbin, 1998) as it allows the researcher to be able to develop a theoretical framework that can fully explain what is happening in the data. The need to deconstruct the realities of the black box also meant a variation in the sample was important in order to uncover the broadest range of realities as possible. Therefore, the sample frame was designed to reflect the range of experiences of general managers and revenue specialists across different hotel standards and ownership structures, although the focus was always on the individual within the organisation and not specifically on

organisation type, structure or behaviour. As the focus of the research was on transient hotel pricing, the hotels that were included in the sample, both initially and as a result of the theoretically sampling process were screened first to ensure that transient room sales made up a significant part of their rooms revenue. They were asked if transient room sales dominated their Monday to Thursday night business and if the answer was yes they could be included in the sample.

Strauss and Corbin (1998) do agree that there has to be a starting site or group for the research to begin and that this often emerges from the main research questions. However, theoretical sampling is a key technique characteristic of grounded theory (Strauss & Corbin, 1998) and that was used in cycle's two to four in order to explore emerging categories from the shadowing, which were the background of the general manager and the influence of the existence of specialist revenue support. Access to new data sources to help explore these emerging categories was gained via snowball sampling techniques from the initial sample used for the shadowing, which is also supported by Strauss and Corbin (1998) as a sampling technique. In this way, theoretical sampling evolves rather than being pre-determined at the start of the research. It is sampling that is directed by the concepts and theoretical categories emerging from the data. Strauss and Corbin (1998) assert that theoretical sampling is directed by asking questions and making comparisons, which means following up on new data and comparing responses to better develop and understand the variety of properties and dimensions found in the emerging concepts and theoretical categories. It resulted in the ability to clearly delineate and justify the existence of the theoretical categories as they represent the findings of the research and explain the variation in each one. Strauss and Corbin (1998) also assert that along with variation in the initial sample, theoretical sampling improves theoretical density and helps verify potential theoretical categories that have emerged from the data. This all increases the value of the substantive theoretical framework that is the result of the data collection and analysis process. In this research, theoretical sampling occurred throughout all the stages of open, axial and selective coding but did become more focused on verification of the theoretical categories during the selective coding stage when no new categories were emerging, and the research was close to theoretical saturation and the emergence of the core theoretical

category was beginning. The full sample of shadowing sessions, in-depth interviews, and email interviews are shown below. In total the sample included twenty participants which agrees with "broad overall norm" of 15-60 participants identified by Saunders and Townsend (2016, p.845) in their work into justifying sample size within organisation and workplace research. Saunders and Townsend (2016) also stress that the overall participant number is contingent on the "approach to analysis" (p.846). Therefore, the sample size in this research can also be justified as it led to the achievement of theoretical saturation which is the key outcome in the grounded theory approach to analysis (Strauss and Corbin, 1998).

Type of Hotel	Cycle 1 – Shadowing Purposive Sample	Cycle 2- In-depth Interviews Theoretical Sampling	Cycle 3 – In-depth Interviews Theoretical Sampling	Cycle 4 – Email Interviews Theoretical Sampling
Managed/Franchised Luxury & Upper scale	Tuesday 24th January and Wednesday 25th January 2017	Thursday 16th February 2017		Email communication completed - Friday 25th August 2017
Managed/Franchised Upscale and upper midscale	Thursday 9th and Friday 10th February 2017	Monday 23rd January 2017	Tuesday 21st February 2017	Email communication completed - Thursday 11th April 2017
Managed/Franchised Midscale and economy	Tuesday 7th March 2017	Monday 30th January 2017		Email communication completed - Monday 24th April 2017
Independent Luxury/ Upper scale	Monday 20th February and Friday 24th February 2017	Monday 6th February 2017	Friday 27th January 2017	Email communication completed - Monday 10th April 2017
Independent Upscale/Upper midscale	Tuesday 7th and Wednesday 15th February 2017	Wednesday 1st February 2017		Email communication completed - Thursday 9th February 2017
Independent Midscale/Economy	Monday 27th February and Tuesday 28th February 2017	Monday 13th February 2017		No revenue specialists for this group

Table 4.1: The Sampling Frame

4.32 Shadowing

An extensive search of Google Scholar and library databases did not highlight any previous use of shadowing techniques in grounded theory studies. However, Strauss (1987) and Strauss and Corbin (1998) do welcome the use of a variety of different data collection methods to support the development of grounded theory, as long as they are suitable for achieving the research objectives. In fact, they offer very little specific guidance on data collection methods in either of their texts. The focus is mainly on the data analysis process and coding procedures. It is,

therefore, possible to say that the use of shadowing in this research is actually making a methodological contribution to the existing grounded theory literature.

4.321 Background to shadowing

Shadowing has its origins in some of the classic management studies according to McDonald (2005). However, if you look more closely at this literature, particularly at the work of Guest (1955) who went on to work on a series of studies looking at the role of foreman in mass production (Walker, Guest & Turner, 1956) and Mintzberg (1970) who studied the behaviour of managers, they don't explicitly use the term shadowing. They both favour the term structured observation and their approach was based around the observation and recording of specific incidents in quantitative detail, such as the timings of when telephone calls were made and how much time foreman spent reading, standing or talking. These incidents were recorded in a strictly chronological manner and were based on pre-determined theoretical categories. Guest (1955, p.21) describes this neatly as "observed behaviour recorded in terms of a time continuum". The use of pre-determined theoretical categories would not be consistent with the grounded theory approach, as it would block findings emerging from the data. However, more contemporary approaches to shadowing have embraced a more emergent, qualitative approach without the use of pre-determined theoretical categories being observed. In its more modern form shadowing is less structured and more fluid in its recording of the activities of the participant being shadowed and is therefore compatible with the key aims of this research, namely to uncover the realities of the impact of big data on price decision-making and the grounded theory approach.

McDonald (2005) appears to be the first to use the term shadowing in this way within the context of organizational and qualitative research. Prior to that, shadowing had mainly been associated with experiential learning techniques used to aid student development from an educational perspective, particularly in nursing and medical care (Saine & Hicks, 1987; Herr & Watts, 1988; Paskiewicz, 2002). McDonald (2005) explored the move of shadowing from the positivistic, quantitative studies of Guest (1955) and Walker et al., 1965) to its later use in qualitative studies where there were no pre-determined theoretical categories but the findings were allowed to emerge from the observations made during the shadowing sessions (Hirsh, 1999; Vukic & Keddy, 2002; Johnson, 2014), fitting

more with grounded theory approaches. These changes in approach increased the interest in shadowing for qualitative researchers such as the work of (Bartkowiak-Theron and Sappey, 2012) and there was even a special edition of the journal “Qualitative Research in Organizations and Management” focusing on shadowing, which included some key articles that helped guide the use of shadowing in this research (McDonald & Simpson, 2014; Noordegraaf, 2014; Johnson, 2014; Czarniawska, 2014; Gill, Barbour & Dean, 2014). These papers evidence the way shadowing has moved from a structured observation method, merely recording the timing and duration of specific activities to a way of gaining a deeper understanding of behaviours of people within the context of the organisation in which they work.

With this increased attention on shadowing a number of different definitions of the method have arisen but they all share key commonalities that are worth recognising in the explanation of shadowing. In simple terms, Gill et al. (2014, p.70) define shadowing as the “following of an individual to learn about their everyday experiences and practices”. The focus is not on the macro but on the micro and the everyday details which often turned out to be vital to the understanding of what was occurring in this research setting (Bartkowiak-Theron & Sappey, 2014). This also fitted well with the desire to deconstruct the black box. There appears to be a common understanding of this, but McDonald (2005, p. 456) takes the definition one step further by highlighting the importance of context, stating that the shadowing takes place over a period of time, and adding that it is “a research technique which involves the researcher closely following a member of an organization over an extended time period.” The aim, McDonald (2005, p.457) is to gain “a detailed, first-hand and multidimensional picture of the role, approach, philosophy and tasks of the person being studied”. The field notes gathered in this research focused on the recording of such dimensions. For this research, this meant that shadowing could be extended from merely recording experiences and practices to being able to have a wider ability to help gain deeper insights into human behaviours and reactions to big data. Shadowing helped the researcher take a holistic but detailed approach to the data collected.

Finally, to truly understand what shadowing is, it is vitally important to highlight that it is distinct from other types of observation. Firstly, it is clearly different from

complete participant observation as the participants are aware of the study and will have agreed to the observation. This helped to avoid the ethical issues surrounding covert research. However, it is not immediately obvious as to what sets it apart from other forms of non-participant observation where the researcher takes a neutral role but the observed is fully aware of their presence. The distinction is claimed by Czarniawska (2014) and fully explored by McDonald and Simpson (2014) who use the metaphor of light sources to explain the differences. They argue that observation is like a floodlight that allows for an overview of the context and actions of the actors but does not “shed any light on the meanings that actors ascribe to their actions, the actions of others, or the organizational context" (p. 12). Shadowing, however, is viewed as the light on the miner’s helmet that “sweeps around the organisation as the researcher turns her head” (p.13). In this sense, during the shadowing sessions the observations were focused directly on the interactions between participants and their environment that were relevant to the research and this enabled more specific, detailed data to be generated, again important in deconstructing the details of the black box. It allowed for data to be gathered on actors' spatial and temporal paths through interactions with the organisation, which is particularly useful for viewing how they interact with data. In this way it also helped the researcher to follow Straussian grounded theory and its focus on the voice and actions of the participants. The sampling frame supported this by reflecting the current realities of the hotel industry. In essence, what makes this technique even more relevant to this study, is McDonald and Simpson’s (2014, p.15) suggestion that shadowing studies are “orientated towards the understanding of the individual rather than the organisation” as the metaphor regarding the direction of light demonstrates. This is supported by Noordegraaf (2014, p.42) who suggests that shadowing is a powerful tool because it allows the researcher to explore how managers really use processes and information within what he calls “embodied spaces”.

4.322 Why was it chosen?

It is firstly important to state that to stay in line with the grounded theory methodology a qualitative and emergent approach to shadowing was used rather than the more structured and pre-determined approaches of Guest (1955) and Mintzberg (1970) since the focus of shadowing in this context was on emerging

categories from the data rather than on recording the presence of pre-determined categories. Both Guest (1955) and Mintzberg (1970) had generated lists of categories before entering the field and then through shadowing took observations to see if they were present in managers' actions and behaviours. This is not in line with the grounded theory approach. However, as McDonald and Simpson (2014, p. 13) describe, shadowing is “philosophically agnostic” and therefore can be applied to a number of different methodological approaches, including, in this case, grounded theory. Additionally, it was seen to be compatible with the objectives of the research. These were to understand managerial behaviours and responses to big data within the organisational context of the individual hotel properties and to uncover the realities of the impact of big data on price decision-making. Shadowing allowed direct and focused observations of this through doing research directly in the field in order to deconstruct the black box through the uncovering of the realities of the phenomena through observation in a real-life setting. McDonald (2005, p.463) agrees that shadowing “is seen as a neutral means of recording what is ‘actually’ happening”. It allows for the researcher to collect data directly from the field which also fits with the calls from researchers in the field of behavioural pricing theory that new research must be conducted in the field to identify the realities of management decision-making (Woodside, 2015). There is also extensive evidence that shadowing has been used in managerial based research in the past, including in the generation of new management theories (Johnson, 2014, Noordegraaf, 2014) and this further supports the use of shadowing in this research study that looks, in part, at manager behaviour. Shadowing techniques, although only called "observation" have also been shown to be used successfully in understanding the job roles of hotel managers (Nebel III and Ghel, 1993, p.28). Saxena and Lamest (2018) also recently used overt observation of managers to explore issues of information overload in the big data context as part of a wider case study methodological approach. Where more quantitative methods, such as surveys have been used by hospitality researchers to understand manager roles and behaviours, there have been limitations cited. In particular, Shortt (1989, p.129) criticised his own survey method by stating that “what may be reported is what the manager thinks is important to managerial performance and not what he/she does in practice”.

The literature also stresses that shadowing is a powerful tool as it generates honest and more precise data since participants are less likely to be tempted to give 'right' answers and they may also give richer descriptions as they are prompted by meaning and connections to the environment they are in. These descriptions were recorded in as much detail as possible in the field notes as the observations were being made. Noordegraaf (2014, p.43) confirms that in shadowing "managerial action and context are observed as fully and openly as possible – without predefined theoretical categories and concepts", which mean the realities of a situation are more likely to be uncovered than with interviews with managers where elements of their roles may be forgotten about or suppressed as they occur out of context. This may happen unintentionally as an interview tends to be conducted over a shorter timeframe and therefore time pressures might result in things being forgotten. On the other hand, it might be a more deliberate attempt on the part of the participant to avoid uncovering certain aspects they wish to keep hidden (Noordegraaf, 2014). McDonald and Simpson (2014, p, 9) argue that the participant is "after all, the hero in his own narrative". This also means not just uncovering what is happening on the surface but also the trivial and the mundane day-to-day elements that make up reality (McDonald 2005, Johnson, 2014).

These nuances may be thought of as not important by a participant in an interview situation and not mentioned, but in a shadowing scenario they come to the fore and add together to complete insights into what is happening and crucially why things are happening. It is these nuances that are the key to uncovering the realities of a situation and without noting them they could continue to lay undiscovered leading to a continuation of the black box. The researcher was careful to record all these small observations in the field notes even if they did not at that time seem important. McDonald (2005, p.458) confirms shadowing's "singular capacity to link actions and purpose, [helping] address many important *why* questions," in their terms revealing the invisible work. Supporting this is also the uncovering and understanding of human behaviours that are possible with shadowing, which makes it so crucial to this research. McDonald (2005) explains that this comes from getting a participant's eye view of their role and states that data is not just gathered on observed behaviours and actions but on the purpose

and meaning behind those actions. For instance, the research may gain insights into the emotions that drive particular behaviours (Gill et al. 2014); such as does a manager ignore a particular revenue report out of feelings of frustration or even tiredness. Shadowing allows the researcher to observe the physical and emotional manifestations of the participants' reaction to processes, circumstances and other people because they are present at the actual time these are taking place. Even if participants try to mask these, it is harder when they are being shadowed than when being interviewed out of their working context. Bartkowiak-Theron and Sappey (2012) agree that shadowing gains the researcher an appreciation of the participants' frame of reference, motivations, intentions, and priorities.

Finally, there were some more practical reasons why shadowing was chosen and these were that the research needed to be conducted within hotel properties with managers who were often operationally involved in the running of the hotel. This meant that the managers were not bound to their desks but were often moving around the hotel engaging with staff and guests and even becoming involved in operational processes, such as setting up for a wedding or clearing tables in the lounge area. The focusing of shadowing on one key participant allowed the researcher to stay with and track that participant as they moved around the hotel. Czarniawska (2007, 2014) confirms that shadowing is useful when a participant moves around a lot in their role. Shadowing was found to be useful because it accommodated the mobility of the participant ensuring vital insights were not lost and the participant's involvement in processes could be fully captured. Shadowing also offered flexibility in terms of engaging possible participants with the study as McDonald (2005) asserted it did not need to be conducted over consecutive days and could be from one day to a whole month in duration. This gave the researcher flexibility to schedule the shadowing sessions and also meant that participants could more easily pick and choose when they took part in the research. The duration could also be adjusted so as to make the process less onerous for the participants and to increase the likelihood of the researcher gaining access.

4.323 The practicalities

This section covers the practicalities of how the shadowing technique was used to collect data and the specific ethical issues that arose as a result. The shadowing sessions occurred over a period of seven consecutive weeks during which the

researcher took a research sabbatical to allow for the focus of attention on the data collection and initial analysis. The sabbatical was planned for January and February 2017 as this is traditionally a quiet period for the hotel industry and therefore access to participants was easier as managers felt less operational pressures than they would perhaps feel at other times, particularly in the run-up to Christmas. Each session lasted two days. Initially, the plan had been for three-day sessions of work shadowing, but it became apparent that it was harder to get participants to commit to that length of time and therefore it was reduced to two days which resulted in the number of shadowing sessions planned being completed. Gill et al (2014) confirm that any duration of shadowing from three-to-four hour periods to eight to twelve working days is suitable if the outcome satisfies the aims of the research. The key transient business nights of Monday-Thursday were always selected as the shadowing days as the focus of the research was on transient room pricing and it was likely that managers would be handling data that focused on this market segment more frequently during these periods rather than at a weekend and therefore the data collected would be more valid and useful, which Saunders and Townsend (2016, p.849) describe as the "saliency of the data" which if thought about carefully can be used to justify inclusion in the sample. Saunders and Townsend (2016) agree that The shorter time periods in the field also meant there was less chance of the researcher “going native” as Johnson (2014) expresses can sometimes be a risk with shadowing, in which the researcher then becomes a form of observer as participant which is contrary to its aims. The researcher remained a non-participant observer throughout despite this sometimes being a challenge. This was especially the case when managers were extremely operationally involved, and the temptation was to help with the set-up of a wedding and get involved. Each shadowing session followed a similar format, with the researcher spending time observing the general manager of the hotel during their day-to-day routines. The shadowing sessions allowed the researcher to observe the interactions that the general manager had with the revenue data, with revenue specialists if they existed and with other members of staff. The general manager was chosen as the focus of the shadowing sessions because previous research indicated that they would be a key decision-maker at the hotel property level, and as will be explained later in the findings, this proved to be the case.

Wherever possible at the beginning of the shadowing session a brief informal meeting was held between the researcher and the participant to go over any questions they had remaining after reading the participant information sheet, to sign the participant consent form and also to reassert the need for the participant to not feel the need to deviate from their normal routine. This also helped to ease any tension or nervousness on behalf of the researcher or the participant. McDonald (2005) did highlight that one of the problems with shadowing is gaining access due to the perception of participants that it will take a lot more time than interviews. Carefully timing the data collection in January and February when hotels were less operationally pressured and also reassuring the participants that they were free to carry out their usual routine and duties helped alleviate this concern. This was also reiterated in the participant information sheet given to them to explain the research and the process of shadowing. Also, to avoid any ethical issues no monetary or any other type of inducement was used to get participants to consent to be involved in the shadowing apart from the offer to share any final findings should they be of interest (Johnson, 2014)

Keeping pace with field notes was the main challenge of this data collection method and to ensure no vital data was lost the field notes were written up straight after each day of the shadowing had been completed, a technique supported by McDonald (2005). This meant the meaning of any short-hand notes was not lost. At the same time and in line with the chosen grounded theory approach the analysis was already beginning and any conceptual memos or emerging themes were recorded in the researchers' research diary and used to inform the next round of shadowing in terms of concepts in order to check using constant comparisons techniques and theoretical sampling. Recording of direct quotes in the field notes was also found to be the key to help evidence the findings during the final stages of analysis and this also helped to ensure that in line with Straussian grounded theory the voice of the participants was recognised. Of course, not everything was relevant to the topic of the research, but seeing an overall picture of the operations allowed for a better understanding of context and the role of revenue data and decision-making in the normal working day at the hotel property level.

During the shadowing, the researcher's previous knowledge of hotel language, etiquette and jargon helped with a speedier understanding off what was going on and meant the researcher did not have to stop and ask basic questions, which meant it was possible to focus on the detail. Noordegraaf (2014) confirms the helpfulness of a priori knowledge to help understand what is going on in the shadowing sessions. However, where it was felt to be important to ask questions to develop an understanding this was done (McDonald & Simpson, 2014). Notes on the answers to these questions were recorded continuously in the field during the shadowing sessions and recorded in the field notebook. Johnson (2014) expressed some concerns that asking questions during shadowing could distract the participant away from their daily duties, so the researcher was careful to avoid this happening. They found that in their studies at least half an hour of the manager's day was spent clarifying observations. It was kept to a minimum in this research but in reality, both the researcher and the participant were prepared for the need to ask questions and this was discussed in the initial meeting at the beginning of the session.

McDonald (2005) states that as much as possible the field notes should be a continuous recording of what is happening in the field. This relied on the quick recording of points, utilising breaks to fill in gaps and also developing short-hand techniques. Shadowing is also tiring both physically and emotionally. Indeed Gill et al. (2014) describe it as an embodied process, so break times were also used to give both the participant and the researcher private time to be able to reflect and relax. Although sometimes the participant and researcher did take lunch together, this was used as a good time to ask additional questions and gain clarification and was only done on the suggestion of the participant. Of course, there are some challenges in shadowing and ethical considerations that need to be taken into account during the data collection and analysis. McDonald (2005) outlines these as firstly, managing the vast quantities of data generated, secondly managing the changes in the relationship between the researcher and the participant from potential unease at the beginning to potential issues of boredom and frustration at the end, and finally as the Hawthorne effect, where the very act of being observed causes actors to change their normal behaviour. To help overcome some of these issues the researcher followed the practical recommendations in the papers by

McDonald (2005) and Gill et al. (2014) which take researchers through the key stages of work shadowing including arriving, shadowing and leaving, for example to help avoid the Hawthorne effect they suggest asking participants to discuss how normal their day has been and also to review transcriptions of observation notes to check for anomalies with the participant.

To cover ethical issues the use of participant information sheets and consent forms was used to explain how confidentiality and anonymity of participants were to be protected and this is fully explained in the section on data management and general ethics in section 3.6 of this chapter. However, during the shadowing there was a need to be constantly aware of confidentiality issues as according to Johnson (2014) the main ethical issue of shadowing is that although you can pre-define ethical issues and counter against them, the very dynamic and changeable nature of shadowing means that new ethical issues that were not anticipated may appear suddenly and therefore the researcher would need to act quickly to assess the best course of action. This may be when a confidential telephone call is received, or when the participants come into contact with a person who has not given informed consent. Once again, to solve these issues the researcher was pragmatic and accepted that withdrawing from some situations would not derail the research process. Spare participant consent forms were also carried by the researcher to be signed by any other colleagues who began to work with the main participant being shadowed. Again, the researcher allowed any additional participants to access the field notes should they wish to do so and to maintain confidentiality they checked on regular occasions as to whether the participant wanted to exclude anything that was happening from the field notes. This practice is encouraged by Gill et al. (2014). These steps are summarised in the flow chart on the following page in figure 3.3.

Figure 4.3: Work Shadowing Process Flow Chart –

adapted from McDonald (2005) and Gill, Barbour and Dean (2014)

4.33 In-depth Interviews

The in-depth interviews occurred during cycles two and three of the data collection and analysis process (see figure 3.2) and were used to follow up on emerging categories from the shadowing sessions conducted in cycle 1. As the interviews in cycle 3, were focused on the specific emerging category related to the career background and experience of the general manager this resulted in fewer interviews in this cycle, explaining the gaps seen in table 3.1. In support of this McDonald (2005) agrees that shadowing is most often used in combination with in-depth interviews. This aided in the development and delineation of the emerging theoretical categories and analysis was ongoing during the period when in-depth interviews were taking place. Again Strauss (1987) and Strauss and Corbin, (1998) do not provide explicit guidance on the use of in-depth interviews as a data collection method in grounded theory but support a number of different approaches to data collection, of which an obvious choice is always in-depth interviews within the field of qualitative research.

The type of in-depth interviews selected were face-to-face semi-structured interviews, which lasted approximately one hour on average. Saunders, Lewis and Thornhill (2009) support the use of semi-structured interviews in qualitative research as they allow for flexibility for the researcher to explore new areas of interest and to respond to the context of the research situation. This is helpful when the findings are emerging directly from the data and emerging concepts may need to be followed up immediately to gain depth and clarity of understanding of what the participant is saying. They also believe it allows for the realities to be uncovered rather than the researcher just focusing on what they want to find out (Saunders, Lewis & Thornhill, 2009). This is crucial when the aim of the research is to deconstruct the black box surrounding the impact of big data on the way price decisions are made by managers, and to expose the participants' true voice and actions in line with Straussian grounded theory. The semi-structured interviews were prepared by listing some initial key areas of discussion and questioning in an interview notebook, but when the interview took place the researcher deviated from these if the participant opened a new line of enquiry or wanted to focus on something else. Corbin and Strauss (2015) voice a concern that when conducting semi-structured interviewing a participant may want to add something but don’t

because they are not asked directly about it by the researcher. This was circumvented by asking a catch-all question at the end of the interview to see if the participant had any general opinions or concluding thoughts or other things they considered the researcher had not covered. In this way, the discussion could follow up on emerging theoretical categories whilst also staying true to the voice of the participant and not forcing the conversation. This helped with the building of theoretical categories because variations and emerging concepts could be explored with a range of participants and compared to expose variations. These were recorded promptly as memos in the research diary. The researcher had the research diary with them throughout the data collection and analysis process to ensure vital thoughts were not lost. In this way, the research diary became central to developing the theoretical categories.

Obviously, the key to grounded theory is to allow the findings to emerge from the data so it was important to use the correct interview technique and not pre-empt or jump-in or ask questions that were phrased in such a way as to elicit a certain response (Corbin & Strauss, 2015). Each interview started with a statement that prompted the participant to feel they could speak openly and provide "unprompted data" (Scerri et al., 2017), such as "Can you tell me a little about your background in hotels and how you got to be a General manager?" All participants consented to the recording of interviews which meant full data sets and transcripts were able to be collected. There are debates over recording and the comfort of the participant but most seemed to forget the voice recorder after a few moments into the interview. They were given access to transcripts if they wished to check them for any information that they later did not want to be included but that had been recorded. This avoided any ethical issues. All interview recordings were transcribed by hand by the researcher and this added to the analysis as the researcher wrote memos and recorded thoughts on the emerging concepts and theoretical categories during the transcription process, ensuring that data collection and analysis were conducted concurrently as is the key for grounded theory. This is explained further in section 3.6 on data management.

4.34 Email Interviews

These were carried out in cycle four of the data collection and analysis process (see figure 3.2) and used to explore further the emerging condition of the influence

of specialist revenue support in the price decision-making process. Asynchronous email interviews, which means they do not happen in real-time, were conducted for more practical reasons because the researcher needed to interview off-site revenue specialists and their geographical spread was too great to visit them in person. Meho (2006) agrees that email interviews are useful if the participants are geographically dispersed and can also serve to be time-saving over synchronous, real-time methods as more than one participant can be interviewed at once. This proved to be particularly useful in the later stages of the sabbatical when the time was pressing. Increased participation through the use of email interviews is also supported by Redlich-Amirav and Higginbottom (2014, p.5) who state that "e-mail interviews enable one to recruit people who would otherwise be excluded from research because of geographical distance, different time zones, or wanting to keep their anonymity for various reasons." This certainly proved true in this research.

Meho (2006, p. 1292) also suggests that email interviews allow for the "interviewing of individuals who prefer online interaction over face-to-face or telephone conversation". Offsite revenue specialists are often used to communicating via email so seemed comfortable with this format. Due to the nature of asynchronous email interviews, the questions were structured but allowed for open responses to be made. However, Meho (2006) states this restriction is balanced by email interviews allowing more time for the participants to interpret the question and compose their response thereby encouraging deeper responses, obviously without the richness of body language. A series of emails were sent to each participant to ask open questions and follow up was carried out to clarify their responses. This did result in some time delay but the overall time-saving in being able to interview more than one participant at a time compensated for this (Saunders, Lewis & Thornhill, 2009). Each email interview was completed and then transcribed into an interview format. This meant all the email conversations were compiled together to ease data analysis.

4.4 Data Analysis

One of the key techniques of all types of grounded theory is that the data collection and analysis happen simultaneously and so as already mentioned in this research over the four cycles of data collection the analysis was also

occurring. However, to ensure clarity of presentation of the methodological approach in this chapter how the data analysis was conducted will again be treated separately. This section will explore how the research data collected through shadowing and interview techniques was analysed. It will explain how the main theoretical categories and sub-categories emerged from the coding and how these led to the ability to identify a core category which could be presented within a wider theoretical framework, which ultimately addressed the aim of the research. All types of grounded theory emphasise the building of theory rather than the application of current theories (Charmaz, 2014). The aims of most grounded theory studies are also the generation of middle-range or substantive theories which address explicit problems in specific areas of study (Charmaz, 2014) rather than formal theories which look at understanding wider problems through finding relationships between abstract concepts across a range of different substantive areas. The former was the aim of this research. This means the key findings in the following chapter will be presented in the format of theoretical categories derived from the grounded theory process (Scerri et al., 2017). Ultimately, the creation of these main theoretical categories and sub-categories through the processes of open, axial and selective coding led to the development of a core category and a substantive theoretical framework that explained the impact of big data on price decision-making at the individual hotel property level and successfully deconstructed the black box. This section will begin with a discussion of how Strauss (1987) and Strauss and Corbin's (1998) coding procedures were used in this research and will conclude with the criteria used for the evaluation of the research.

It is important to make clear before this discussion commences that the coding was carried out manually. Although Strauss and Corbin (1998) do make a brief reference to the use of computer-assisted data analysis they are clear that they are not familiar with these types of analysis. Of course, this could have been due to the lack of advancement in the computer-assisted qualitative analysis that existed in the late 1990s, such as ATLAS (Weitzman & Miles, 1995), rather than being due to an explicit commitment to manual coding. However, having chosen to conduct the original Straussian grounded theory method it seemed to be most authentic to code the data manually as they would have done. Most importantly

even though it was potentially more time-consuming, manual coding allowed the researcher to gain an invaluable closeness to the data and an overall understanding of it, so as not to miss crucial nuances that may later have proved to be important in delineating the main theoretical categories and identifying the key findings of the research. It was especially helpful as data collection and analysis were happening concurrently. Woods, Paulus, Atkins and Macklin (2016) suggest that computer-assisted qualitative programs are most often successfully used in data management and analysis rather than for data collection. A manual method allowed for codes to be created as the field notes were typed up and the interview transcripts subscribed, allowing both data collection and analysis to happen at the same time.

4.41 Implementing the Straussian coding paradigm

This section explores how the coding procedures of the Straussian strand of grounded theory were implemented in practice to identify the findings from the data and develop a substantive theoretical framework that met the aims of the research. The whole process of data collection and coding was completed over a period of eight months. The coding process was guided by the creation of a diagram (see figure 3.4) that was adapted from the guidance given by Strauss (1987) and Strauss and Corbin (1998). This provided a useful visual reference point for the researcher during the data collection and analysis process. It also provided a reminder of the key elements of the coding paradigm, which are consequences, conditions and action/interactions which help to develop an understanding of process and structure. This was useful because during all the stages of coding, as already touched upon, the researcher was sensitive to the appearance of these aspects of the coding paradigm in the data. The coding process covered the three main areas of open, axial and selective coding. It is important to note that this was not a linear process. As the data collection and analysis progressed the researcher moved between the stages, particularly of open and axial coding. Strauss and Corbin (1998) agree that the various types of coding can often occur simultaneously and sometimes not even consciously.

It also important to highlight that Straussian grounded theory blends inductive and deductive approaches, in the sense that it allows concepts to emerge directly from the data but then encourages the researcher to check these emerging hypotheses

around concepts and theoretical categories against the existing data and to explore them further in continuing data collection to help increase the theoretical density of the theoretical categories. Scerri et al. (2017, p.84) describe this as an "inductive-deductive interplay of data collection and analysis". Richardson and Kramer (2006) assert that abductive reasoning shaped Strauss's thoughts on grounded theory. Charmaz (2014) connected verification with statistical measures but this was not what Strauss was meaning by abduction.

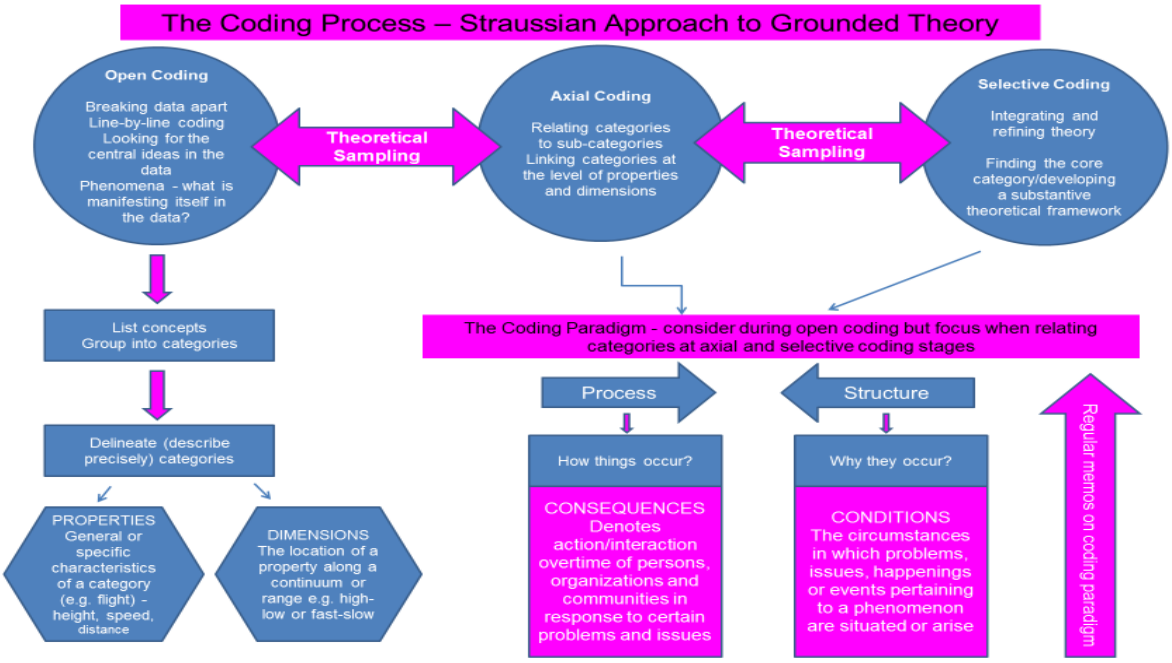


Figure 4.4: Coding Stages and Coding Paradigm - adapted from Strauss (1987) and Strauss and Corbin (1998)

Abduction has its origins in the work of Charles Sanders Pierce, who is also considered to be the founding father of pragmatism (Thayer, 1982). Richardson and Kramer (2006) explain how Pierce viewed abduction as the finding of explanations for observed facts which can be built into a substantive theoretical framework that explains a situation. This is how Strauss (1987) and Strauss and Corbin (1998) view it, rather than scientific, positivist confirmations. Also, according to Cunningham (1998), abduction is the appropriate method for making sense of new (or unknown) situations, which means this inductive-deductive approach facilitates the achievement of the aim of the research to deconstruct the black box.

This process of induction-deduction can be demonstrated in this research through the use of the constant comparison technique. Categories were allowed to emerge from the data based on the voice of the participants but then they were checked for validity against other data previously collected. The researcher was particularly looking for variations and common areas of agreement, for example, general manager involvement in the price decision was found to be an emerging category in the data but by checking back against previously collected data it was shown that the degree of involvement changed under the varying conditions of job history and revenue experience. The original emerging category was inductive but the checking back against previous data to develop the category further and identify variations was more deductive. The diagram below (figure 4.5) shows the main theoretical categories, sub-categories and core category that emerged from the data using the open, axial and selective coding processes and the coding paradigm as will be discussed in more detail in the findings and discussion chapter.

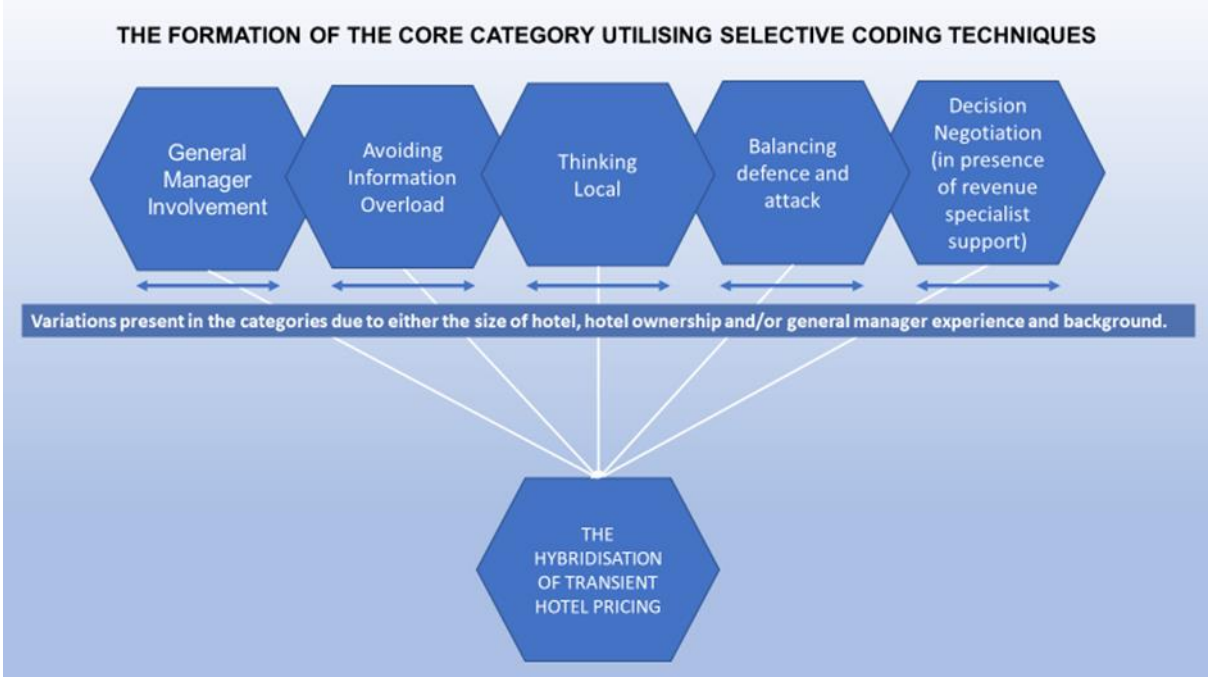


Figure 4.5: Summary of the Main Categories and the Core Category

An example of this coding process is provided in figure 4.6 below which shows how the category of "General Management Involvement" was arrived at through the distinct stages of open and axial coding using the coding paradigm, which are explored in more detail in the following sections of this chapter and are also

evidenced in appendices 2-5. Figure 4.6 shows an example of how open coding (see appendix 2 and section 4.411) was used to uncover the initial thoughts on concepts from the data, how the coding paradigm was used to delineate the emerging categories and identify variations in the categories (see appendix 3) and how axial coding was used to identify relationships between categories (see appendix 4 and section 4.412). The final stage of selective coding is discussed further in section 4.413 and appendix 5, where the discovery of the core category and theoretical framework are discussed.

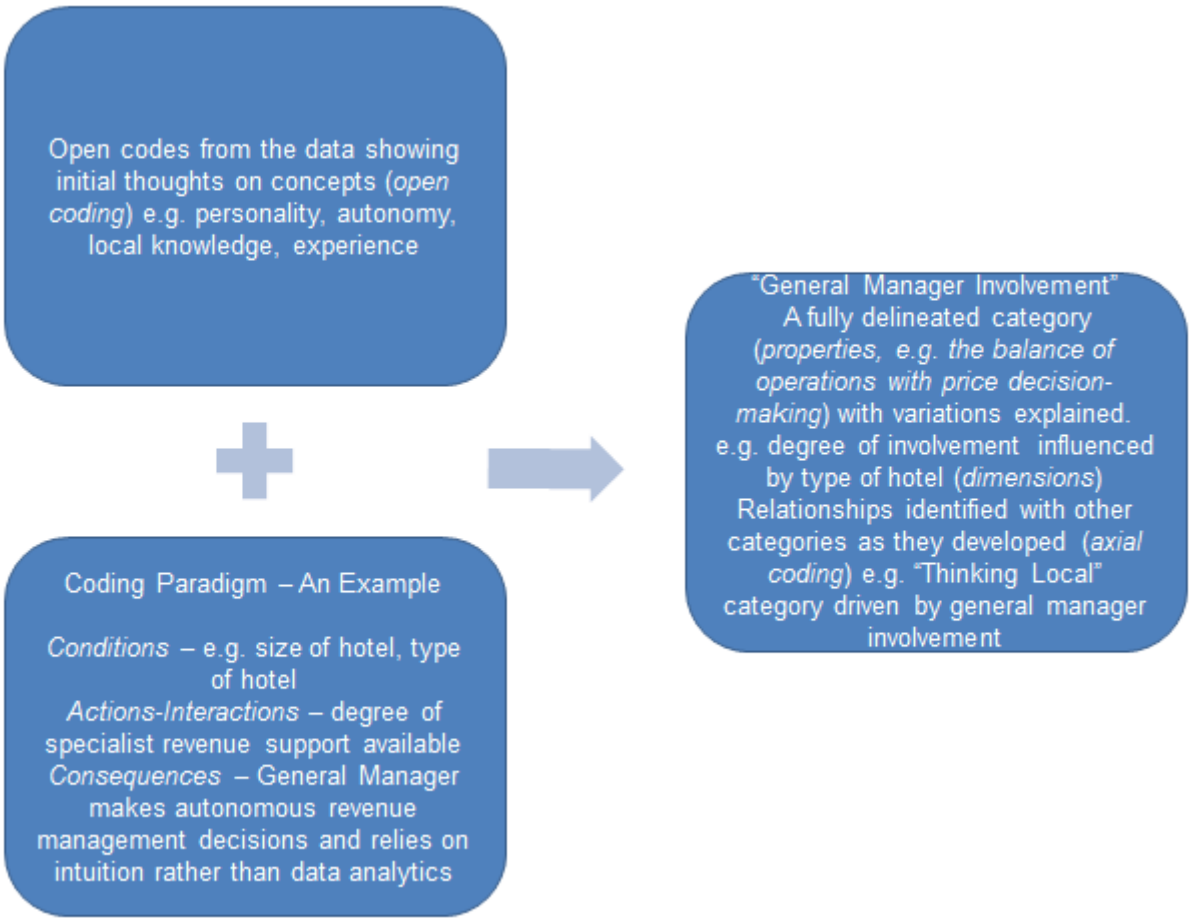


Figure 4.6: Coding Example

4.411 Open Coding

Open coding is an analytical process that allows for the identification of concepts and ultimately theoretical categories in the data that has been collected. Theoretical categories are simply concepts that stand for particular phenomena

(Strauss, 1987; Strauss & Corbin, 1998). In this research, the first stage was breaking the data down into small pieces, through detailed line-by-line analysis. The open coding began as the shadowing field notes were typed up and the interview recordings transcribed. This was a line-by-line analysis of the data, where ideas of concepts were typed in red text directly next to the data that represented that concept (see appendix 2). At this point there was a constant search for what central ideas were emerging and the key phenomena that were appearing, with a focus on the key aspects of the coding paradigm. Figure 4.6 also shows how the application of the coding paradigm to the emerging concepts or open codes from the data helps add detail to the emerging main theoretical category and show the variations within it. Here for example, the open code of operational pressures was explored further using the key aspects of the coding paradigm, and hence the conditions, action-interactions, and consequences surrounding that open code were identified. This was done for all the open codes, and by comparing them, the dimensions and variations of the main category were also identified, for example, the level of general manager involvement in pricing was found to vary depending on the type of hotel, the ownership structure of the hotel and the level of specialist revenue support available. As further categories emerged in this way the relationships between them were considered, for example the local focus category was driven by the category looking at general manager involvement. This process will be discussed further in the next section on axial coding.

In essence, the focus during the open coding was on understanding what was happening in the data and ensuring a sufficient understanding was gained to be able to describe the key concepts and theoretical categories in detail. This means that the properties and dimensions of the theoretical categories needed to be identified. Therefore, the coding also focused on identifying the properties of each of the emerging theoretical categories and their dimensions, for example, if the concept was flight one of its characteristics might be speed. The dimension would then be how slow or fast that occurred. Ultimately the aim was to identify what was also causing variations in the dimensions of the theoretical categories through the identification of specific conditions, for instance, the weather or the presence of other aircraft may influence the speed an aircraft can travel at. With more

details on the properties and dimensions, it was then possible to group concepts together to form wider, more detailed theoretical categories with sub-categories that related to them. This was achieved by writing all the emerging concepts written in red in the field notes and interview transcripts onto post-it notes and grouping them together. This was on-going as more data was collected and analysed and emerging hypotheses about concepts and theoretical categories were checked back against existing data and explored in new interviews using the constant comparison method.

4.412 Axial Coding

Over time, as the theoretical categories began to become saturated it was possible to delineate them more precisely in terms of describing their properties and dimensions. These were written up onto large sheets of A3 paper; using spider diagrams (see an example in Appendix 4). During this process, using axial coding techniques, the relationships between the theoretical categories and sub-theoretical categories and the variations within each category were considered in more detail. Theoretical memos centred on these ideas were recorded daily in the research diary. Axial coding is where, once the theoretical categories are delineated in terms of properties and dimensions, they can be viewed in terms of the relationships they have with each other using constant comparison techniques (Strauss & Corbin, 1998). This is often done by linking theoretical categories at the level of properties and dimensions which is why it was so important to make these clear during the open coding. These properties and theoretical categories are considered to be the axis of the theoretical category, hence the term axial coding. These relationships and variations are what enabled the core category to begin to emerge, which ultimately leads to an understanding of how that core category could fit into a theoretical framework. The core category is a merging of the main theoretical categories in order to explain the relationships between them. At the same time, theoretical sampling and constant comparison techniques continued to be used to explore and verify ideas on new emerging details within theoretical categories.

The memos were also written with consideration of the coding paradigm and this focus ensured the dimensions of process and structure were always considered when analysing the data, as it was important to the Straussian strand of grounded

theory to be able to show in the findings the conditions under which things occurred, what the consequences were and how the action/interactions of people to problems and issues changed over time (Strauss & Corbin, 1998). The paradigm is defined as an “analytical tool devised to help analysts integrate structure with process” (Strauss & Corbin, 1998, p.123). In Straussian grounded theory terminology, structure simply refers to the conditions under which a phenomenon occurs, for example, in the case of this research, the presence of specialist revenue support is one of the conditions that influence the impact of big data on the way price decisions are made. Structure is concerned with context. Process, however, is linked to the sequences of action/interaction “pertaining to a phenomenon as they evolve over time” (Strauss & Corbin, 1998, p.123). In this research, an example may be the changing nature of the relationship between the revenue specialist and general manager over time, where trust is seen to increase. Structure looks at why things occur, for example one memo noted that “there seems to be something about a hard/challenging market reducing the number of choices that could be made” with the why being the impact of market dynamics. Process looks at how they occur, for example, another memo commented that there “never seems to be a total reliance on data” with the how being the amount of data used in decision-making. Considering both in the analysis allowed for a more detailed picture of what is happening in the data to be created.

4.413 Selective Coding

Selective coding is the final stage of the coding procedure and is where the core theoretical category is identified. It was reached once theoretical saturation had occurred and no new theoretical categories were found to be emerging from the data. Once the main theoretical categories were known to have become saturated, the level of abstraction and theoretical thinking increased during the selective coding stage. The aim of this part of the coding was to identify a core category and then fit that core category into a wider substantive theoretical framework that could address and fully explain what was occurring in the black box. The key to developing the core category and fitting it into a theoretical framework centred heavily on identifying the wider relationships between the main theoretical categories and also on looking back at the variations that emerged in

the main theoretical categories developed in the open and axial coding stages. As Strauss and Corbin (1998) confirm, the core theoretical category and the theoretical framework must be able to explain the variations that have been found in the theoretical categories and pull together the main theoretical categories to explain them as a whole. This was achieved gradually through the use of spider diagrams and rough sketches of frameworks (see appendix 5). During this period the researcher carried the research diary with them at all times so that sudden thoughts on theoretical ideas and the framework could be captured and inputted into the emerging framework at a later date. Strauss and Corbin (1998) agree that this process can take time and say that researchers need to be creative and move from description to conceptualization at this stage. Therefore memos became more abstract and theoretical in nature than at the beginning of the open coding process. Once it was felt that the theoretical framework was complete, its key points were then checked back against the original data and the description of the main theoretical categories to ensure it fully explained the findings and represented what was found in the data. This was because it was crucial that the theoretical framework reflected what the data and participants were saying. This again shows the use of the inductive-deductive methods of Straussian grounded theory.

4.414 Supporting coding with memo writing

As already mentioned, the researcher relied heavily on the use of memos during the coding process and they became increasingly theoretical over time as the analysis progressed. Memos were developed through the use of questioning which is the key analytical tool suggested by Strauss and Corbin (1998). Throughout the open, axial and selective coding, questions were continually asked of the data, such as what is happening, why it is happening, how is it happening and what occurred as a result. This was recorded in the memos. The memos provided a written record of the analysis which was extremely helpful during the final stages of the development of the core category and the substantive theoretical framework as the researcher used them to refer back to, checking that the core category and the theoretical framework was consistent with earlier findings and supported inductive-deductive methods. Operational memos, of a more practical nature, were also written and they recorded notes on the

methodological approach such as comments on improving interview techniques, reflections on how the shadowing sessions were progressing and reminders for following up fresh leads for data collection for theoretical sampling. A hand-written research diary was used to record the memos on methodological issues, emerging concepts, theoretical categories, the relationships between theoretical categories and sub-theoretical categories and potential theoretical ideas as well as comments on the development of any potential biases (Strauss & Corbin, 1998). Memos were also recorded alongside the interview transcripts and field notes to show how they related to the codes and emerging theoretical categories.

4.42 Criteria for evaluation

Morse, Barrett, Mayan, Olson and Spiers (2002, p.15) state there is a lack of clarity around the selection of the criteria used to judge the rigour of qualitative studies. They explain that this has led to the use of a lot of what they term “post hoc” evaluations’ which have the potential for reducing the rigor of qualitative research since they are not being built into the research process. Therefore it was felt to be important to evaluate and select these criteria before embarking on the data collection and analysis process so that they could be used consistently and continually through the data collection and analysis process and not just at the end. Although other approaches to the evaluation of qualitative research were considered, in particular, Lincoln and Guba’s (1985) refined criteria of credibility, transferability, dependability, and confirmability, it was decided to follow the criteria offered by Strauss and Corbin (1998). It made sense to follow through the commitment to the Straussian grounded theory approach by utilising their evaluation criteria since it was specifically designed to complement their data collection and analysis procedures, which were specifically aimed at “discussing criteria for judging the merits of theory-building research” (Strauss & Corbin, 1998, p.265). It is important to note that these evaluating criteria were only explicitly covered in Strauss and Corbin (1998) and an earlier paper by Corbin and Strauss (1990). There was little direct coverage of evaluation criteria in Strauss (1987), where the focus lay on the data analysis procedures. Strauss and Corbin (1998) agree there is much debate surrounding the evaluation of qualitative research and therefore they stress the importance of the researcher being explicit in the criteria they use to evaluate their research. This is the purpose of this section.

To begin with, Strauss and Corbin (1998) redefined the evaluation criteria of reproducibility and generalization in the context of theory-building research. Usually, reproducibility proves the credibility of research through the ability of the original research to be replicated, following the same data collection and analysis processes, to reproduce the same findings. However, Strauss and Corbin (1998) argue that due to the fact that grounded theory, as is the case in this research, studies social phenomena, this is not a realistic way to claim credibility. Social phenomena are thought to be too fluid and changeable to be perfectly replicable in theory-building research. Instead, they accept that if other researchers were of the same theoretical perspective as the original researcher, followed the same general rules for data collection and analysis and assumed similar sets of conditions, similar problems and issues would arise from the data, although they may be interpreted differently in the discussion. To ensure this was achievable for this research it was important to outline clearly at the beginning of the research process the researcher's theoretical and philosophical perspective as well as recording the exact procedures used for data collection and analysis in this methodology chapter, for future use if necessary.

In addition, Strauss and Corbin (1998) made clear that generalisability was not the aim of theory-building research and instead argued the focus should be on the explanatory power of the research. The elements of the theoretical framework and core category were checked against the original data in the selective coding process to ensure it explained what was happening in the data. Strauss and Corbin (1998, p.267) express plainly that the “the real merit of a substantive theory lies in its ability to speak specifically for the populations from which it was derived and to apply back to them”. In this research great effort was made to delineate the main theoretical categories in as much detail as possible and to identify a range of conditions and variations within each theoretical category, as can be evidenced by the findings chapter. Memos recorded the development of those theoretical categories. Corbin and Strauss (1990) and Strauss and Corbin (1998) believe that by doing this the explanatory power of any substantive theory that results from the findings is increased. However, the key elements of Strauss and Corbin’s (1998, p.265) approach is summarised by their desire to develop “valid and grounded theory that speaks to the issues and concerns of those we study”. In this case, the

people being studied were general managers and revenue specialists and through the checking of the theoretical framework against the original shadowing field notes and interview transcripts, it helped ensure their voices were represented. The researcher was, therefore, able to demonstrate that the data collection and analysis procedures in the research were adequate and that the findings are grounded in and have emerged from the data and the voice of the participants. Strauss and Corbin (1998) went on to suggest a number of specific criteria both for evaluating the research process and for ensuring the empirical grounding of the theory. How these criteria were considered in this research is considered in the next sections.

4.431 Evaluating the research process

Strauss and Corbin (1998) ask researchers seven questions to make up the criteria for evaluating and demonstrating the adequacy of the research process. A brief answer will be given to each one within the context of this research.

1. ***How was the original sample selected?*** – This was considered early in the research process. An initial sample of six hotels was selected using purposive sampling techniques for cycle one of the data collection and analysis. The aim was to build in adequate variation in the sample to effectively develop the main theoretical categories. Therefore, hotels of different standards from midscale/economy to luxury/upper scale were selected. The STR Global property classifications were used as a benchmarking tool to differentiate the different hotel standards. Variation was also built in to the sample by considering the standards of hotels over two different hotel ownership structures. These were independent hotels and managed/franchised hotels with links to a major brand or chain.
2. ***What major theoretical categories emerged?*** – Five main theoretical categories emerged from the data and these are fully delineated and explained in the findings chapter. Memos exist to evidence how these categories were arrived at (see appendix 3). The titles of the main theoretical categories are general manager involvement, avoiding information overload, thinking local, balancing defence and attack and finally, decision negotiation. Each theoretical category had two to three sub-theoretical categories to help detail the findings.

3. ***What were the events, incidents, or actions that pointed to some of these major theoretical categories?*** – The five main theoretical categories that emerged from the data were illustrated by a number of events, incidents and actions that were witnessed during the shadowing sessions and gathered from the interview transcripts. These events, incidents and actions are highlighted in the findings chapter through brief examples written about from the shadowing field notes and direct quotations from the interview transcripts. These evidence how the main theoretical categories were formed and also they help to make it clear that the findings were based upon the voice of the participants.
4. ***On the basis of what theoretical categories did theoretical sampling proceed?*** – Theoretical sampling was carried out through cycle two to four of the data collection and analysis process as already demonstrated. Cycle two used in-depth interviews to explore any emerging categories from the shadowing sessions with the managers observed. Cycle three explored the emerging category of the influence of the general manager in pricing and that their background influenced the impact of big data on price decision-making. This ensured that the interviewing addressed a varied sample of general managers, some with revenue backgrounds and some with food and beverage backgrounds, due to the emerging category examining the importance of the career background of the general manager on their use of data. In a similar way the emergence of the influence of revenue specialists in the price decision-making process led to further interviews with these revenue specialists who were supporting the hotels in cycle four. This helped develop variety in the theoretical categories and identified the different conditions under which things occurred.
5. ***What were some of the hypotheses pertaining to conceptual relations and on what grounds were they formulated and validated?*** – Hypotheses are “hunches” (Strauss & Corbin, 1998, p.135) that the researchers gain from the data on how concepts might be related to each other, for example as above, the researcher developed a hypothesis that the background of the general manager influenced the way they handled the big data available to them in the price decision-making process and that this impacted upon their level of engagement with the data. This was

formulated through the constant writing of memos during data collection and analysis and was validated by doing further interviews to check if background did influence in this way and also by checking back against previously collected and analysed data to see if the concept also arose there. The final theoretical framework and core category were checked back against the original data. Therefore, at the heart of the formulation and validations of the categories, core categories and the theoretical framework was the use of Straussian inductive-deductive methods of data collection and analysis.

6. **Were there instances in which hypotheses did not explain what was happening in the data and how were these discrepancies accounted for?** – Fresh incoming data did not necessarily prove hypotheses to be wrong but simply denoted variations in the concepts that were being discovered, for example it emerged that in independent, small hotels, no revenue specialist support was available so general manager involvement in revenue-management decision-making was autonomous, whereas at the other extreme in a branded budget hotel the general manager had no control over pricing at all as it was all covered centrally and by automated systems. This did not mean the theoretical category of general manager involvement was wrong, simply that there was variation within the theoretical category that needed to be highlighted as a finding.
7. ***How and why was the core theoretical category selected? Was this process sudden or gradual, difficult or easy?*** – The core theoretical category emerged gradually over time through reading, writing and re-writing of theoretical memos and sketching out framework ideas. The procedures for selective coding were also used. The researcher was satisfied that by the point the core category and the substantive theoretical category had emerged it was saturated and no new key findings were emerging from the data. The core theoretical category was checked back against the data and against the main theoretical categories to ensure it represented what the data was saying and that it could represent the variations in the main theoretical categories.

The responses to these seven questions serve to demonstrate that the findings of this research which is to be discussed later in this thesis can be evidenced as

being grounded in the data collected and analysed, that theoretical sampling was correctly used to develop theoretical categories and ultimately a core category that could formulate a substantive theoretical framework. It serves to provide evidence that the grounded approach has been followed.

4.432 Ensuring the empirical grounding of theory

Again, Strauss and Corbin (1998) provide seven criteria for the research to consider when ensuring the empirical grounding of theory. A brief consideration will be made of each one in the context of this research. In this section concepts refer to the original central ideas of what is happening in the data that emerged during the open coding process. These concepts were grouped together to form theoretical categories over time.

1. ***Are concepts generated?*** – Concepts were generated in this research via the data utilising the open coding procedures described above. The concepts were often drawn from common usage but represented conceptual thinking about the data. A glossary of terms at the beginning of the thesis helps demonstrate the existence of these concepts, as does the findings chapter, which shows how concepts have been linked together to develop theoretical categories.
2. ***Are the concepts systematically related?*** – Axial and selective coding procedures enabled the researcher to relate the concepts to each other. The reader can see how they are interwoven into the exploration of the findings and the discussion chapter, as well as the substantive theoretical framework that was created. The existence of memos also demonstrates that this process occurred.
3. ***Do theoretical categories have conceptual density?*** – This refers to whether the properties of the theoretical categories are explained in detail and "dimensionalized" (Strauss & Corbin, 1998, p.271). The findings chapter shows this to be the case in the way it delineates each theoretical category, in how explanations are also made of the core theoretical category and in how the main theoretical categories relate to each other to develop a theoretical framework in the discussion chapter.
4. ***Is variation built into the theory?*** – Variation was built into the original sample as already discussed but variations were also reflected upon whilst

developing the main theoretical categories. Dedicated sections of the findings chapter are provided to highlight the variations in each of the main theoretical categories.

5. ***Are the conditions under which variation can be found built into the study and explained?*** – The conditions, such as the degree of specialist revenue support, under which the variations occur, are also included in the findings chapter. This was all about identifying the context in which things occurred and in the coding paradigm relates to the term structure.
6. ***Has process been taken into account?*** – Process, in the coding paradigm denotes the movement of action/interactions over time "in response to prevailing conditions." (Strauss & Corbin, 1998, p.272). Memos were specifically written that documented thoughts on emerging concepts around process from the data, such as the changing dynamics of the relationships between general manger and revenue specialists over time.
7. ***Do the theoretical findings seem significant and to what extent?*** – The discussion chapter highlights the significant findings of the research and concludes that the research makes three key contributions to knowledge in this area of big data and hotel price decision-making, although it is felt inappropriate to elaborate further on these contributions in this methodologically focused chapter. The conclusion chapter reflects on the implications of the findings on industry and hospitality revenue management education.

4.5 Data Management and General Ethical Issues

The full details of the data management plan produced in advance of the data collection are provided in Appendix 1. Full ethical approval was granted before data collection began. Nevertheless, it is worth highlighting some of the key actions that ensured the secure, ethical and practical handling of the research data during the collection and analysis process. To begin with, prior to any data collection taking place, be that shadowing sessions or in-depth interviews, all participants were required to complete and sign a participant consent form. Amongst other questions these forms specifically asked participants whether they were happy for the data, once collected and anonymised, to be used for any other

research purposes outside of the current project. This was deemed important for the further post-doctoral progression of the research. The participant consent form also explained that no confidential corporate data would be collected or shared and that participants would be allowed access to the field notes and interview transcripts should they wish to confirm this. Participants were also offered the opportunity at this stage to check for any material that they wished to remove or that they did not wish to be included in the data analysis. However, it was made clear that no personal or company names or any other identifying features would be used in the field notes, transcriptions or any other documentation including the main thesis and their anonymity would be protected. No participants asked for any changes to be made.

In addition, any participants taking part in the shadowing elements of the data collection were made directly aware that they could request a pause in the shadowing process at any time to allow for confidential calls or meetings to take place. This did occur on a couple of occasions and caused minimal disruption to the data collection process. Any other people who came into contact with the participant being shadowed were also asked to sign a participant consent form and every participant was also given an information sheet outlining all relevant details of the study and the nature of their participation. Participants were made aware of their right to completely withdraw from the research through the signing of the participant consent form. However, no major negative consequences could be foreseen with this research in terms of impact on the participants, especially as the shadowing element of the data collection was conducted completely overtly, therefore none of the potential ethical issues of covert research where encountered, such lack of consent.

In fact, one of the important areas of considerations prior to the data collection beginning was the personal safety of the researcher as they were going to be working alone on off-site visits. To ensure personal safety was guaranteed the guidelines outlined in the Sheffield Hallam University Personal Safety and Lone Working Guide, Appendix A, Section 3 Offsite Visits (Sheffield Hallam University, 2013) were followed by the researcher and a separate risk assessment was also conducted. The main preventative measure utilised was to keep in regular contact with the Director of Studies. A data collection schedule was produced for the

period of data collection and this was made available for the Director of Studies so that he was aware of the timings of the shadowing sessions and interviews. The Director of Studies also had access to the contact details of the researcher including mobile numbers and also the contact details of the locations where the shadowing sessions and interviews were to be carried out. They were also aware of emergency contact procedures should contact be lost with the researcher during the data collection period.

Once consent had been granted by the participants and the data collection process was underway a large amount of qualitative data was produced through field notes generated in the field, in-depth interview recordings, email responses to interview questions and entries in a research diary. Therefore, the formats used for data collection where both non-digital and digital. The data from the shadowing sessions was captured in real-time and therefore was particularly unique and irreplaceable and required careful handling. Apart from the research diary, which contained handwritten conceptual and methodological memos, the other data was transferred to Microsoft Excel files. Field notes were typed up, interview recordings were transcribed personally by the researcher and any email interviews were placed in an interview format and typed up, all into Microsoft Excel. In total six Excel files were created for the field notes, fourteen for the interview transcripts and five for the emailed interviews. The UK Data Service (2016) supports the use of MS Excel files for long-term data storage. MS Excel was also found to be useful for the easy numbering of lines in the transcripts. Conceptual memos written outside of the field and therefore not recorded in the research diary were recorded on another Excel sheet in the file that they corresponded to.

To store and order the Excel files a directory structure was utilised and the Excel files went into three folders, entitled: Work Shadowing Field Notes, Interview Transcriptions, and Email Interviews. Within the first folder each file was labelled Shadowing session 1, 2 etc. and in the second folder, each file was labelled Interview 1, 2 etc. Each file was also clearly dated using the format of YYYY-MM-DD for ease of searching. Versioning was not required for field notes and interview transcripts as once they were created they become static data, however, the coding and memos did evolve and therefore version numbers were used to track these changes. In terms of storage of the digital data folders and

files, Sheffield Hallam's Research Store (Q:\Research) was used to back-up and store the data. The Director of Studies also had access to this data store. Due to the level of security of this research store, it was advised that no further back-ups in other places were necessary by data support services at the university library. Finally, according to the Data Protection Act (1998) the data that was collected was not considered to be either personal or sensitive as the participants in the research could not be identified in the study and there was no collection of sensitive personal data, such as race, religion or ethnic origin. This meant that there was no need for the research data to be destroyed and there was no further need to comply with any other aspects of the Data Protection Act (1998).

4.6 Chapter Summary

This chapter has put the case forward for the use of Straussian grounded theory for this research (Strauss, 1987; Strauss & Corbin's, 1998). It was chosen to allow for the exploration of an area of revenue management that had previously not been fully explored and because of its ability to address the current, detailed voices of the participants. It proved successful in uncovering the realities of price decision-making at an individual hotel property level which had previously existed within a black box. The coding paradigm and procedures allowed for the development of a robust theoretical framework that emerged from the data and represented the voices of the participants and their realities. This deconstructed the black box and gave the theoretical framework the ability to fully explain what was actually happening around price decision-making from a hotel property perspective in the era of big data. The chapter has also demonstrated the thoughtful and detailed way that Straussian grounded theory has been operationalised in this research in terms of open, axial and selective coding, memo writing, and sensitivity to the key aspects of the coding paradigm and ethical/data management issues. This careful and thorough approach to the methodology allowed there to be confidence in the robustness of the theoretical framework that was ultimately arrived at. The next chapter which outlines the findings is the product of this methodological process. It will present the findings of the research as they emerged from the data analysis process by delineating the main theoretical categories and the core category. The substantive theoretical framework that emerged from the coding process is the subject of the discussion

chapter where it completes the deconstruction of the black box and highlights the contributions of the research.

5. Findings

5.1 Introduction

This chapter presents the findings as theoretical categories derived from the grounded theory process through the various stages of coding from open to selective (Strauss, 1987; Scerri et al., 2017). The findings that are represented by each of the main theoretical categories and their related sub-categories will be described through the delineation of each category. The diagram below (figure 5.1) provides an overview of the theoretical categories to which the findings relate and were generated as a result of the grounded theory coding process. An example of how the coding process resulted in one of these main categories and its sub-categories can be found in figure 4.6, with supporting evidence of the process can be found in appendices 2-5.

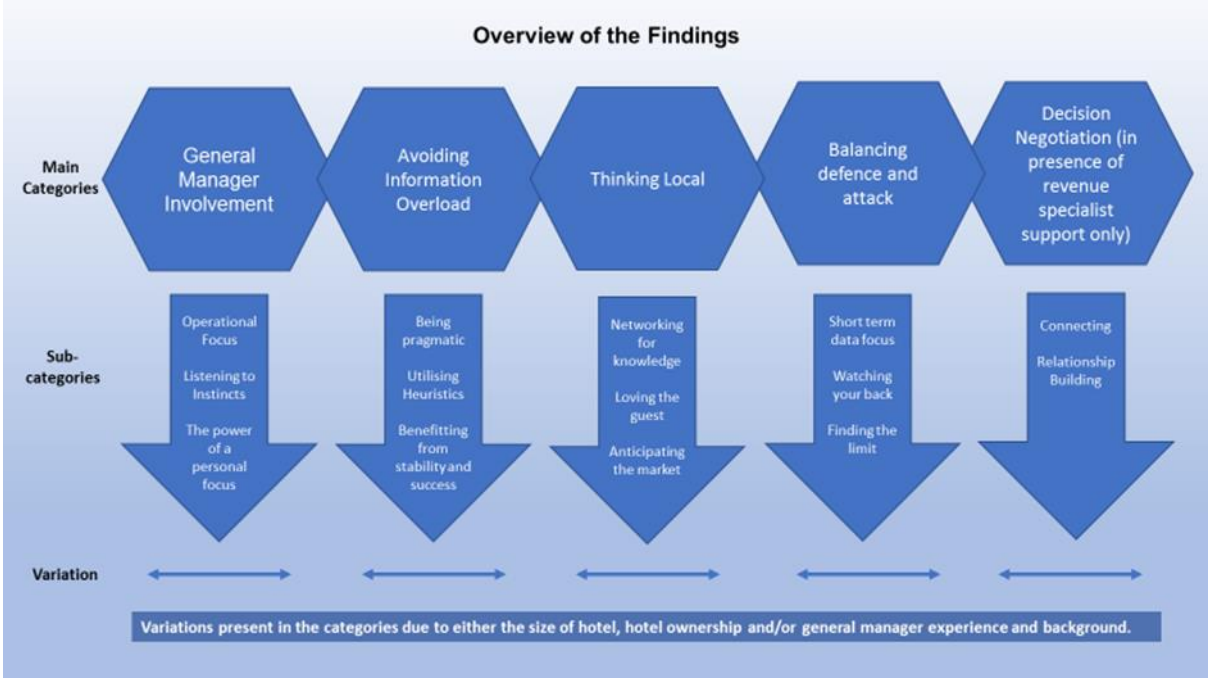


Figure 5.1: Overview of Theoretical Categories, Sub-Categories, and Key Variations.

Delineating the theoretical categories refers to describing in detail the properties and dimensions found in the data and also relates back to the coding paradigm developed by Strauss (1987) and further advanced by Strauss and Corbin (1998). This was the data analysis method used in this research, as outlined in the methodology, again an example of which can be found in figure 4.6 with

supporting appendices 2-5. This coding paradigm asserts that the categories must reflect the conditions, actions/interactions and consequences found in the data (Strauss, 1987; Strauss & Corbin, 1998). Consideration of these allows for the development of an understanding of both structure and process so that both how and why things occur can be understood (Strauss & Corbin, 1998). Therefore, before presenting the findings around each theoretical category it is perhaps useful to review Strauss's definitions of these terms. Simply, conditions are the circumstances and situations in which things happen, actions/interactions are the responses made by individuals or groups to issues or events that occur under those conditions and consequences are what occurs as a result of these actions/interactions. Structure looks at the conditional context in which things occur and process looks at how things evolve overtime given a sequence of actions/interactions (Strauss & Corbin, 1998). The findings in this chapter, therefore, explore how big data is used in the price decision-making process at an individual hotel property level and why, in terms of the conditions and actions/interactions that drive these uses and the consequences of them.

The chapter will then go onto to describe in more detail the core category that emerged from the data. It will explain briefly how the complexities of the core category were deconstructed further and positioned within a wider substantive theoretical framework, although a deeper examination of this will be covered in the discussion chapter. The core category is represented graphically in this chapter and was designed to integrate the variations found in each of the main theoretical categories. These variations have emerged from the analysis of the data and will be evidenced with a number of key quotations from the field notes and interview transcripts. The identification of variations present in each of the theoretical categories is central to grounded theory (Strauss, 1987; Strauss & Corbin, 1998) as it helps to demonstrate the dimensional range of a category and the impact of various conditions on the category. Without the identification of these variations, it would be hard to develop a complete theoretical framework that explained the full picture of what is occurring in the data. Strauss, (1987, p. 36) summarises that the "the core category allows for building in the *maximum variation* to the analysis, since the researcher is coding in terms of its dimensions, properties, conditions, consequences, strategies and so on". The variations found in the categories

guided this research towards the core category of the hybridisation of transient hotel pricing and enabled it to demonstrate under what conditions the hybridisation of transient hotel pricing did occur and where it did not and therefore under what condition a black box was most likely to be present. This, in turn, enabled the development of a substantive theoretical framework that could deconstruct the black box completely. Where a hybridisation of transient hotel pricing did not occur the pricing process was simplified and the complexities that made up the black box were not present.

In this way, the findings that are represented in this chapter demonstrate how there has been a consideration of all the elements of the coding paradigm central to this type of grounded theory. The findings represent the processes and actions/interactions that occur when people use the data in the price decision-making process and highlight both the conditions in which these processes might be different and the consequences of these variations. To sum up, the findings chapter will address the question of "what has been found in the research data?" The discussion chapter will answer the question of "what do these findings mean for our understanding of the impact of big data on price decision-making at the individual hotel level?" and "how can they be represented with a substantive, explanatory theoretical framework that completes the deconstruction of the black box?"

5.2 The Findings – Delineation of the Categories

The findings that have emerged from the data and relate to one of the five main theoretical categories and their sub-categories, along with the variations present in the category, will now be explored in the following sections.

5.21 General manager Involvement

The first key finding to present itself early in the analysis was that the general manager for an individual property was always to some degree involved in the making of price decisions. They were always engaged, although to varying degrees, with the price decision-making process through the expression of their viewpoint and interpretation of the types of revenue data they had available to them. In this way, the general manager was found to influence and have an impact upon the outcome of the price decision. In essence, they were shown to

hold a vested interest in pricing as they saw it as supporting the commercial success of their hotel. The involvement of the general manager did mean that they interacted more regularly with revenue related data and consequently needed to find ways to manage and interpret these data flows, given the generalist nature of their role. This will be explored further in the category entitled “avoiding information overload”. In this way, this category heavily influences the findings in the categories that follow because who actually interacts with the data and how this happens were discovered to be central to the findings of this research. The discoveries in this category are centred on three sub-categories which will now be explored.

5.211 – Operational Focus

Due to the involvement of the general manager in price decision-making a balancing act was observed between the financial operation of the business from a broader, commercial viewpoint and the day-to-day practical running of the hotel, such as staffing, maintaining customer service standards or delivering food and beverage operations. The involvement to a lesser or greater extent of general managers in the practical operations of their hotels resulted in the creation of the term, operational focus. Fundamentally, it was seen that despite the general managers' involvement in pricing their primary responsibility was to be a generalist rather than a revenue specialist and therefore they needed to maintain an operational focus, overseeing the smooth running of the hotel. Whilst it was clearly key for them to achieve their wider budget targets in terms of profitability they recognised the role of both operational and revenue decision-making in achieving that outcome.

5.212 – Listening to instincts

The involvement of the general manager in price decision-making was seen to be led by gut instinct, and this relates to the use of intuition in decision-making. The general managers' intuitive abilities were found to stem from their observations of the local market, customer behaviour and the recollection of the historical outcomes of local events and past revenue decisions with the major focus being on customer reactions to these decisions. These were often not formally stored but held in mental stores to be recalled by managers when it was felt they might be relevant to a decision. In the shadowing sessions, this was characterised by

managers saying they "*remembered*" something happening rather than searching for the data in a report or spreadsheet. Intuition is often linked to the use of instinctive responses to events that are not always based on fact or that show an absence of conscious reasoning. However, in the case of these findings, gut instinct and intuition were viewed by general managers to be almost factual, and part of a conscious process to gather data so as to build up a picture of their local environment. They believed that this accumulated knowledge of their hotel, customers and local market meant that their gut instincts became more accurate over time as they were based on knowledge built from a large portfolio of local observations.

General managers were also seen under some circumstances to use big data to provide the check and balance to their gut instincts and local observations. They were also happier to follow their gut instincts knowing the results of their decisions could be monitored by the comparisons of data sets, such as year on year revenue growth. However, although gut instinct was an element for the all the general managers the level of trust they placed in it was affected by the managers' personality and their feelings towards risk. Risk-adverse managers seemed more likely to make a more detailed analysis of the data than the managers who were more willing to take risks and who consequently relied less on instincts.

5.213 - The power of a personal focus

The involvement of the general manager also means that they were found to assert their personal focus on the decision-making process. This personal focus centred on their own personal measurement of success, what motivated them individually in their role and the achievement of which targets they considered when making a pricing decision. The targets set for general managers seemed to be extremely varied, covering revenue, staffing, costs and customer service and the variation in targets did seem to mean that general managers were having to overview a massive variety of data on different topics on a daily basis. However, general managers were not found to be particularly interested in breaking down the focus of revenue decision-making into these specific targets but rather they took a broader approach, focusing in on the achievement of the hotels overall annual budget target. This perhaps led to them concentrating on key metrics they

could access quickly and easily. In this way, their motivations to reach an overall target helped them to simplify the data they needed to review.

5.214 – Variations in the category of General manager Involvement

As already mentioned, although there was always some degree of involvement of the general manager in revenue decision-making this varied in amount and type of involvement depending on the presence of certain key circumstances. The mediating conditions were found to be the background and level of revenue experience of the general manager, the organisational structure surrounding the individual hotel, the size of the hotel and how both those related to the amount of specialist revenue support available to the general manager. Finally, the general priorities of the general manager were also found to be important.

The first condition is the background and level of revenue experience of the general manager. This relates to the exposure to revenue management that they may have had in their previous or current roles and their route to the position of general manager. The majority of general managers involved in the research did not gain promotion to their position through revenue roles, instead, they came from a strongly operational, and particularly food and beverage related background. These types of general managers, exhibited a more relaxed and hands-off approach to pricing, however, they still wished to include their local insights in the decision-making process. In addition, some of these managers who talked about their personal interest in increasing their knowledge of revenue management did make a conscious effort to go on courses or absorb knowledge from more experienced revenue colleagues. Therefore, the personal focus of the general manager appears to play a part in their degree of involvement. If the general manager personally held an interest in revenue management their involvement was likely to increase. This is evidenced by the following general manager, who had a strong operational, food and beverage background and described his desire to focus on revenue management. However, he also talked about his concerns around the constant danger of being pulled back into his operational comfort zone.

“At the start of my GM career I made a conscious effort to focus more on that side [revenue management], um but that doesn't always ring true

because you do get pulled into the operation. So, you do get pulled into what you know best and yeah, so my background isn't from that kind of analytical, data kind of thing because my background is from being operationally focused".

However, if a general manager had moved to their current position from a revenue role they clearly cited their revenue expertise as the reason they were more likely to increase their involvement in pricing and take a more analytical approach, maintaining control of the detail, often despite the presence of additional revenue specialist support. The following quotation illustrates one such general manager talking about the impact of their revenue background on their approach to pricing.

"It [my revenue background] means that I'm much more analytical and not just about revenue and room rate decisions but also about anything we do, whether that be a post-Christmas review to finding out what went well and what didn't."

The next conditions are interrelated in the sense that the ownership structure in which the hotel operates and its size were found to affect the amount and type of specialist revenue support available to the general manager, which in turn influenced the degree of involvement that the general manager had to have in pricing decision-making. At one end of the spectrum was the fully owned and operated branded economy chain where pricing was totally centralised and the general manager could only feed minimal local knowledge to the specialist revenue team through their area manager. At the other end of the spectrum, small, economy hotels with less than fifty bedrooms were found to have no specialist revenue support. The majority shared access to specialist revenue support through a cluster or central team. Centralisation occurred both for branded and independent hotels but only those independent hotels that had access to either revenue support through a marketing consortia organisation, such as Best Western, had a small resource at a group office or on-property for luxury, larger, independent hotels. These variations in the level of revenue specialist support available to general managers impacted directly on their level of involvement in pricing.

In smaller, independent hotels where there was a lack of specialist revenue support, the general manager was left with no choice but to make all the revenue decisions single-handily, however, it was also found that their ability to focus on this revenue decision-making process was often diluted by operational distractions. The general manager was often seen engaging with practical, frontline operational tasks such as banking, human resources functions and even serving customers, whilst in-between briefly scanning revenue data and making pricing changes. The balance, therefore, shifted away from a commercial focus to an operational one and revenue decisions were often made quickly and with less analysis of the data. General managers in hotels without revenue support were also seen to rely far more on instinct than managers with revenue support in place, as they had less to data to work with. This is evidenced in the following excerpt from the shadowing field notes where one general manager of a small, independent hotel is recalling having complete involvement in pricing.

"The manager out of necessity due to a small team and also seeing no return in investment of revenue specialist support for a small hotel of less than forty bedrooms makes all the revenue management decisions himself based purely on two metrics; occupancy levels on a certain day and competitor prices from Booking.com on that day".

Where revenue specialist support is available, price decision-making becomes more about a joint-decision making process between the general manager and the revenue specialist. However, even where specialist revenue support is available in fully owned and operated brands, if the hotel was small with a small operational team this might also result in the general manager getting more operationally involved despite their still not having full responsibility for making revenue decisions. To demonstrate this the general manager of a small, budget branded hotel talks about the challenge of being operationally involved and the limitations this puts on price involvement, then adds that the lessening of their concern about this is due to the availability of centralised revenue support.

"The thing is that the revenue manager is only focusing on that…rate…and even if they have ten hotels to look after that's their only job ok, but with me having two hundred jobs at the same time here and I have to look after the

team, the guest, the quality, the housekeeping, the maintenance everything ok, so, even if I had all this information I wouldn't be able to play with it all the time because I wouldn't do any other thing".

However, even with specialist revenue support the general manager's personal focus also mediated the degree of involvement in pricing. Again, this was driven by either their operational or commercial focus. Some general managers seemed more wedded to the traditional ideas of hospitality and the concept of "Mein Host" whereas others viewed it as more of a commercial business. Traditional, operationally focused general managers appeared more willing to relinquish control of pricing where specialist revenue support was available.

5.22 Avoiding Information Overload

In view of the fact that big data is defined as data that is high volume, high velocity and high variety (Laney, 2001) it might be expected that the impact of its presence on general managers involved in making price decisions would lead to information overload, where information overload is defined as the difficulties caused by having too much data when trying to understand an issue or make a decision. This may especially be considered to be so if as highlighted above, the general manager's role involves not just processing pricing data but also copious amounts of operational and administrative data. However, what emerged from the data actually proved the opposite to be true at a hotel level. General managers found ways to avoid the information overload potentially caused by big data and although they recognised the volumes of data they faced, none seemed to feel that this led to a feeling of being overwhelmed by the data, as would be the case if information overload was present. This was found to be due to deliberate attempts by general managers at the hotel level to actively avoid information overload by taking a range of steps to narrow the focus of the data they look at. These are described in the following sub-categories.

5.221 – Being Pragmatic

It was found that general managers were being pragmatic in their approaches to data and that the consequence of this was the avoidance of information overload. In this context being pragmatic meant taking a practical, realistic and simplistic approach to data and pricing rather than a more complex, theoretically driven one.

They perceived that analysing all the data was not practical given their involvement in the operational running of the hotel and also, even if they did have some time to dedicate to price decision-making they still believed it involved a degree of trial and error. During the shadowing sessions, general managers were observed choosing to only review a select amount of data that they felt was practicable to analyse given the pressures of their role and this was often in order to check the impacts of their previous decisions.

General managers were also seen to exercise pragmatism in the upper boundaries they placed on prices based on their knowledge of the quality of their hotels' product. One general manager of a budget hotel explained that although in periods of extremely high market demand revenue management theory may suggest dramatic price hikes, their knowledge of the product told them this was unrealistic when taking into account increased guest expectations brought on by higher prices. They would prefer to be pragmatic, accept a lower price and keep the guest happy. Finally, general managers were also seen to be prepared to exercise compromise in the setting of revenue strategies and took an overall view of the decision, accepting that there may sometimes be trade-offs such as the gain of food and beverage business from a customer offered a lower room rate.

5.222 – Utilising heuristics

It was also found that general managers used heuristics to filter and reduce the volumes of data available. In the decision-making literature, heuristics can be summarised as 'rules of thumb' or in other words, a variety of methods used to allow the simplification of the decision-making process without unnecessary amounts of computation on the behalf of the decision-maker. The use of heuristics to simplify decision-making especially under the conditions of having high volumes, variety, and speed of data is already recognised in price decision-making literature (Liozu, 2013; Woodside, 2015, 2017), but what is interesting here is the specific way that heuristics are applied by general managers at the individual hotel level. The most extreme heuristic used by all general managers at some point was avoiding and ignoring data. During the work shadowing sessions, general managers were seen deleting emails from their inbox that contained revenue data, without even looking at them and they exhibited a tendency to rely on analysing one or two favourite reports. This appeared to occur due to a number of different

factors. The first one was that they felt the data was not relevant to their level of involvement in pricing, normally that it was too in-depth, or that they didn't have the expertise to understand it, and they felt someone else, in particular, centralised revenue support, would be more appropriate to look and understand that report than them. The final factor was that they felt the information was merely a duplication of data supplied elsewhere.

General managers focused on trends and rankings rather than analysing the fundamental quantitative data driving those trends and rankings. In simple terms, they ignored the raw numerical data behind the trends. Particularly where managers were tracking their performance against their competitor set they would tend to look at graphical representations of their performance or the trend of their rankings rather than the actual rate growth index figures or comparative rate, occupancy or RevPAR figures. This was described by many as "*sense-checking*", which meant a quick overview or scan of the data to get a sense of the overall picture of performance, although they often combined two or more different data sets together to gain a better overview. As a generalist, rather than a specialist the general manager seemed to view this as the limit of the analysis they needed to do and they relied on centralised revenue support where it was available to fill in the gaps in the analysis and to look at the detail. This was unless their interest in revenue management drew them to a deeper focus on the detail of the data. Where specialist revenue support was not available those gaps appeared to remain unfilled. The speed of overviewing the data in this way increased with time and familiarity. As the reports they focused on were often updated on a daily basis the general managers commented that it was never totally fresh data that they were looking at but merely changes in existing data sets which made it quicker to scan as they had some previous knowledge of the data.

5.223 – Benefitting from stability and success

The final sub-category is where general managers avoided information overload by chance through the stability of the market they operated in or the level of success of their business. Both independent and branded general managers felt that if the market in which they operated was stable then the level of data analysis required was less. This was further evidenced by the fact that even if they operated in unstable markets characterised by unpredictable demand they felt that

dealing with and understanding these fluctuations took more detailed analysis and monitoring of the data than in a stable market. This was because they were constantly required to understand what could be driving the changes, what impacts it was having, and how strategies might need to be adapted. In some more extreme cases avoiding information overload was a product of the hotel being successful and targets being achieved by the general manager which led to a laissez-faire attitude towards the data. They felt if everything was going well and budgets were being achieved, why would they need to do further analysis. To this end, a degree of complacency was revealed by some general managers in their attitudes towards data analysis.

5.224 Variations in the category of Avoiding Information Overload

What also emerged from the data was that general managers did not avoid information overload to the same degree, particularly in their use of heuristics in decision-making. This variance was found to be dependent once again on their revenue experience in the past and the level of revenue specialist support available. General managers with a revenue background appeared to embrace a wider range of complex data into their decision-making processes compared to general managers of a non-revenue background but this was still where they had revenue support available and a larger team to support them operationally. Where revenue specialist support was available, even if general managers did not have a revenue management background, exposure to discussions and the more detailed analysis of data undertaken by revenue specialists was made possible. However, without revenue support, even a general manager with revenue experience was still shown to be attempting to avoid information overload. In these smaller, independent, economy hotels, it was found to be time pressures and operational distractions that drove general managers to scan the data. Hence, where specialist revenue support was available scanning data seemed to be a choice, but in independent economy hotels, it was a necessity, due to the need for greater involvement in day to day operations.

To evidence this, a general manager for a branded hotel, with a non-revenue background discusses that they only look at two reports and leave any further analysis to the centralised revenue team to complete the analysis. This general manager went on to illustrate the notion of avoiding information overload through

ignoring certain data sources but also highlights that with time and experience filtering and sense-checking the useful data becomes easier.

"The others [reports] I don't really look at...we have analysts for that. I think just because I know what…kind of what I want to look for and what I want to know really through experience. I think if you want to know it, ok it's there…if you chose to use it or not…it's very easy to hit a delete button if it's not relevant to you or set up your emails to send it to an alternative folder or whatever so, I don't struggle with it [information overload] in that respect."

In contrast, another branded general manager with a revenue background clearly analyses a wider range of reports and uses the outcomes of this analysis to challenge the centralised revenue team to make certain actions based on this analysis. They are embracing a range of data rather than trying to reduce it.

"So, there are many reports, there is not really any one, key specific thing, you've just got to know how to use them and when to use them, which also comes back to my revenue days… so I might challenge my regional revenue manager to say actually, next month we've got a lot of business on the books so I need you yielding."

The increased use of heuristics in the cases of small, independent economy hotels was also seen to be a consequence of a simple lack of access to some data sources in independent hotels compared to branded hotels, for example small, independent hotels seemed to rely purely on data pulled from the property management system and online data provided by the online travel agents, such as Booking.com. General managers in branded hotels had access to generally more complex reports driven by the automated collection of data through systems, such as automated revenue systems through their specialist revenue support teams, Smith Travel Global competitor and market reports and group or cluster performance data. This is evidenced by the general manager of an independent economy hotel who is heavily operationally involved and only looks at what they perceive as a basic level of data in their revenue analysis, sourced from online travel agents.

"I'm basically just purely looking at what other hotels are selling at."

This means in terms of data, this general manager views competitor selling prices as relevant but straightforward. Finally, an independent general manager with no revenue support suggests that their avoidance of information overload comes from a personal feeling that for their size of property pricing strategies could be kept simple and that this reduces the need for analysing all the data. The simplification comes from a feeling that mistakes can be made but that the margins of error in their property are smaller than for others.

"My business isn't that complex that I could get it that wrong, for example, if I was running a hotel in the centre of London and I price rooms at £200 when in fact I could be getting £400 a room for them because you know it's the Changing of the Guard or whatever else…if I've got 300 rooms and I've priced them all wrong by £200 that's a massive, massive error. I've not got that. I've got 38 rooms and they generally go between £65 and £79 during the week...I can't get it that wrong".

5.23 Thinking Local

This category focuses on the finding that the general manager's perspective on pricing is driven by their observation, interpretation, and knowledge of their hotel, customers, competitors and local market. They were found to gather local data through their daily presence in the business and direct contact with the customers and market they operate in. Local data is data that develops within the boundaries of the hotel property and local geographical market or competitor set. When they think about pricing they think primarily from a local standpoint and will attempt to inject that local focus on the price decision-making process. All general managers were found to believe in the power and relevance of local data as already touched upon. They built up intuition through their local knowledge. Three sub-categories help to explain this further. These are "networking for knowledge", "loving the guest" and "anticipating the market". The first one examines the collection of local data and the second two are more related to the local data the general manager chose to focus on.

5.231 – Networking for knowledge

This sub-category examines the findings around the degree to which general managers used local market networks to gather data on their competitors.

Interestingly it was found that general managers distrusted their local competitor networks and did not find them a source of accurate information. Although they still took part in activities such as local general managers' meetings, tourist board organised discussions and even informal chats with neighbouring general managers', they remained sceptical over the value of any insights they obtained through these channels. A lack of honesty and a concern over the sharing of deliberately false data concerned them, caused by people not wanting to admit they were struggling or not wanting to reveal their strategy. This encouraged the general manager to look inwards at internal data. To gain competitor rate and occupancy information they relied on a mixture of monitoring competitor prices through online sources, such as price comparison sites or online travel agents or the aggregated, competitor set data provided by external companies such as STR Global. However, the general managers still expressed a realisation that although this data gave them insights into competitor occupancy, rates, and market share performance, the strategies their competitors employed to achieve those results still remained hidden.

5.232 – Loving the guest

However, where general managers did believe in utilising networks was found to be around the gathering of information and feedback from guests. Their focus was very much about gathering guest intel through networking with the guest and getting to know them or by obtaining data second-hand from the operational team that interfaces with the guest in the restaurant or on check-in. They recognised the wider impacts revenue decisions have on guests in terms of the messages that are sent to potential customers through their pricing strategies and how these may impact upon their expectations being met when the guest arrives at the hotel and sees the room they have paid for. General managers were found to be extremely conscious of the price, value and quality balance. One budget general manager of a hotel near a major concert arena explained that when they were told by central revenue support to sell hotel rooms at five hundred pounds per night when demand was extremely high due to a major concert they avoided doing so as they got negative feedback with guests commenting that they felt exploited by having to pay so much for what was, in essence, a budget product. Another general manager used their knowledge of the local market to protect the longer-term

image of their hotel by keeping rates artificially high during the weekends to dissuade a certain crowd of customers using the hotel on Friday and Saturday nights as what the general manager described as a “drugs den”.

5.233 – Anticipating the market

General managers were found to face challenges in anticipating the movements of the local markets. The degree of stability of the local market they operated in also influenced how easy the general manager found it to actually interpret and rely on the local information they collected in the price decision-making process. One general manager commented during the shadowing sessions that sometimes the city is just really busy and that they just do not know why no matter how much research and analysis of the data they did. So, there were often gaps in their understanding of market dynamics and if the market was unstable they found it hard to predict what would happen next. In terms of market dynamics, general managers were also found to focus on demand factors rather than supply. Where they did focus on supply factors it was very informal and short-term, for example through their sales staff comments they might get to know of a large conference that a competitor had won and so knew that competitor would be full on a particular weekend. The longer-term impacts of supply, such as new hotels opening up in the area, were less well considered. No general managers were seen to be scanning the pipeline reports for their areas provided by external companies such as STR Global. One general manager was heard to comment that there was nothing they could do about a new hotel opening up in eight months’ time and therefore they did not account for it in their revenue decision-making.

5.234 – Variations in the category of Thinking Local

There was less variation found in this category, as all the general managers stressed the importance of local knowledge and gathering intelligence through localised market, competitor and customer data, although the main focus was on customer data. This viewpoint seemed mainly to defy the distinctions between general manager background, hotel ownership or the size of the property. Below, a branded general manager responds to the question of what information they contribute to the revenue decision, displaying both a concern for the local market

and also guest knowledge and customer reactions to the strength of the brand and location as discussed in the sub-categories.

"I guess first and foremost is understanding your position in the market, so understanding your brand and the perceived value of your brand…leverage points…so where you can leverage on brand loyalty and your location comparative to other hotels and comparative to either the business district or the leisure district."

In a similar way, a general manager from an independent, budget hotel displays the intricacies of the local knowledge and data collected and the many local factors they consider when setting prices but also displays the issue of hidden knowledge and concealment of strategies by competitor hotels.

"As much as you can't get any information out of another hotel you can tell what's going on in the city. I mean we don't get too much out the local concert stadium because there's a hotel right next door but for example we might get somebody coming to visit family at university who'll come maybe two or three days...can park the car up and go do...um...I've put a thing out for the Yorkshire Show...a five-minute walk down to the train station and that's the Harrogate line so…"

Where specialist revenue support was available it just meant that the general manager would share and discuss this local knowledge with them. Even in the branded budget chain where the general manager was not involved in pricing, they still gathered local data that through their area manager they attempted to feed into the central revenue team, although they were not always successful and the process took time. The value that revenue specialists also hold for the local knowledge held by general managers is expressed in their comments below.

"GMs are key for providing local market intel. As we are remote based, we need the GMs to advise us on local activity that will impact decisions we make in regards to pricing".

"The GM is in the hotel on a daily basis, they get to know guests and different companies that I may not know go to the hotel".

Another two central revenue managers respond to the question of what data general managers contribute to the revenue decision, the second highlights the issue of the price and quality balance and general manager insights into it.

"Local market/city knowledge; information gathered by speaking to in-house guests; knowledge about the history of the hotel: change of impact for events; different trends".

"Mostly quality information. Sometimes, although the dates are looking optimistic, there may be an issue with quality if we priced ourselves too high".

However, some inequalities were found in access to competitor data, especially competitor set data provided by STR Global, as several smaller, independent hotels did not have access to this data and instead relied on the historic performance data provided by the online travel agents and price comparison sites for their competitor data collection, and these provided them with a less complete set of competitor data. Larger independent hotels, those independent hotels linked to a marketing consortium and branded hotels all had access to STR Global data. Branded hotels that were clustered geographically also benefitted from competitor data generated through their internal cluster or group network.

5.24 Balancing defence and attack

This category explores the finding in the research data that showed a tendency for price decision-making to be characterised by a constant balancing act between defence and attack in the market, as characterised by some of the language used by participants, as exemplified below. This was shown to impact upon how data is used in the price decision-making process. Defence was shown to be where rate growth was restricted to protect occupancy levels. Attack was when there was more bravery around rate growth and increases in prices were made, but the impact on occupancy was still monitored through the use of data. Initially general managers were heard to make comments about their desire to "***beat the market***" or wanting to "***win in the market***" but after lengthier discussions it became apparent that there was often a sense of only being able to push so far in terms of rate growth before occupancy was affected by reductions in customer demand and that there was, as already mentioned, a degree of trial and error in finding that

tipping point. Based on this, the category is divided into three sub-categories of “short-term data focus”, “watching your back” and “finding the limit”. These link to the overall category of balancing defence and attack in the following ways. The focus on short-term relates to general managers' emphasis on winning the battle not the war, thinking short-term not long-term in terms of their data analysis. “Watching your back” relates to the general managers feeling personally defensive as their overall responsibility is to ensure the success of their hotel, and finally “finding the limit” represents the continuing challenge of deciding whether to defend or attack when taking into account the balance of rate and occupancy.

5.241 – Short-term data focus

The first sub-category relates to the finding that due to the balancing act between defence and attack, constant, often short-term adjustments were made to the balance between rate and occupancy. This was found to influence the data that general managers chose to focus on and their decisions about what to analyse further or discuss with their specialist revenue support team if present. They were constantly scanning for the impacts of these rate and occupancy adjustments on top line ranking and trends, and this appeared to limit their focus on searching the data for what could be termed “red flags”. These red flags can be described as data that highlighted signs of danger or problems in the market either that have already occurred or that are likely to occur in the short term. It was rare to see a general manager using the data to analyse periods of time where revenue strategies had proved to be successful in order to help them understand why and replicate them for the future. Wherever they saw a missed opportunity, a gap that needed to be filled in terms of rate or occupancy on a certain day or an error in pricing they would either look at this more closely or demand someone else within the centralised revenue team do so. However, where they had days of full occupancy or rate growth these were skipped over. The timeframes of revenue data analysis within the hotel, unless annual historical comparisons were being made, were typically based on no more than the following day, week or month.

5.242 – Watching your back

If general managers were found to favour a more defensive position in their approach to price decision-making this appeared to be due to their desire to protect their individual position and employment and in these cases they often

used data as evidence to present to their line managers or owners to support a case for why they had made the decisions they had. The data was used as proof that the price decisions had been sensibly thought through, perhaps in some instances to avoid blame or criticism. It was clear that general managers of individual hotel properties felt overall responsibility for the success of their hotels, which they viewed as their business. They often had individual targets related directly to this success. One general manager summed this up nicely by saying that the *"**buck stops with me**".* This led on to a sense that their personal success was linked to the success of their hotel because they were in charge and this caused them to manage risk closely and focus on data that would give them a picture of that risk and support their decisions.

5.243 – Finding the limit

As already mentioned, a key element of price decision-making was found to be about carefully pushing the limits of what can be achieved through rate maximisation before occupancy is negatively affected. This was found to distil the data that was used in price decision-making down into those that gave insight into the two metrics of rate and occupancy at the individual hotel property level. Consequently, data once again appeared to become a tool for monitoring the impact of small, incremental changes to rate on both occupancy and on the hotel's position relative to its competitors. It became focused on past decisions. Although some revenue forecast data was used, particularly in unstable or unpredictable markets, that characterised many of the markets these general managers operated in, it was of limited use. Market changes were hard to predict and therefore the strategies of competitors and competitive reactions to their changes in strategy could never be fully known or predicted. Therefore the general managers expressed that finding the limit between rate and occupancy was an on-going challenge and could never be totally perfected.

5.244 – Variations in the category of Balancing Defence and Attack

The conditions of general manager background, hotel size, and hotel ownership appeared to impact little on these sub-categories as they all seemed to be expressing the constant trial and error balance between rate and occupancy. Several general managers from both independent and branded hotels, large and

small, with and without revenue experience express, as seen below, express the same opinions.

"You know, it's the challenge of the pricing stuff, just being a bit braver sometimes - it's hard. I mean this year for us is just being a bit braver and trying to push the rate and it doesn't necessarily come off all the time but at least we've tried it".

"It's not until we try and start pushing rates by market segment that you start to see resistance or results".

"We look at it daily [STR Global competitor set data] to see what have we missed out on…maybe we've under-priced...if we've not got our fair share on the rate side of things...or maybe we've missed out on a trick somewhere if its occupancy, so we'd have to be looking at those things".

"For Tuesdays for the next eight weeks I'm going to put five pounds on our rate and I'm just going to see what happens and that might not sound extreme changes but it stops the tap [turns off demand]."

However, any desire to push for rate growth rather than to manage risk and take a more defensive position was seen to be made more likely if centralised revenue specialist support was involved in the price decision-making process. General managers expressed the opinion that specialist revenue support was often driven by an agenda to drive revenue through increasing rate. However, this was mediated by the type of general manager and how prepared they were to counter the opinion of the revenue specialist with evidence concerning local product quality issues and customer reactions. This is clearly evidenced by the following general manager discussing his and other colleagues' relationships within the brand with their central revenue specialists.

"We get along quite well because in the beginning it's because as I said he's looking after revenue and making more money but then when he starts understanding that you are the GM and you are looking for quality as well and there must be a balance between both, when he starts knowing ok, this guy he wants this or he wants that. Maybe he's got some GMs...I wouldn't say who don't care about quality but doesn't give the importance that I give

to quality...so I'm sure that in that case he will go ok we can push that rate and the GM will go ok push".

5.25 Decision Negotiation

This category only applies to the findings where a general manager had access to specialist revenue support of some type and therefore the price decision-making process became a negotiation between two people. This means that the revenue specialist and the general managers were found to have discussions which were aimed at making an agreement on the revenue decision. Both have influence over the decision but with the general manager bringing the local knowledge and insights to a more scientific, analytical approach from the revenue specialist. Both the general manager and the revenue manager bring different knowledge to the table when making revenue decisions and have been seen to use data in varying ways. Therefore, there was found to be a degree of asymmetry in the relationship that exists between the general manager and the revenue manager. Here asymmetry does not relate directly to inequality in the relationship between the revenue specialist and the general manager, but rather to the fact that their functions in the price decision-making process are different. In other words, they have different roles to play. These dynamics will be further explored through the sub-categories of "connecting" and "relationship building."

5.251 - Connecting

This sub-category focuses on the way general managers and revenue specialists were found to connect through communication and what influences the way they communicated. It was found that the purpose of the communications between the general manager and the revenue specialists was to exchange different forms of data. Through their communications, the aim was to convert these different types of data into increased knowledge for both parties and ultimately turn that knowledge into the basis for making a decision. In this way, the general manager and the revenue manager interact with each other to share the data that represents their particular viewpoints and insights. The general manager felt the revenue specialist brought their scientific viewpoint and statistical analysis of the data, whereas they themselves contributed more informally gathered insights into local market dynamics, competitor actions and customer feedback. The differences in perspectives of the general manager and the revenue specialist

were found to be fuelled by inequalities in data access. Revenue specialists were shown to have full access to a wider range of data sources and the full capacities of any automated revenue systems that were available, whereas the general manager only had limited access to systems and partial views of data, for example, one general manager commented that they could see their rankings against their competitor set provided by STR Global but that only their revenue manager had full access to the complete competitor set report on a daily, weekly and monthly basis.

Interestingly, the communications that facilitated the sharing of these different types' data and knowledge were not haphazard or irregular in their timing but followed a carefully planned routine and structure, whether they occurred face-to-face, over the phone or via email. This was reflected through observations made during the shadowing sessions where calls to revenue support were made on a daily or monthly basis at a set time each day. These calls had a set agenda which was followed. These routines did appear to be driven by the revenue specialist. It seemed that only if something unusual was occurring or if there was a problem that needed discussion or further investigation would communication would occur outside of these set times. There was a focus on regular and frequent communication, at a minimum daily, to keep pace with the fact that rates change at least daily, and the impacts of changes to the rate and occupancy balances could often be seen immediately.

5.252 – Relationship Building

From the research data, it was clear that at the heart of successful communication and the data exchanges mentioned above was the development of a positive relationship between the revenue specialist and the general manager, whether that revenue specialist is based centrally or inside the hotel. Perhaps not surprisingly these relationships were seen to take time to develop as they were expressed as being grounded on a personal level of understanding between two people. This was not expressed as a friendship but as a professional, working relationship. Although the general manager and the revenue specialist held different spheres of influence based on access to different data, the relationship was found to be most successful when through communication these spheres of influence could overlap to strengthen the revenue decisions made. The key

element required for building a strong relationship was the development of trust on both sides and this was often based on honesty and the willingness to share data openly on request and to explain clearly their different viewpoints. Data was used as supporting evidence and explanation of the advice offered by each person in the relationship.

5.253 – Variations in the category of Decision Negotiation

The major variation in this category is of course whether a general manager has access to specialist revenue support in the first place. Where a general manager was in a small, independent economy hotel with no revenue support available they were solely responsible for making an autonomous revenue decision. At the other end of the spectrum was the case of the branded economy chain where all revenue decisions were made by the centralised revenue team and the general manager was not involved. Again, there was found here to be limited negotiation in the process of making revenue decisions. According to the general manager of this hotel, this was due to a large number of hotels in the brand network and the specialist revenue support at the central office could not cope with individual communications from a large number of general managers. Therefore the revenue strategy was set for the group and not for individual hotels.

However, where revenue specialist support did exist it was found that whether the specialist revenue support came from a centralised team, was an off-site revenue manager working from home or an on-property revenue manager did not influence the way the general manager and revenue specialist communicated, built their relationships and ultimately made decisions. The same discussions were had but they were just conducted face to face if on-site rather than via telephone or email for centralized support with perhaps one to two face-to-face visits to the property per year. Although occasionally another variation occurred when automated revenue systems were added to the price decision-making process and the human decision-makers.

This was found to be the case only for branded hotels, where the system was developed for the brand. However, the automated revenue systems were only used as a guide by both revenue specialists and general managers. On one revenue call witnessed during the shadowing sessions both the general manager

and revenue specialist discussed how they "*didn't like*" the system. The research data appeared to suggest that these opinions were based on a belief that the systems could not be infallible because they were designed by humans and the data they used was often inputted by humans and humans are fallible. General managers also felt they weren't capable of reacting to local dynamics, in particular, guest insights, for instance, one general manager described talking to a guest one evening who explained that they paid for their Christmas with their brand loyalty club points. The guest said that they could stay somewhere cheaper and they didn't mind paying a higher rate to stay at a hotel where they could earn loyalty points. This encouraged the general manager to suggest pricing above the price the automated system was charging by over fifty pounds per night midweek.

The final variation is that the research data did occasionally show some discrepancies over whether after exchanging data and discussing the different options it was the revenue specialist or the general manager who made the final price decision, for instance on one occasion the revenue specialist categorically said that they made the final decision whereas the corresponding general manager also felt they did. However, this was an anomaly and perhaps due to that particular general manager having a strong revenue background and having previously held the revenue specialist's job. In the majority of cases, it was found that the decision was reached via compromise and the merging of two different pathways of knowledge and data into one outcome. The general managers provided the final checks and balance and sign-off to the decision suggested by the revenue manager and borne out of a discussion between them. Using local knowledge, data and insights the general manager interpreted the data and knowledge of the revenue manager to ensure they agreed with it. The following quotations from revenue specialists highlight the typical negotiations and discussions that happen with general managers to reach a decision and highlight the usual reaching of a compromise through joint understanding.

"I am quite sensitive when it comes to the rates that I have set but if a general manager has a different way they want to go we will talk through it and find the best solution".

"Communication, trust, transparency; making sure you discuss before taking a decision; you involve your general manager in the decision process and get their approval - show them facts/have data to back up your arguments".

The same opinions were expressed by a number of general managers with varying types of revenue specialist support and different ownership structures, evidencing that where the specialist revenue support comes from does not impact on the relationship and the joint decision-making process. Firstly, a general manager of an independent hotel, who works with the revenue specialist hired through their marketing consortia talks about working together to achieve a shared goal.

"So, trust is probably one of the paramount things. It's like trust again...it's that working relationship that we know ultimately what we both want to achieve which ultimately is achieving budget".

Here the general manager works for a branded hotel but with specialist revenue support employed by the management contractor expresses their viewpoint.

"I've got 100% confidence in my revenue manager. That is probably because I've worked with her before, but I know the data that she is getting is the same data that I'm getting. She has other reports to look at but then she needs these. I don't get visibility of the automated revenue system but I don't need to because she gets that. Yeah, total confidence to be honest".

Here the general manager is from a branded hotel but with revenue support from the brand's corporate office.

"It's keep it alive…you know…I mean our revenue agent that looks after us I speak to on a daily basis and I pick up the phone to her and it's about making the relationship comfortable…you know the reality is I'm the most experienced person in the property. It's about making sure we can both work together to get the best results and we do that so it's a good relationship".

The last one comes from a general manager whose revenue manager is on-site. This shows that there is little difference in the relationships between on and off-site revenue managers and their corresponding general managers.

"We both meet in the middle…I think if you were continually challenging the revenue director on their pricing and what they're doing...a distrust would soon appear".

Of course, due to the twenty-four-hour nature of the hotel industry, the office hours typically worked by revenue specialists and the tendency of general managers to be working outside office hours, there were occasions when, even where revenue specialists were normally there to support the revenue decision, general managers were the only ones available to make the decision. Therefore, sometimes who made the final revenue decision was time dependent. If the revenue specialists were not available out of office hours the general manager would often make an autonomous revenue decision, because they felt that if they waited, opportunities to adjust the rate and occupancy balance to improve performance might be lost, due to the ever-changing demand pattern of their market. To support this, technological advances were shown to allow general managers to access pricing and revenue systems via their mobile devices. This allowed for the constant updating of rates again outside of the context of any discussions with revenue specialists or even supporting operational teams at the hotel. Some general managers commented on their ability to change rates when at home on the sofa or even on holiday.

"You know we've both [the general manager and deputy general manager] had our system [property management system] put onto our I-pads so we can sit home at night and check rates and things like that"

5.3 The hybridisation of transient hotel pricing – the findings of the grounded theory

The core category and key finding that emerged from the data was termed the hybridisation of transient hotel pricing. It was felt that due to the complexities of the hybridisation the core category represented where a black box existed. Due to the identification of variations in each of the main theoretical categories, it was possible to explain how and why the hybridisation of transient hotel pricing

occurred and under what conditions it might not occur. The key conditions identified as impacting upon the existence of a hybridisation of transient hotel pricing were the size of the hotel, the hotel ownership structure the individual hotel operated and the general manager's background and level of revenue management experience. Just as the findings surrounding the five main categories and their sub-categories have been described in detail, so the core category will also be delineated and the variations identified. Figure 4.2 serves as a reminder of the five main categories and how the relationships between them were considered to develop a core category.

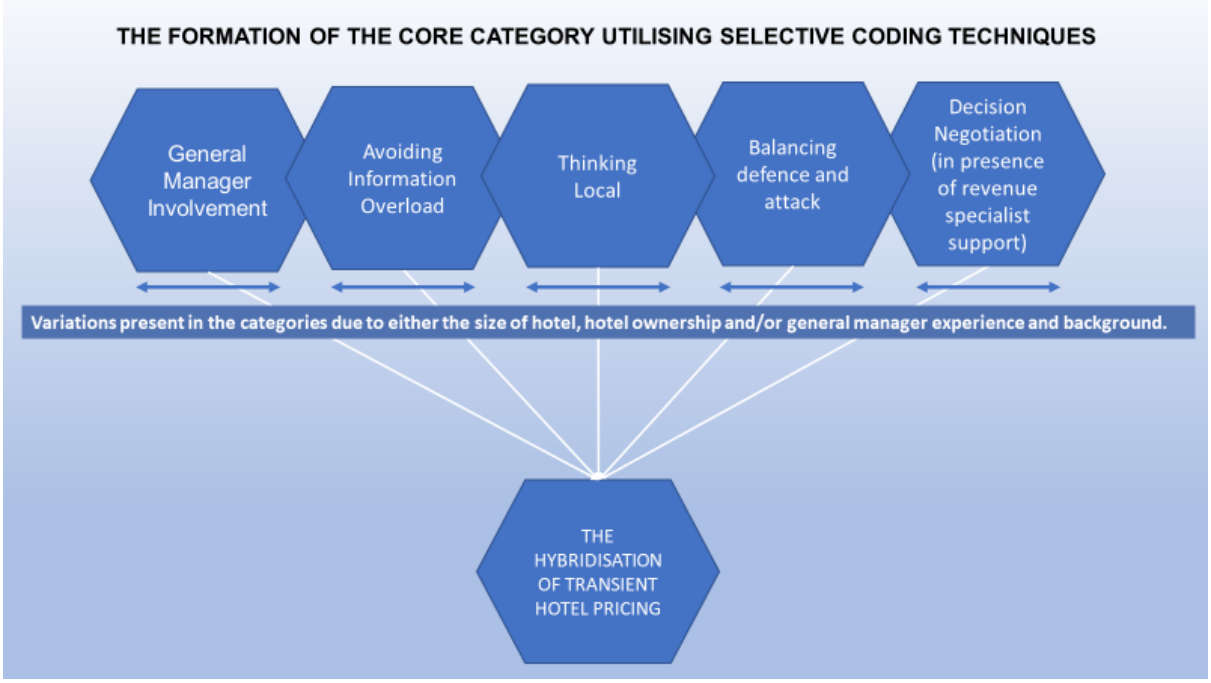


Figure 5.2: The Emergence of the Core Category

Hybridisation in this research is considered to represent the combining of complementary elements in a joint price decision-making process between revenue specialists and general managers. The details of the findings surrounding the core category are shown graphically in figure 4.3. The hybridisation of transient hotel pricing occurs when revenue specialists, the people whose roles and expertise focus on revenue management, merge their thinking with the general managers of individual hotel properties. In essence, they transfer their knowledge between each other in a mutually beneficial way because they are able

to share knowledge that each did not hold before they amalgamated their decision-making processes. This is because both the revenue specialist and the general manager build their knowledge base from different data inputs. The revenue specialist uses macro big data and the general manager uses micro local data. Both types of data are also obtained in a different way. Macro big data is automatically harvested and stored for future use via revenue reporting systems and can be drawn upon by revenue specialists on demand for scientific based analysis based on complex algorithms. Micro local data takes time to develop, therefore is described as cumulative. Big data may arrive without a pre-defined purpose whereas the collection of local data is more focused, and the general manager filters out from the big data what is not important to the priorities of the individual hotel property. The general managers actively build-up the local data over time through networking with customers, observing the operational and commercial workings of their hotel and making constant discoveries of small hints and clues that are collected to inform and humanise the price decision-making process and give customer insights. Through data exchange and knowledge transfer the data that the revenue manager and the general manager each bring is refined to arrive at a price decision that takes into account the balance of rate and occupancy. When this reaches the market, customers and competitors react to the price decisions made, and further data is generated and fed back. Macro big data is harvested from the market responses and fed back to the revenue specialist and the local data insights are gathered by the general manager and so the cycle continues.

At the extremes are where the general manager has no specialist support and makes all the revenue decisions themselves. The opposite case is where all decisions are made by the revenue specialist with no or limited contribution from the general manager. Here no hybridisation occurred, price decision-making appeared more simplistic and there was no black box requiring further deconstruction. There was autonomy of decision-making but also a lack of data exchange and knowledge transfer which resulted in each case on a reliance on only one type of data. In the case of the general manager with no revenue support they relied nearly total on the local data, with some input from competitor data gathered from the online travel agents and therefore the decision-making was

heavily behaviourally driven. Where the revenue specialist did not call on the general manager for local insights the decision was made predominately in a scientific manner using macro big data. The feedback loop was still present but only the type of data used to make the original decision was fed back as that was the only data they had access to. Hybridisation is found to merge complementary data sets and perspectives together in the price decision-making process. The findings of the grounded theory are presented graphically in figure 4.3 providing a visualisation of the research data. Symbols are used as an effective way of summarising the qualitative data and delineation of the theoretical categories.

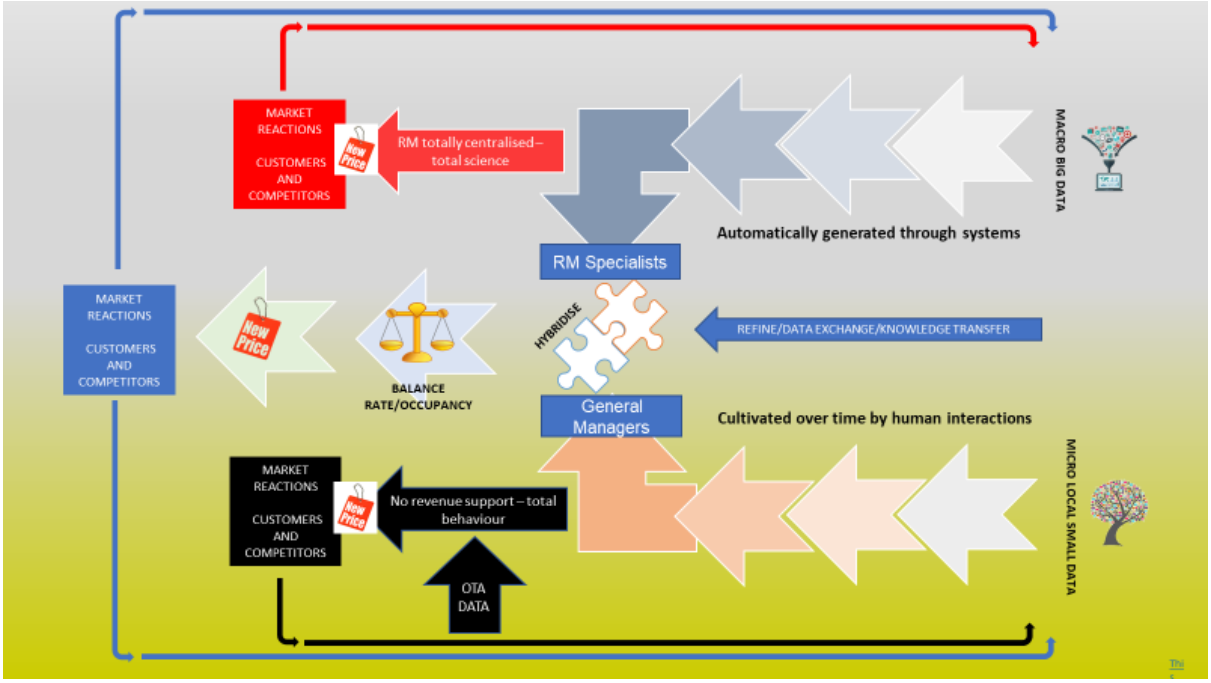


Figure 5.3: Graphical Representation - Results of the Grounded Theory and Core Category

To summarise, the key elements of the hybridisation are as follows:

- The protagonists that conduct the hybridisation are the revenue specialist and the general manager. The revenue specialist may work internally or externally to the hotel property, but this has limited effect on the way the hybridisation occurs.
- In this context there is a data asymmetry present in the relationship between the revenue specialist and the general manager, in terms of both the volume and the depth of explanatory power of the data. The revenue

specialist brings the macro big data element (high volume, low depth of explanatory power and the general manager brings the micro, local, small data element (low volume, high depth of explanatory power to the hybridisation).

- Small data and big data are sourced in different ways. Big data comes from different sources outside the immediate operational function of the hotel at property level. It arrives automatically through various systems harvesting data from other digital sources and is stored digitally in revenue systems. Automated revenue systems store the data and can analyse it, but revenue specialists may also still interpret the systems resulting in them sometimes being used just as a guide. Small data is more organically cultivated and gathered by human managers rather than digital systems. This occurs through observation and talking to people within the hotel property and is always interpreted by humans not systems. It is often discovered by chance.
- Through the hybridisation both big data and small data are combined and transformed into more comprehensive information and knowledge through exchanges between revenue specialists and general managers. The more focused small data may serve to add richness and thereby refine the generic messages provided by the big data.
- Data is interpreted in different ways by different people taking different viewpoints. The revenue specialist is using focused thinking using big data whereas the general manager is using wider thinking using small data. Big data focuses on broad trends rather than the specifics of customers and local factors.
- The outcome of the hybridisation is to set a price that balances the revenue metrics of occupancy and rate to maximise RevPAR and deliver performance that meets or exceeds budgets, with further monitoring of customer and market reactions to these price decisions being fed-back into the hybridisation process in a cyclical manner.

5.4 Chapter Summary

This chapter has presented the findings of the research in terms of the five main categories that emerged from the research data based on the grounded theory methodology. Findings were presented centred on the five main theoretical categories of general manager involvement, avoiding information overload, thinking local, balancing defence and attack and finally, decision negotiation. The key findings are that the general manager remains important in the price decision-making process and that this means pricing tactics and strategies are often made and developed through a lens of local hotel and market knowledge and data. However, where there is specialist revenue support available the relationship and communication between the general manager and the revenue manager is vital, as the decision-making process then becomes a negotiation between two parties and data is exchanged to help develop knowledge on both sides. This has been termed the hybridisation of price decision-making. This hybridisation is driven by the general manager through their perception that locally gathered data needs to be used to strengthen the value of macro big data in the price decision-making process. The suggestion is that big data cannot operate alone or without human guidance and that price decision-making may benefit from a balanced perspective utilising different data sources. Figure 4.3 above further demonstrates that where the price is set autonomously only one type of data is included in the decision-making process and this balance no longer exists. This occurs both where the general manager is solely responsible for the price decisions and where the pricing process is entirely centralised, and the hotel at property level has limited or no input in that decision. Therefore, the findings have illustrated clearly what is meant by the hybridisation of pricing and the specific conditions under which it might occur. How the black box surrounding the hybridisation of transient hotel pricing can be further deconstructed and developed into a substantive theoretical framework is the subject of the next chapter.

6. Discussion

6.1 Introduction

The preceding chapter presented the key findings of the research as a series of categories and identified a core category in line with the Straussian grounded theory approach chosen for this research. The core category identified that under certain conditions the transient price decision-making process at the individual hotel property level became a hybridisation of different types of big and small data brought together by revenue specialists and general managers. This chapter will extend these discussions. The first part will further analyse the findings within the core category in order to complete the deconstruction of the black box by fully detailing all the facets of the hybridisation to develop a substantive, explanatory theoretical framework. This is in line with the methodological approach for this study, as Straussian grounded theory encourages reflection on the main categories and the core category that have emerged from the data collection and analysis, using the coding paradigm to develop theoretical frameworks with a focus on incorporating an analysis of structure and process (Strauss, 1987; Strauss & Corbin, 1998). This ensures that the substantive theoretical framework answers the questions of both how and why things occur. The second part of the chapter discusses the research findings in the context of the existing literature. It highlights and reflects upon how the research has answered the questions posed by this literature. However, before commencing these more detailed discussions it is worth pausing to summarise the findings of the research based on the five key categories that emerged from the data collection and analysis as well as reflecting on the key elements of the core category and the conditions under which it exists.

The five key findings are summarised below;

1. The general manager remains critically important to the process of transient price decision-making, although the degree of involvement is dependent on the quality level of the hotel which impacts on the degree of involvement of specialist revenue support and the career background and level of revenue experience of the general manager.

2. The information overload that may exist because of big data is avoided at the individual hotel property level due to the deliberate attempts of the

general manager to filter out what they consider to be unimportant data, reducing data volumes, whilst leaving revenue specialists, where they exist, to manage the incoming flow of big data.

3. The general manager perceives their contribution to the transient price decision to lie in their ability to gather and store local market data with a focus on demand factors led by customer insights, defined as small data. Where revenue specialists exist, they also agree that this is the strength of the general manager's contribution to the price decision-making process.

4. Despite the amount of big data available to aid revenue management decision-making, there is still typically a simplified focus only on average room rate and occupancy percentage metrics extending only as far as RevPAR. Revenue management is reduced to a balance between rate and occupancy, responding to market conditions, which results in either bravery around rate growth or defence of occupancy levels.

5. Where there is a presence of specialist revenue support, either on-property or from a centralised team, the general manager and revenue specialist form a special, co-dependent relationship and decisions are made based on each of their individual data sets and approaches, blending local insights and small data on the one hand with broader revenue trends from big data on the other. This has been termed in this research as the hybridisation of transient hotel pricing.

The hybridisation of transient hotel pricing essentially refers to the blending of macro big data and micro local, small data in the transient hotel price decision-making process where there is the presence of a revenue specialist to work with the general manager of an individual hotel property, as represented in figure 5.1 below. This chapter will further analyse the processes taking place within this hybridisation.

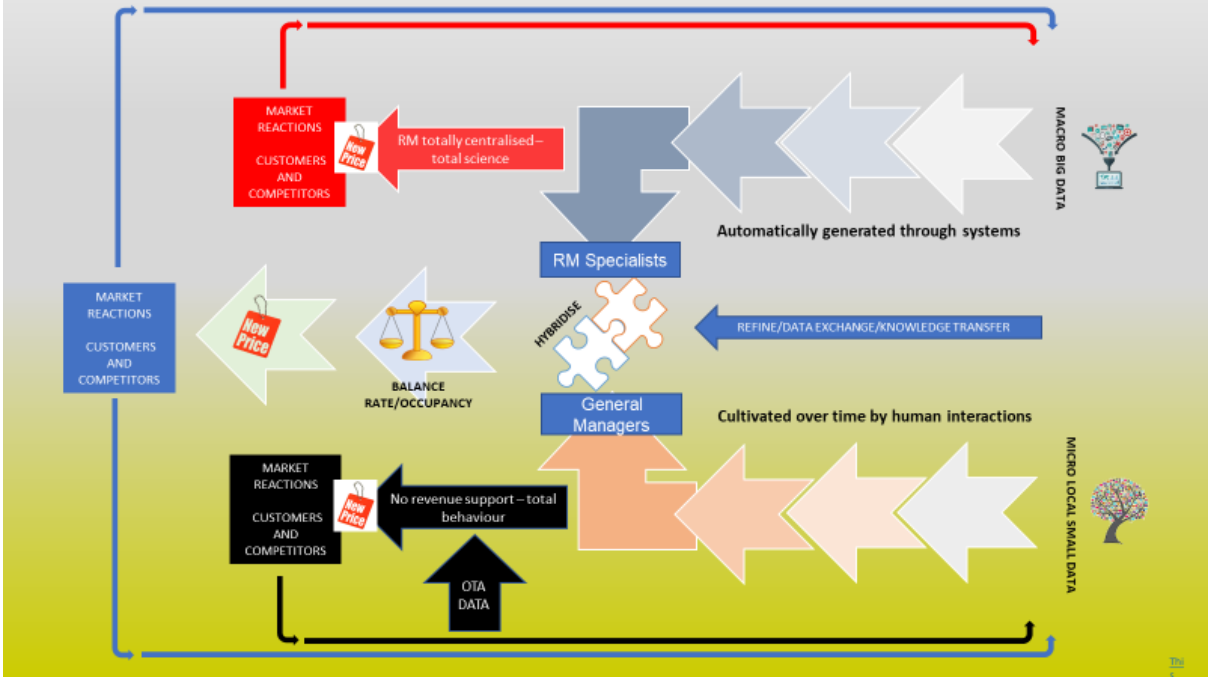


Figure 6.1: The Occurrence of the Hybridisation of Transient Hotel Pricing Data

However, it is important to recognise that the hybridisation does not occur where the price decision is made under one of either two different conditions, although both of which are related to the role definitions of revenue specialists or their availability to hotel properties. Where there is no specialist revenue support available the decision is made autonomously by the general manager, using only the local small data and some input from data gathered from the online travel agents. Under these conditions, a hybridisation process does not occur. At the other extreme the revenue specialist has complete control over the pricing decision due to the centralised control of revenue management decision-making within the organisational structure. Here the general manager has practically no input, so again no hybridisation occurs. Where no specialist revenue support was available the hotel was an independent and where there was total control by the revenue specialist it was a chain hotel. At first sight, this may indicate some differences in price decision-making between independent and chain hotels. However, this research suggested that it was more likely to be the standard of the hotel rather than its ownership structure that resulted in the lack of hybridisation, despite the literature review reflecting on potential differences between the practice of revenue management across independent and chain hotels (Luciani, 1999; Enz et al., 2015). Literature in this area was however not found to be

widespread. The key to this was that specialist revenue support was found to exist in both independent hotels and chain hotels and therefore the hybridisation occurred across both ownership structures. The only difference was in the origins of that revenue specialist support. For chain hotels, the revenue specialists would be employed within the organisation but for independents, the support was more likely to come from third-party providers or from the marketing consortia the hotels belonged to. At the luxury end of the independent hotel market, the larger properties in the study had revenue managers working within the property. Therefore, the only commonality found between the two hotels where the hybridisation did not occur was the standard of the hotel, and in this case, both were economy hotels.

Interestingly though, the reasons that caused hybridisation not to occur in the independent economy hotel and the chain economy hotel were different in each case. In the independent economy hotel, it was due to lack of specialised revenue support, but for economy chain hotels it was the presence of revenue support and its central control. The outcome, however, is the same in both cases. The transient price decision is made without a complete set of data and there is a sole reliance on either macro big data in the case of economy chain hotels or micro small data for economy independent hotels and we see that less data is interpreted prior to price decisions being made. Essentially, where a hybridisation did not occur the transient price decision-making processes contained fewer complexities and therefore the black box was considered to be opaque, although this could also be attributed to the simpler nature of the room inventory of economy hotels where less data on additional revenue streams and room types are required, although this was not further investigated by this research. Whatever the cause, it was felt to be more important to focus the construction of the substantive theoretical framework around the hybridisation where there were more complexities and a solid black box existed.

6.2 The development of the substantive theoretical framework

In order to fully deconstruct the complexities of this black box, a substantive theoretical framework needed development, and this is the focus of this section. It is important to highlight the key elements of the framework found in figure 5.1 and make clear how they relate to the coding paradigm taken from Straussian

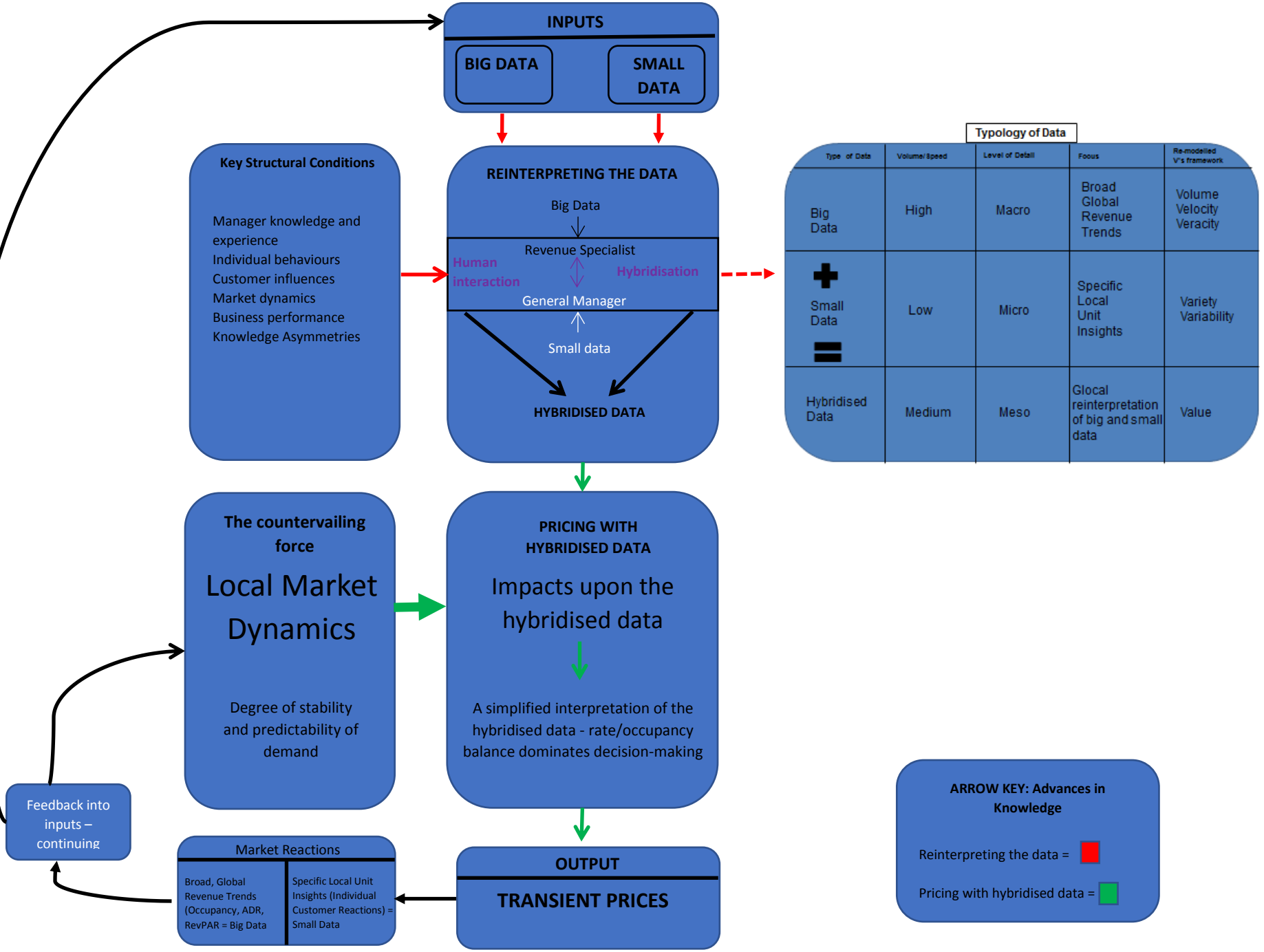
grounded theory and how they are utilised in this research to complete the analysis of the core category. This will demonstrate how the framework is grounded in the research data. The substantive theoretical framework identifies two key processes that exist within the core category and which are influenced by a variety of structural conditions covering how and why things occur. In this way, the framework deconstructs the black box surrounding the use of data in transient hotel price decision-making as identified through the examination of the literature in chapter two. The aim of this section is to describe the key processes and their corresponding structural conditions and forces. It is worth noting briefly here, in order to place the framework in its wider context, that the framework advances knowledge in two main ways. Firstly, it has allowed for the reinterpretation of the definitions of different types of data within a hotel price decision-making context. A new type of data has been identified and is presented within a new typology of pricing data based on the process of how managers and specialists interact with each other and with the data. Secondly, it provides fresh insights into the use of this new form of data in practice at the point where the transient hotel room price decision is actually made. This research has not just allowed insights into what occurs inside the black box, but also concluded by adding to the knowledge around the inputs into the transient room price decision both in terms of the types of data used and the outputs of the decision, and in terms of the countervailing forces that influence the setting of that final transient price point. These key processes and structural conditions will now be outlined.

The first key process in the framework is the reinterpretation of data. The inputs into this process are big data and small data. What occurs here is that the revenue specialist and the general manager interact through various discussion processes to hybridise the different data types of big and small data to create a new form of data, now defined in this research as hybridised data. This process of reinterpreting the data was conceived through an examination of the main categories taken from the research data (shown below in italics) and summarised as the following key structural conditions in the substantive theoretical framework; manager knowledge and experience (*general manager involvement*), individual behaviours (*general manager involvement/avoiding information overload*), customer influences (*thinking local/avoiding information overload*), market

dynamics (*balancing defence and attack*), business performance (*balancing defence and attack*) and knowledge asymmetries (*decision negotiation*). These structural conditions combined to explain why general managers and revenue specialists prioritise different types of data. Through the identification of this reinterpretation of data and the definition of new a type of data, it was then possible to create a new typology that redefined big and small data to re-model the Vs framework based on the findings of this research. The Vs framework had originally been developed by Laney (2001) and later extended by IBM (2013), SAS (2013) and Oracle (2014) as well as academics (Ekbia et al., 2015; Phillips-Wren & Hoskisson, 2015; Lee, 2017).

The second key process that follows on from the identification of this new type of hybridised data was how it is utilised in the transient price decision-making process. Here, in simple terms, the countervailing forces of the local market dynamics, characterised by the degree of stability and predictability of demand, resulted in a simplified interpretation of the hybridised data, as the market and not the hybridised data dominated the price decision. This led to the balance between rate and occupancy dominating decision-making processes. It was found that the value of the richness of hybridised data was potentially being diluted in terms of the output of transient prices by the countervailing forces coming from local market dynamics. Market and customer reactions to changes in price then created more data that either fed back in the form of big or small data, which was then be favoured by either revenue specialists or general managers to continue a new cycle of data hybridisation and the continued development of market forces.

Figure 6.2: Deconstructing the Black Box - Transient Room Price Decision-Making with Hybridised Data



6.3 The hybridisation of data within transient hotel price decision-making

This section will now consider the substantive theoretical framework in light of the existing knowledge of hotel price decision-making and wider revenue management practices. Three key areas are discussed. The first two relate directly to the processes identified in the framework, whilst the final one is more general, as this research has also brought insights into the role of the general manager up-to-date which up until now has been an area of the academic literature currently neglected, as identified in section 2.23 of the literature review. However, the first key areas that will be discussed do relate to the theoretical framework that explores the hybridisation of data within transient hotel price decision-making. Knowledge advanced through gaining a deeper understanding of the reinterpretations of different forms of data and through insights into what influences the use of this data in the price decision-making process. The first discussion is around the identification of a new type of hybridised data, which led to the re-modelling of the Vs framework of big data, originated from the work of Laney (2001) and since added to by several different parties as outlined in section 2.22 of the literature review. The second discussion surrounds the discovery that when pricing decisions are made at the hotel level, despite the existence of hybridised data, the countervailing economic forces of the market overtake the complexity and richness of that hybridised data, and this resulted in a simplification of the interpretation of the data when price decisions are actually made. This is contrary to the claims of the academic literature that revenue management and pricing is increasing in complexity (Altin, Schwartz & Uysal, 2017).

6.31 Discovering the hybridisation of data process and creating a new data typology

This research has identified that a hybridisation of two different data types occurs within the transient hotel price decision-making process, which has culminated in the discovery of a new type of data, labelled in this research as hybridised data. This suggests that contrary to the thinking of Gandomi and Haider (2015), who suggested big data analytics and automated data systems would dominate decision-making within the sphere of contemporary business, in practice a combination of different data types is found rather than big data supremacy. This is driven through the human interactions between revenue specialists and general managers and their close relationships that increase in trust over time through consistent and open

communications. As a result, this research contributes to existing knowledge by developing a clearer understanding of how to define both small and big data, which was highlighted as a key gap in knowledge in the literature review. It has also created a new typology of pricing data that challenges the current Vs framework commonly accepted as a description of the main characteristics of big data. In summary, this research has allowed for more detailed conclusions to be reached on the use of big data in hotel pricing by answering the questions of what small data is, how and where it is collected and how it compares to and interacts with big data, all driven by the human interaction of revenue specialists and general managers which creates hybridised data.

6.311 – Discovering the hybridisation process

These findings centred on the fact that small data was found to be gathered manually by general managers with the focus of that data being on specific local property insights, typically, insights into their customers' perceptions of the price and value equation. In contrast, big data was found to be within the domain of the revenue specialist and derived from digital and information technology-led sources that provided insights into broader, macro, revenue trends. This does broadly agree with some of the existing definitions of small data found in the literature, such as Lindstrom's (2016) proposition that big data is about machines and small data is about people, and later, Pal's (2017) belief that small data is a commentary by people on what is occurring. However, it disagrees with the thoughts of Korzh and Onyshchuk (2018) that small data is information drawn from hotel systems and the sales channel manager as this research has shown that small data is channelled through the general manager, not automated systems. In essence, through uncovering the existence of a hybridisation of small and big data in transient hotel pricing this research has found that when revenue specialists and general managers work together to share these different data types a complete set of information is used which should serve to make the pricing decision more robust as it is made using a more varied dataset.

This is achieved through the broad macro revenue trends of the big data centred on metrics such as occupancy, average daily and RevPAR prioritised by the revenue specialists and reinterpreted with more unique, hotel property-specific data gathered by the general manager to gain a more detailed picture as a basis for price decision-

making. The subtle complexities of this data hybridisation process are connected to the general manager's perception of the high value and importance of utilising small data in the transient hotel price decision-making process, with a specific focus on unique customer insights. This is in contrast to van der Rest et al. (2015) who found it more challenging for hotel property managers to gather these customer insights. The value of this type of data is emphasised by the fact that revenue specialists accepted the importance of small data if it is used to reinterpret the broader trends identified in the big data. Without this acceptance from both parties, the hybridisation would be unlikely to form, and big data may have been seen to dominate the price decision-making process more than it does. Phillips-Wren et al (2015) had stressed the importance of bringing different skills types to the decision-making process and this is what we see here. It seems almost as if the general manager, who is seen to be a driving force with the responsibility of delivering profit for their hotel property, perceives small data to fulfil the role of increasing the rationality of the decision as it provides unique and specific insights into their customers who will actually pay the prices. However, even general managers with revenue experience, who may be more hands-on in analysing the big data trends, valued small data too. The direct and personal nature of the way this small data is collected also increases the level of trust that general managers hold in this type of data, whereas the sources of big data, especially when complicated by automated systems and complex algorithms may be less clear and more indirect. This may lead the general manager to perceive them as less reliable when used in isolation as they understand less about the original source of the data.

Essentially general manager's trust small data to be almost more accurate than the big data generated by the revenue systems and are supported in this by revenue specialists who perhaps, although more focused on the big data believe the contributions of small data to be valid. The key to this is that customer data is viewed as valuable and reliable feedback on pricing and the customer's specific motivations to buy the hotel's products and services, which are intricacies and unique factors influencing the pricing decision. These factors are perceived by both general managers and revenue specialists to not be picked up by the data automatically collected by big data systems which to them tend to appear to cover broader trends and be more general in nature. This agrees with Coplin (2014) who argued that big

data was less good at spotting the exception, and it also aligns with the argument that a focus on big data has led to an understanding of correlation, not causation and an inability to explain why things actually occur (Barnes, 2013; Fox & Do, 2013; Ekbia et al., 2015). It also broadly agrees with the work of Cetin et al. (2016), Richard (2017) and Phillips-Wren et al (2017) who said that big data might not be useful in identifying nuances in the context of the decision but found the focus of searching for these nuances was on the customer. The small data that is collected by general managers was found in this research to be all about searching for that one exceptional piece of customer information that could tell them more about how to price and why customers were prepared to pay different prices. Therefore, customer insights came primarily from the small data rather than the big data, despite the existence of unstructured big data on customer price and value feedback generated through digital sources, such as TripAdvisor. However, small data continued to dominate, as this type of unstructured big data was largely ignored by both general managers and revenue specialists, as mentioned in the previous chapter. This appears to come down to an issue of trust, as general managers appeared to be less believing of customer feedback that came through indirect sources such as TripAdvisor than they were of direct communications with the customer within the hotel property, for example, they commented on how it was possible for customers to make comments about the wrong hotel on these websites.

The high level of trust in small data is also derived from the hotel manager's perception that this type of data is about more than just intuition. Of course, for general managers without a revenue background this belief may stem from a lack of experience of dealing with the broader, big data trends within revenue management, but this was not overtly recognised by the general managers and as already mentioned the value of small data was accepted by general managers even when they had a background in revenue management. They viewed their customer insights as concrete data that could be transformed into information that was as valuable, if not more so, than the big data, and they pressed for the centrality of the customer in the price decision-making process. Therefore we can say that hotel managers perceived that the small data added to, not detracted from the rationality of the pricing decision as it was adding specific details to the big data, making it more, not less accurate. This adds interestingly to the debate around the use of

intuition in decision-making, and the effect big data has on tempering the use of intuition and increasing the rationality and reliability of decision-making through automated data analytics. The debate is widely engaged within the academic literature and discussed in sections 2.42 and 2.43 of the literature review chapter. If there are high levels of human involvement in the collection and interpretation of small data then the concepts of bounded rationality (Simon, 1957) might be thought to come into play where small data is used in decision-making. However, this research has proved there is less of a dichotomy between small data and big data in terms of their impact on the rationality of decision-making than may have been expected. This contrasts with the literature that often asserts it is big data that serves to increase the rationality of the decision (McQuillin & Sugden, 2012; Håkonsson and Carroll, 2016). In this research, one is not viewed as rational and the other irrational. Instead, both are viewed as being factual, rational contributors to the pricing decision, just in different ways and to different degrees. Mayer-Schönberger and Cukier (2013) agree that big data lacks accuracy at the micro level but say that this is made up for by the insight gained at a macro level. Of course, as indicated in the literature review, academics have recognised the basic need for heterogeneous sources of information in revenue management decision-making (Wang et al., 2015) and Kitchin (2013, p.264) agreed that big data could not speak for itself and needed to be interpreted in the context of “domain-specific knowledge”, or as this research has defined it, small data. However, the complexities of how big data and small data join to add value to transient hotel pricing in practice have not been fully exposed until now. We now know that within price decision-making at the hotel property level, the focus of this “domain-specific knowledge” is on developing customer insights.

Finally, there is a process of re-shaping the big and small data. Whilst revenue specialists had the statistical, numerical big data on revenue performance such as occupancy, average room rates, and market share indexes and could therefore, make an algorithmic based scientific decision using this data, the general manager could tell the local story to help create a narrative to explain the figures, based on more unstructured, property-specific, customer small data. This is also in contrast to some of the literature that suggested that revenue specialists only acted on the big data but did not interpret it (Bowker, 2014; Ekbia et al., 2015). It is almost as if the general manager encourages the revenue specialist to interpret the big data using a

wider-ranging data set. The hybridised data is the result of piecing together different types of data from different sources from different angles of approach. Therefore we see in fact that in this context the informational asymmetries that exist between the revenue specialist and the general manager are beneficial, rather than problematic, as suggested by Hodari et al. (2017) as they lead to a more complete data set and more in-depth knowledge. Where revenue support was lacking, again there appeared to be vital pieces missing in terms of the scientific analysis of data. There was also missing pieces where total revenue specialist control existed there were also missing pieces in terms of the localised small data. Where a hybridisation of data occurred through the interactions between a general manager and revenue specialist, both parties brought different types of data and knowledge to the relationship and there appears to become an element of co-dependency in the relationship in that neither party could make a fully considered decision without the knowledge of the other. Although some of the literature did agree that collaboration is needed in decision-making within hospitality (Kiron and Shockley, 2011; Ransbotham et al., 2016), what we see is not necessarily direct collaboration in making the final decision as sometimes one party made the final call on setting the price, but collaboration in building a shared interpretation of different forms of data.

The revenue manager seems to assume the role of technocrat where the general manager builds their knowledge through local, informal insights. Some general managers even commented that they were pleased to have off-site support, as a revenue specialist was less invested in the individual property than the general managers themselves, and the off-site could, therefore, make more objective decisions. One general manager gave the example of the offering of a lower rate to a customer who is liked by the team. When this was followed up through theoretical sampling it appeared that many general managers agreed. In some ways, this agrees with the work of Beck et al. (2011) who encouraged the revenue specialist to influence decision-making in a non-emotional way. However, in this research, it seemed both parties were happy for the other one to check their decision-making approach rather than it just being the revenue specialist checking the emotions of the general manager. It is almost as if through access to different data sets each party could double-check their own thinking and analysis of their own data against another viewpoint to prove or disprove their thinking with the consequence that a better-

informed decision was being made. Therefore, small data drives the big data transformation process through the application of wisdom, suggested by Ackoff (1989) as a major challenge in achieving the full transformation of data into action in the decision-making process. In addition, when returning to the extended Vs framework it was stressed that the value of big data could only be extracted using data analytics (Gandomi & Haider, 2015). What this research has shown is that its value can be enhanced by interpreting it in the light of another type of data that is small data generated by humans rather than through complex automated analytics. If there is value in wisdom, which Ackoff (1989) agreed, then that value and wisdom are reached by interpreting the big data in the light of a deeper insight which comes from the small data achieved through human interactions rather than purely through data analytics. This agrees with Batra's (2014) definition of wisdom that cumulative knowledge is tempered by experience, which in this research is found to be led by the roles of general manager and small data in this research. However, it is again important to recognise that the findings of this research did suggest that the general manager's past job history and experience may influence the use of big data, since if they had considerable revenue experience prior to becoming a general manager they may factor more of the macro big data trends into their decision-making. This did not mean though that they considered the influence of small data to be any less important.

Ultimately this research has found that big data does not dominate in the way that the hype around it suggests, examples of which were highlighted in the literature review (Terrier, 2017; Richard, 2017; Crozier, 2017; Prakash, 2017), the same hype that is widely flagged as a concern in the academic literature (Weinberg et al., 2013; Pearson & Wegener, 2013). In fact, big data is more of an influencer than it is a key driver. This is because the small data is used by the general manager and the revenue specialist to interpret the big data, although this is likely to be driven by the influence of the general manager and their high levels of involvement in the price decision-making process. Human interactions between different types of managers influence heavily the balance of power between big and small data. General managers use the local guest intel, in combination with their overall product and property knowledge to influence the revenue management decision. Ultimately, they are property managers, and are responsible for the success of that hotel, as the

literature review agrees, and naturally, that specific hotel and customer data, the small data, is where their focus and priorities lie. This influences their attitudes towards big data and encourages them to focus on this more localised data. The general manager exhibits a lack of belief in the reliability of big data, as they perceive that this data may not pick up on the unique characteristics of the hotel property about which they have built up a factual base of specialist knowledge. The general manager translates the big data within the filter of their knowledge of the local property needs. General managers don't just interpret the big data, as suggested by Steen et al. (2016); they interpret it with the use of another type of data, the small data, to create a new type of information – hybridised data. As follows, small data does not replace big data but complements it. This broadly agrees with the work of Tuominen et al. (2005) who suggested information behaviour would be in part a product of social relationships. It is also in line with Monino (2016) who believed collaboration could help extract more value from big data. Ivanov (2014), Günther et al. (2017) and Altin, Schwartz and Uysal (2017) also all agree that collaboration can strengthen price and revenue management decision-making. Yet, this research sheds further light on how this actually occurs in practice and provides a more detailed understanding than existed previously in the literature of how different forms of data are brought together by the collaboration of the general manager and the revenue specialist. In particular, it shows that the complexities present in these relationships, such as informational asymmetries that may exist due to the centralisation of revenue management or through more complex ownership structures appear to have a more positive effect on decision-making and data sharing than the literature had previously suggested (Migdal, 2015).

Finally, the suggestion of this research that the value of data is increased through human interactions between the general manager and the revenue specialist offers further insights into developing our understanding of the balance between human decision-making and automated revenue management systems in setting prices. The literature review in section 2.431, for example, the work of Phillips-Wren and Hoskisson (2014) and Steen et al. (2016) made clear that the current belief was that some human involvement and interpretation was required to some extent, but it was not clear what the balance was in practice. This research widely agrees with the existing literature that says human managers can help put the decisions made by

automated systems into a wider context of customer and local market knowledge. However this research, suggests that the automation of data handling and analytics does not reduce the involvement of managers in tactical, daily price changes but has shown that general managers and revenue managers are still actively involved in discussing and shaping regular daily changes in transient prices. So, this sits opposed to the work of Cross et al. (2009) and Guha Thakurta (2016) who believed automated systems would remove the need for managers to be involved in day to day data crunching, tactical pricing, and matching rate offers, and shows that the faith placed in systems in the early revenue management literature has not played out as expected in practice (Kimes, 1989; Lieberman, 1993; Marriott Jr & Cross, 2000). This research suggests that in practice, regardless of whether they are a revenue specialist or a general manager, managers are not willing to relinquish control of the transient room pricing decision due to a lack of trust in the ability of the systems to put the decision-making process within the context of the local property. Another factor in this lack of trust is the high value they have been found to put upon personally sourced customer insights. This seems to apply whether it's a tactical decision or a more strategic one.

6.312 – Developing a new typology of pricing data

From this deeper knowledge of the realities of the way revenue specialists and general managers interact to reinterpret the big and small data in a process of hybridisation it has also been possible to reach a clearer definition of both small and big data than currently exists. This has led to the creation of a new typology of pricing data within the context of hotel revenue management and the next section shows how this typology challenges and re-models previous notions of using the Vs framework to define the term big data. The new typology can be found in the substantive theoretical framework in figure 5.2 but also in isolation in figure 5.3 below. Through the findings of this research, this typology of pricing data examines three key characteristics of data and then re-applies them to a new Vs framework. The three qualities of data that emerged from the findings as being central to how we define a data type were volume/speed, level of detail and the focus of the data.

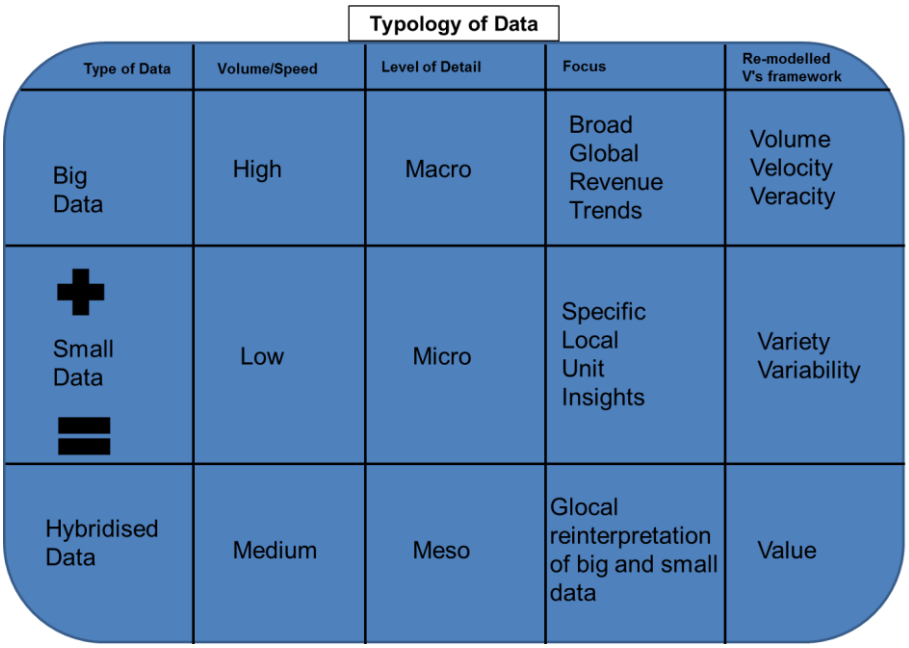


Figure 6.3: The Typology of Pricing Data

Firstly, in terms of volume and speed, this research agreed with the Vs framework through identifying big data as arriving at high speed and in high volumes, and small data to be contrary to this, being small in volume and slower to be generated. Therefore, the new typology still attributes volume and velocity to big data. Small data appeared to be gathered over an extended period with little regularity, through observation and direct human communications by the general manager with customers, and also by front-line staff who may have additional customer insights to those collected directly by the general manager. Through storing the small data, the general manager gradually builds a picture of their hotel business over time that can be fed into the pricing decision when necessary. Therefore, the speed at which small data is collected is slower than that of big data, which through this research, was seen to be generated automatically on a regular basis and at a quick pace through interactions between various digital systems. This agrees with the existing definitions of big data in the literature which stress its digital nature (Weinberg et al., 2013; Puschmann & Burgess, 2014 Alharthi, Krotov & Bowman, 2017).

However, the large volumes of big data and its automatic generation meant that it was broader and more global in its definition, with a focus on macro trends in key revenue metrics whereas small data was more specific and localised in terms of its insights and more micro in focus. This disagrees with the description of big data as

granular in nature given by George, Haas and Pentland (2014) and Yaqoob et al. (2016) and also Kitchin (2013) who described it as being exhaustive in scope. It seems clear that small data originates from within definable localised boundaries with a specific target group being its focus. Small data is collected within the physical boundaries of the hotel property by general managers focusing on the responses of customers to elements such as price, brand, loyalty, and value. In this sense, the term local in relation to small data can be defined as specific local property insights with a focus on its customers. Due to the unique and specific nature of individual customer responses to price and the general understanding that customer approaches vary, small data could be described in terms of variety and variability, terms normally reserved in the literature (Laney, 2001; IBM, 2013; SAS; 2013) for big data. So this research began to re-model the Vs framework by attributing typical big data characteristics to small data, in this case, variety and variability. Interestingly, if small data is often gathered by chance it means that this research has also uncovered a similarity between big and small data in the sense that both types of data seem to appear to be collected without a pre-defined purpose. Even though small data specifically focuses on the customer, the general manager does not know at the time of gathering it what use it may have in any future pricing decisions. This also serves to support the existing literature on big data which argues that because big data is generated automatically from digital sources, it means the whole data set is always collected, rather than specific data being selected to answer a specific question (Constantiou & Kallinikos, 2015; Günther et al., 2017; van den Broek & van Veenstra, 2017). Interestingly, the lack of a pre-defined purpose for collection is not a characteristic of small data currently identified in the literature.

This research also suggests that big data is more structured than some of the later thinking suggests. Phillips-Wren et al (2015) talked about the volatility of big data which was termed 'variability' by others, for example, major consultants SAS (2018), exploring the definition of big data, still refer to the variability of big data in their web pages. Both terms refer to the variability of data flows and suggest big data velocity may not be constant but rather may follow peaks and troughs. In this research, it seems that the peaks and troughs existed in the small data rather than the big data as general managers could never anticipate when opportunities to gain unique customer insights would arise, but they were aware of when reports generated by big

data systems would arrive. However, it must be recognised that the perception of big data found to be held by the participants in this research was that big data was fundamentally numerical data, whereas the unstructured nature of big data in terms of qualitative data has been stressed in the literature (Duan & Xiong, 2015) and specifically in terms of its need to be embraced and decoded by hotels (Shafiee & Ghatari, 2016). Both revenue specialists and general managers stressed the qualitative, unstructured nature of small data and the numeric, structured nature of big data. This may come from an ignorance of the unstructured elements of big data such as the user-generated content coming from social media and other online channels, which was found to be largely ignored for pricing purposes in this research. This agrees with Davenport (2013) who argued hotels may be slow to adapt to using unstructured big data, and may not use the sentiment analysis of social media platforms as suggested by Richard (2017).

This focus on customer feedback through the gathering of small data also suggests that the move towards a more customer value-led approach to revenue management and the incorporation of wider elements in revenue decision-making, including customer relationship management and marketing (Wang et al, 2015; Josephi et al., 2016; Altin, Schwartz & Uysal, 2017; Yeoman & McMahon-Beattie, 2017), is present but is not being driven by big data. It is small data that encourages a wider range of customer-led factors to be included in the decision, such as reactions to brand marketing and price changes. This research indicates that the intricacies of customer motivations to pay prices appear to be coming from the small data rather than from the big data. It also seems to show that the veracity of big data, defined by IBM (2013) such as its uncertain and imprecise nature can be reduced when reinterpreted with small data, which does suggest that veracity should remain attached to big data in the Vs framework. However, this is primarily driven by the perceived importance of the specific localised context generated by small data from the viewpoint of the general managers. To them, big data is more generic in nature than the literature suggests, and small data is more intricate and unique and therefore likely to add the necessary information and depth of knowledge. Small data is about causation and is a check and balance to the macro, numerical nature of the big data, which would otherwise only tell a story based on correlation, which may not be specific enough to uncover the details and idiosyncrasies of what was occurring

on the ground at the hotel property. Mayer-Schönberger and Cukier (2013) had argued that big data would mean accepting imprecision, searching for correlation, not causality. Small data brings the focus back onto causality, which regarding pricing is where the value lies as it allows for an understanding of why the customer would pay a certain price.

What this research has uncovered is that through the reinterpretation of small and big data the actual data used in the transient price decision-making process at the property level can be defined as hybridised data as this reflects the blending of big and small data that occurs during the human interactions that take place between the general manager and the revenue specialist. It is this process that adds value. The blending of big and small data also means that hybridised data can be defined as arriving at a medium speed, with its volume mediated and with a meso level of detail. This is described in this research as the focus being on a glocal reinterpretation of the big and small data, which would begin to consider macro revenue trends reinterpreted in the light of small data customer insights to provide a new understanding. Therefore, value within the Vs framework cannot be solely reserved for big or small data but for the hybridised data. Value was created by using different types of data, and therefore not one source of data seemed to be dominant, for example the literature review put evidence on the centrality of STR competitor set data with Smith and Zheng (2001, p.371) describing it as “ubiquitous” and saying that although used as a data source it was by no means the only data used by managers.

To conclude this section, it is worth highlighting that this research has suggested that discussions around how big data is used in hotel transient price decision-making should be focused not on the volume of available data but on the intricacies of what that data is telling managers. This broadly agrees with the agenda of some of the existing academic literature that suggests the focus on volume should be taken off definitions of big data to allow for a more process-orientated approach to the concept (George, Hass and Pentland, 2014; Laney et al., 2014; Carillo, 2017). Instead, this research points to the importance of managers being able to extract property-specific information from the data to build a relevant knowledge base relating to the price decision rather than just having greater quantities of data. Fascinatingly, what appears to arise in this research is that large volumes of big data do not

automatically correlate to high levels of complexity of the data as suggested by the literature. The complexities of big data are typically characterised in the literature through its sheer volume, such as Phillips-Wren and Hoskisson (2015) and Yaqoob et al. (2016) who both argue that the complexity of big data comes from the large variety of data sources that constitute it, This is substantiated by Puschmann and Burgess (2014) who argued that big data should be characterised by a marked shift towards even greater computability of volumes of data. Ekbia et al. (2015) also highlighted that what is meant by the complexity of big data and where that complexity originates is not widely expanded upon in the literature, therefore this is where one of the main contributions of this research lies, by casting light on where the complexities of pricing data originate. It is in the reinterpretation of big data by small data in the creation of hybridised data.

6.32 Pricing with hybridised data – the power of economics over data

As just discussed, this research has uncovered a new type of hybridised pricing data. It has also allowed for observations into the way this new type of data is actually applied at the point that transient room price decisions are made. This has led to an interesting finding around the true value of data in the price decision-making process, which suggests that the hybridised data does not direct the pricing process as much as the literature on data would suggest. What is actually occurring is a disconnect between the process of generating data to inform the pricing decision and the process of actually setting the price. It seems that at the moment the price is actually set there is a tendency for the general manager not to use all of the hybridised data available and this means that prices are often set based on an incomplete data set, despite the effort that has gone into creating it. This is exaggerated due to the general manager often being the one to make the final decision on the price to be set as they are responsible for meeting revenue budget targets. With the pressures of the responsibility of a specific hotel property removed from their shoulders generally revenue specialists or where general managers had a revenue background, seemed to promote looking for opportunities for revenue growth in the data rather than taking a defensive position.

The reason for this behaviour of general managers has been found to be the countervailing forces from local market dynamics. These forces led to a simplified interpretation of the data, focused only on “red flags” that might highlight risk factors

in market demand. This led to price decisions which tended towards a focus on the balance between rate and occupancy. It is actually the local market forces that craft the transient price set and this causes the value of hybridised data to be reduced. Price decisions are reduced to protecting the hotel property against negative market dynamics in order to protect occupancy levels or to take advantage of short-term increases in demand to increase rate. This appears to result in more tactical, trial-and-error based decisions being made rather than longer-term strategic approaches to pricing. It is almost as if a two-step process exists where the general managers and revenue specialists generate the hybridised data they feel will be useful in the price decision-making process and then use it in a very narrow way when they come under pressure from the market or feel the market is out of their control. Even if the market was performing well a sense of complacency could be seen to set in. General managers also looked at less data as they felt more comfortable in making decisions, perceiving themselves to be in a position of strength with less risk. However, this was not found in the majority, with most hotels sensing more risk and unpredictability in the local market.

In these unstable markets, perfect information meant nothing when the impacts of pricing decisions are hard to predict. Here data seems more likely to be used to defend decisions rather than to make them. This agrees with the principles of prospect theory developed through the thinking of Kahneman and Tversky (1979) and Tversky and Kahneman (1992). They argued that when outcomes were uncertain, irrational asymmetries formed between the way gains and losses were considered in the decision-making process, resulting in people being more concerned with suffering losses than they were about achieving gains. Data analysis took a very narrow focus and was led by a sense of protectionism against falling or failing demand in the market rather than growth. It is felt that the existing literature has underestimated the strength of the countervailing forces coming from the local market which put too much emphasis on the role of data in guiding the decision-making process when other forces are clearly at play. Local market forces are stronger than either big data, small data or hybridised data making this research closer to some of the findings of Woodside (2015, 2017) who in his development of the theory of behavioural pricing argued that economics was a key factor that would influence price decision-making, although his research was conducted in a business

to business context. The key driving force behind the price decision remains the working of the market. Data is there but it is not a key driver as the hype surrounding it may lead people to believe.

The general manager's desire to protect their local position within a local market context and their focus on demand factors also suggests a tendency towards short-termism in the transient hotel price decision-making process as they focused on factors they could quickly respond to, defending their market position using price changes to balance rate and occupancy to achieve budget. In this simplified approach to pricing the profit focus emphasised by Noone, Enz and Glassmire (2017) and Altin, Schwartz and Uysal (2017) seemed to be forgotten as long as budgeted targets for occupancy and rate were achieved. The focus on making quick responses to the market also meant that if any data was used, not only did it focus on the "red flags" but it emphasised real-time data such as rate shopping tools. The historical trend data provided by STR did not appear to be as prominent as perhaps it once was. There was also a lack of focus on longer-term, supply factors such as the market pipeline reports supplied by STR Global that would show managers future increases in supply through the opening of new hotels in their market. Although, as already discussed, general managers exhibited patience in building up a picture of customer responses to value, price, brand and other factors over the longer-term through the collection of small data, this same patience did not seem to exist when it came to actually setting the price, as general managers seem to feel under pressure to respond to changes in the market forces. General managers are conflicted in terms of the time taken to generate hybridised data and turn it into knowledge within the context of the fast-paced and often unpredictable market. This returns to the thinking of Mintzberg (1973) and Dann (1990) that the managerial function would be dominated by short-term attempts at coping and reactivity. Pricing practices have gone full circle at the hotel property level.

The focus on reacting to market forces also seems to suggest a tension between short-term pressures and long-term customer relationship and profit building that helps to explain why tensions between strategy and tactics in revenue management and pricing were highlighted in the literature review. This is where strategies are viewed as long-term and tactics are viewed as short-term. This research broadly disagrees with existing literature that suggests revenue management is becoming

more strategic, even if short-term tactics may have their place (Noone & Mattilla, 2009; Anderson & Xie, 2010; Erden and Jiang, 2016). It agrees with Hung et al. (2010) who felt that despite the increase in forecasting abilities, unpredictable market forces would still lead to tactical decisions being made, as well as Mattimoe (2007) who argued that the uncertain nature of the environment was a challenge for managers in optimal hotel pricing. Certainly, this research has shown that in practice tactical decisions still dominate due to market forces and that they stand alone rather than being part of a wider strategy as suggested by Noone and Mattilla (2009), Anderson and Xie (2010) and Enz et al. (2015). Despite that fact that Cross et al. (2009) and Noone, Enz and Glassmire (2017) stress that a customer-centric approach lies at the heart of a strategic approach to revenue management, we only see customer data applied to tactics rather than to strategy in this research. Even if it is collected with the intention of a wider strategy it is not used in this way due to the pressures of the market. The intention to make more strategic decisions is present in the hybridisation of the data but does not seem to play out when the actual price is set. In fact, some general managers discussed a desire to try to encourage a stabilisation of prices and reduce price changes based on the small data they had created from customer perceptions of price changes, but again this was not always translated into actions. It seems that whilst general managers were conscious of the negative impact of constant price fluctuations on customers when driven by the pressures to react to the unpredictability of the market they were still not always able to carry this out when they felt under time pressure to decide a price.

Under these conditions, it seems the countervailing forces of the local market drive the use of gut instinct rather than there being an issue of information overload caused by having too much data. It is the unpredictable nature of demand within the local market that leads managers to exhibit the satisficing behaviours found to be a key element of bounded rationality within a behavioural model of decision-making (Simon, 1957). Essentially general managers and revenue specialists could have perfect information but the pressures arising from the unpredictability of market dynamics would ensure that it would be distilled down into this balance between average room rate and occupancy, as these could be most quickly adjusted to respond to change. This was expressed as a concern that the reactions of the market to price changes could never be fully predicted and that this meant an

element of trial and error in price decision-making. The existing literature as presented in section 2.433 of the literature review exhibited a clear focus on the question of whether having more data would increase the rationality of decision-making with a focus on big data. The debate around rationality of decision-making was focused on the role of information in decision-making wherein the neo-classical approach to decision-making theory considered there to be an optimal level of information (McQuilin and Sugeden, 2012). This research suggests that placing too much focus on the role of data in the rationality of decision-making may be wrong within the context of hotel pricing and that it is more likely that it is the countervailing forces of the market and the current performance of the hotel property that influence how rational the price decisions are. Managers are conscious, it appears, that it would take too much time to incorporate all the data into the pricing decision when the market forces are moving so quickly. After all, Håkonsson and Carroll (2016) did suggest that data can slow down decision-making processes. This also links to the theory of planned behaviour (Ajzen, 1991) who discussed the issue of perceived behavioural control which referred to a person's perceptions of their ability to perform a given behaviour. In this research, managers did not seem to perceive they had control over the market and therefore did not believe it was always worth considering all the data.

What this research has found is that in practice at hotel property level transient price decision-making processes remain simple and centred on balancing the metrics of rate and occupancy to hit the budget figures set for the specific property. Historically these two metrics have been at the heart of both early yield management and later revenue management. The overall lack of sophistication of the transient pricing processes at hotel property level and its focus on traditional revenue metrics comes as a surprise given the increasing dynamic nature and complexity of revenue management and pricing suggested by researchers cited in the literature review (Mattila and Gao, 2016; Altin, Schwartz & Uysal, 2017). This is coupled with the increasing range of revenue metrics available that focus on total revenue management (Wang et al., 2015; Josephi et al., 2016) and profit management and delivery (Noone, Enz & Glassmire, 2017). Finally, it perhaps also resulted in a lack of creativity in pricing practice. There was a distinct lack of evidence of risk-taking in new forms of pricing such as the participative pricing strategies mentioned by Mattila

and Gao (2016), for example, name-your-own price strategies. Essentially the potential of new pricing practices identified by academics is not being realised in practice due to the predominance of relatively antiquated trial and error adjustments in price to balance rate and occupancy metrics influenced by the local market forces.

6.33 Insights into the contemporary general manager

On a more general level, this research helps to contribute towards bringing up-to-date the existing literature concerning the role of the general manager as there have been few recent studies that have examined this role as the literature review demonstrated. Concerns around this lack of focus on the general manager in academic research have already been reflected upon in this thesis. This is especially given its finding that the general manager remains central to the process of setting transient hotel prices despite the existence of specialist revenue support and in some cases automated revenue systems, agreeing with the work of Ivankovič and Jerman (2010), Cross, et al. (2011) and Richard (2017). This research brings the literature on the general manager back full circle to agree with much of the literature on the function of the general manager from the 1980s and 1990s that key elements of the role were around information gathering and dissemination (Arnaldo, 1981; Shortt, 1989; Dann, 1990; Kim; 1994), but it has allowed greater insights into what type of information or data is gathered and how it is used. The general manager was found to bring unique and valuable data and knowledge to the interpretation of big data and be heavily involved in guiding that process towards the specific needs of the hotel they were in overall charge of even if the market forces did dominate that thinking. The pressures of the general manager role clearly came from the market forces and not from issues of information overload. Essentially, the general manager remains instrumental and their perceptions of the importance of the small data they can generate appear to stem from their belief that they are responsible for the hotel's success. This agrees with the thinking of Bharwani and Talib (2017) and Hodari et al. (2017) on the centrality of general managers' role in the pricing role. They perceive their influence to lie in the deep knowledge of the consumer to whom they have easy access. In the case of more complex ownership structures, the goal incongruence mentioned by Hodari et al. (2017) seemed to be avoided with the autonomy of the general manager still present. General managers focus their data collection on

where they have knowledge even if market forces are sometimes perceived as being out of their control.

In terms of the existence of revenue specialists and the impact that they have on the commercial and operational tensions that exist around the role of the general manager, this research has shown that the expectations of the earlier literature have come to fruition in ways which are different from those anticipated. Donaghy and McMahon-Beattie (1998) predicted that having more revenue specialists would make decision-making in this area less dependent on the general manager and that they could (p.226) have “more time to spend with their guests”, suggesting an increased operational involvement in the hotel through direct customer interaction. However, what this research suggests is that this does not widen the dichotomy between operational and commercial roles, but rather the operational role helps to inform the commercial role by allowing the general manager to contribute valuable customer insights to the more commercially oriented processes involved in running a hotel business, such as price decision-making, even if the market often curtails their efforts. Essentially the involvement of general managers in operations allows them different insights into the commercial aspects of the decisions they must make. The role should not be described as either commercial or operational but as a blend. This research suggests that the complexity of the role is not driven by a move away from operations to a commercial function for general managers but by a continued need to be involved in both. Of course, it is important to bear in mind that the degree of commercial acumen that a general manager may bring to a role is suggested by these research findings to be influenced by their career background. Of the impact factors on manager decision-making outlined by Martin and Fellenz (2014), who looked at the framing effects that managers applied to decision-making, past experiences, was the only one that appeared to have an impact in this research. If they had a revenue background, they potentially became more involved in analysing the broader trends of the big data but still stressed the value of small data. To conclude, whatever the background of the general manager, they still remain central to the pricing process but so does the market. It releases its own fresh set of pressures on the general manager in the transient price decision-making process.

6.4 Chapter Summary

This chapter has explained the findings in more depth and offered a full deconstruction of the black box that surrounded how transient prices are set at the individual hotel level. It has also fulfilled the main aim of the research, which was to assess the impact of big data on the way transient hotel prices are set in practice. The literature review highlighted a clear gap in the knowledge of the impact of big data on hotel price decision-making at a practice-based level and this has been addressed through the discussions contained within this chapter. The research has provided a clear definition of both big and small data and has explained how they are integrated to form a new type of hybridised data, whilst also shedding more light on the relationship between the revenue specialist and the general manager and exploring further the balance of automation and human decision-making. The research has also suggested that the complexity of revenue management and room pricing that was thought to exist due to an increase in the available data and supporting technologies is not as prevalent in practice as first thought due to the countervailing forces of the local market. This appears to reduce pricing back down to a simplistic consideration of demand factors and trial-and-error based pricing that has a primary focus on balancing rate and occupancy. This led to the suggestion that it was the concentration of managers on market forces rather than on the volumes of big data that might drive a degree of irrationality in price decision-making and that information overload is not as serious an issue as suggested in the literature. In fact, this research has suggested that the existing literature on pricing and revenue management has potentially not fully considered the importance of local market dynamics on manager behaviours in decision-making. Despite the huge amounts of interest in big data, and the way the literature stresses the increased complexity of revenue management and hotel pricing, this research has discovered that big data is not a key driver of the transient price decision-making process at the hotel property level and that pricing remains wedded to a simplistic balance of rate and occupancy, responding to market pressures and constantly trying to anticipate demand factors. Overall the key message of this research is that big data, hailed as being the panacea for many a commercial and operational issue, cannot stand alone when setting transient hotel pricing, at least at the hotel property level. The perceptions general managers had about the strength of their local knowledge, particularly of customers, was key, as were the market pressures driven by managing and

predicting demand factors. At the hotel property level transient hotel pricing appears to have not changed as significantly since the arrival of yield management as the academic literature suggests, despite the advent of big data.

7. Conclusion

7.1 Introduction

The purpose of this chapter is to bring the thesis to a close and reflect on how and why the research was conducted as well as providing a reflection on how the contributions of the research have addressed the aims and objectives of the research and contributed to closing the gaps found in the existing literature on the research topic. Beyond this summary, the chapter will also consider the practical implications of the findings of this research for general managers, revenue specialists and the wider implementation of pricing and revenue management practices in the hospitality industry. It will also consider the impact of this research on the delivery of hospitality revenue management education in order to suggest ways of closing the gap between theory and practice in revenue education. The chapter will conclude with a consideration of the future directions for this research and how it is planned that the research path will continue to contribute to the development of knowledge in the field of hotel revenue management and the use of data in price decision-making.

7.2 Reflections on the research journey

The researcher set off to explore the use of big data in the transient hotel room price decision-making process from a practical viewpoint. The aim was to develop a substantive theoretical framework that could be used to explain the true use of big data to decide transient hotel room prices at the individual hotel property level. This meant the focus was very much on the practical application of data to pricing. This was seen as a valuable area of investigation given that a gap in knowledge was found in the existing literature around the complexities and realities of how big data was used in practice to set transient hotel room prices. In essence, the examination of the extant literature identified a black box that existed around the practical application of big data to hotel price decision-making that required deconstruction. With consideration of the thinking around black box theory this meant placing a clear focus on exploring the realities and minutiae of the use of big data in the transient pricing process (Peńa Garcia Pardo et al., 2009), moving beyond the superficial and the hype surrounding big data, to explore the complex human interactions that occur within organisations (Boxall et al., 2011) and with data, and attempting to identify the mediating mechanisms that occur in the process (Jiang et al., 2013).

This led to the consideration of the following three key objectives for the research, the fulfilment of which will be assessed in the next section of the chapter:

- To explore the intricacies of the systems behind the way transient price decisions are made at the individual hotel property level and the types of data that are used to make those decisions.
- To investigate how general managers of individual hotels interact with and use big data and big data driven-technologies to make transient room price decisions within the context of revenue management strategy.
- To explore the impact of the existence of revenue specialists on the use of big data in the transient price decision-making process at hotel property level and uncover how data is exchanged in this collaborative decision-making process in practice.

This research was conducted using the methodological approach of Straussian grounded theory as it was felt this was a suitable qualitative approach given the wide gap in knowledge and the need to develop new theories to deconstruct the black box that had been identified. The use of work-shadowing techniques within this methodological approach, supported by in-depth interviews, also allowed for the successful identification of the realities of the use of big data in hotel transient price decision-making. It was felt that the rapid development of big data as a concept and the literature that surrounded (Youtie et al., 2016) it would also make developing valid hypotheses to test very difficult, so a methodology centred on the development of new theory was selected. Through the careful alignment of data collection and analysis using theoretical sampling and the coding paradigm provided as part of Straussian grounded theory, this research can be seen to be grounded in the data provided by participants and gives a good insight into both the structure and process of the realities of using data in transient hotel price decision-making. Through the development of the substantive theoretical framework, it was possible to explain how and why things happen that make clear contributions to existing knowledge in this area. It also enabled the deconstruction of the black box.

7.3 Key findings and contributions

The section will now highlight the key contributions of the research and consider how they have addressed the objectives set out at the beginning of the research and crucially how they have advanced knowledge in the field of big data and hotel pricing

and revenue management. Through utilising Straussian grounded theory a series of five categories were identified and these fed into the development of a core category characterised as the hybridisation of big and small data through the collaboration of general managers and revenue specialists. The five main categories that fed into the core category consisted of general management involvement, avoiding information overload, thinking local, balancing defence and attack and decision negotiation. These categories represented some of the key findings of the research. The first one, general management involvement, represented the finding that the general manager remained critically important to the process of transient price decision-making. The second, information overload, referred to the discovery that information overload when in the presence of big data, did not exist to the extent suggested in the literature. This was because the general manager took active steps to filter out what they perceived to be unimportant data, thereby reducing the volumes of data before it became a problem. The category thinking local focused on the importance of customer insights into the price decision, which were considered highly valuable by general managers and revenue specialists. Balancing defence and attack referred to the focus of decision-making on a restricted number of revenue metrics despite the amount of detailed data available. Here there was a particular focus on the balance of rate and occupancy in response to market dynamics. This resulted in either bravery around rate increases or more typically defence of occupancy levels. Finally, decision negotiation highlighted the co-dependent relationship that was found to exist between general managers and revenue specialists and the fact that there is a blending of the different data sets they each have specialist access to and knowledge of.

These findings were then developed using the coding paradigm of Straussian grounded theory to further deconstruct the complexities of the findings and complete the deconstruction of the black box through the development of a new substantive theoretical framework. This framework identified that when examining the impact of big data on transient hotel price decision-making there were two processes at work which were influenced by a variety of structural conditions and forces. The first process identified in the substantive theoretical framework was the reinterpretation of data. Here the inputs were small and big data and through various discussion processes the general manager and revenue specialists interacted to reinterpret that

big and small data to become a new form of data, defined in this research as hybridised data. This process was conceived from the findings in the main categories and summarised as a series of key structural conditions, outlined in more detail in the discussion chapter. Once the process of generating hybridised data was uncovered, the research was then able to observe the use of this data within the actual price decision-making process. Here a clear second process was uncovered where the countervailing forces of the local market dynamics, characterised by the stability and predictability of demand factors, resulted in a simplified interpretation of the hybridised data. General managers felt a pressure to make a defensive or attack-based decision that often, given the unpredictability of the market, became a decision made using trial and error, short-term, tactical approaches that did not incorporate the full range of hybridised data available to them.

Understanding the workings of these two processes led to this research being able to claim three key contributions to knowledge. Firstly, the discovery of the process of the hybridisation of big and small data to create hybridised data has led to a more detailed understanding of the definitions of big and small data. This was highlighted as a key gap in the literature. We also now know that the general manager remains central to the price decision-making process despite the existence of revenue specialists and through their co-dependent relationship they re-shape and reinterpret the big and small data. Small data consists of specific and unique customer insights and is used to put the big data in context to increase its value. Defining more clearly the terms big and small data and witnessing their interaction to create hybridised data has also allowed this research to lay claim to a new typology of pricing data which has taken a unique look at the Vs framework which up until now has been commonly used to outline the key characteristics of big data. This research suggests that actually only three of the main six Vs of the framework can be claimed to be attributable to big data, namely volume, velocity, and veracity. Variety and variability are more suited to describing small data and the final V of the framework which stands for value can only be generated through the hybridisation of small and big data and therefore is connected to hybridised data. This new typology of data can be found in figure 5.3 of chapter 5.

The second key contribution is the finding that ultimately when it comes to actually setting the transient room prices the hybridised data does not play as significant a

role as the literature on the use of data would lead you to suspect. In fact, what we see is a simplified interpretation of the hybridised data as a result of pressures from the countervailing local market forces. This leads to an overall simplification of the pricing process, with fewer revenue metrics being used and the price becoming a trial and error-based decision to balance rate and occupancy. This finding is perhaps one of the most interesting of this research given that not only does the literature on data in decision-making suggest its dominance in the decision-making process but it also suggests a general increase in the complexity of pricing and revenue practices. In fact, in practice, we have seen the opposite. General managers spend time increasing the rationality of the data they have available to them for the price decision-making process by hybridising big and small data to build up a complex set of supporting knowledge, but ultimately they do not fully utilise the full value of that data when it comes to actually setting the price. This is due to their perceived need to make quick reactions to demand changes in the market and overall we see a use of simplified pricing tactics rather than the suggested increases in complexity. It is felt that the existing literature on the use of data in price decision-making had under-estimated the power of the market as a countervailing force.

The final, more general contribution of this research is in bringing up to date insights into the role of the general manager. This research brought the literature on the role back full circle to the 1980s and 1990s by identifying key aspects of the job that centre on information gathering and dissemination. Crucially, it found how important the role of the contemporary general manager is in gathering small data on customer insights and how key the role still is in setting prices despite the increased involvement and even centralisation of specialist revenue support. However, this research did move knowledge forward on the debate around whether the role of the general manager was shifting from an operational one to one that was more commercially focused. This debate was highlighted in the few contemporary research papers on the role of the general manager. This research has suggested this debate is not worth continuing with, as there should not be a dichotomy between operational and commercial viewpoints of the role. In fact what should be recognised is that general managers use the knowledge they absorb through their operational duties and responsibilities to feed into the commercial side of their job, for instance, whilst meeting and greeting guests they pick up on the customers' responses to price

and value that could be fed into pricing and revenue management decision-making and which in turn represents the more commercial side of their role. Only the reactive responses to the market forces encourage general managers to not do this.

In addition to the three contributions to knowledge, this research has also made two contributions to methodology. Firstly, the successful application of Straussian grounded theory has given new insights into the use of this approach into the study of big data, which may have impacts on future management research, especially that which may examine the impacts of other quickly emerging technologies like big data. Although it is often presumed that studies involving big data should be examined using quantitative methodological approaches (Jin et al., 2015) often based on pre-conceived hypotheses from the existing literature, this research has proved that where a technology is evolving rapidly a method such as Straussian grounded theory, in fact, works well. This research has proved that Straussian grounded theory, which allows the researcher to absorb the rapidly evolving literature into the research as the data collection and analysis process evolves, ensures the required flexibility to generate valuable research contributions that reflect current practice rather than being based on potentially out-dated hypotheses. In the case of this research both big data and revenue management technologies and consequently the literature surrounding it have been evolving at this kind of rapid pace. Of course, the constant application of new literature to the data collection and analysis process in Straussian grounded theory does present its challenges to the researcher in terms of time needed and the degree of complexity of data generated but with careful planning and by following the coding paradigm offered by Strauss (1987) and further developed by Strauss and Corbin (1998) these challenges were successfully overcome.

Secondly, this research, through the use of work-shadowing, has provided new insights into the use of a new data collection method in Straussian grounded theory which could also be utilised by researchers engaging in this and other forms of grounded theory. An extensive search of Google Scholar and library databases did not highlight any previous use of work-shadowing techniques in grounded theory but Strauss (1987) and Strauss and Corbin (1998) were open to the use of new data collection techniques. As predicted and highlighted in the methodological literature, work-shadowing was successful in allowing this research to gain a true

understanding of the practical aspects of the use of big data in the transient room price decision-making with an in-depth picture of behaviours, actions and crucially the meaning behind those behaviours and actions (McDonald, 2005), such as emotions (Gill et al., 2014). However, it was found that work-shadowing would work best where, as in this research, it was supported with in-depth interviews with the general managers who were shadowed. This aided the clarification of the data collected and also supported theoretical sampling. The impact of the Hawthorne effect, suggested as a risk by McDonald (2005), was not felt, as general managers seemed to be comfortable in acting normally, although it was probably also down to the researcher's background in hotels that the general managers felt there was a tacit understanding of the challenges they faced and therefore they felt there was less need to cover up their true behaviours and emotions. Yes, some of the challenges of large amounts of data and accurate recording of that data were often felt, and work-shadowing was found to be a time-intensive and often emotionally draining method of data collection, but these factors were reduced by an organised approach and an in-depth consideration of the practicalities of the method in advance of the work-shadowing sessions, as shown in figure 3.3 in chapter 3.

7.4 Practical Implications for industry and education

Now the key findings and contributions of the research have been highlighted for the final time in this thesis it is important to turn the attention of this chapter to the practical implications of this research on price and revenue management practices within the hotel industry and also the way in which revenue management education is delivered in further and higher education settings.

7.41 Implications for industry

The two key findings that have implications for the practice of revenue management and pricing in the hotel industry are the remaining importance of human interactions and decision-making processes in transient room pricing and also the high level of influence of market forces on the price decision-making process. Firstly, let's examine the implications of the finding that the human interactions and decision-making processes of the general manager and the revenue specialist still lie at the heart of the transient hotel room price decision-making process despite the existence of automated systems that could technically make the decision for them. These findings around the importance of human decision-making sit in contrast to opinions

in the key academic literature that place significantly more faith in the increasing automation of revenue management decision-making using big data and analytics which should require no user input (Wang *et al*, 2015; Kimes, 2017). This research has provided a fresh understanding of the perceptions that general managers have of big data, and this raises questions for industry around the design of revenue systems and technologies as despite the increase in automated systems and the rise of the revenue specialist, the value of big data is perceived as being only truly extracted when it is reinterpreted with small data gathered manually through customer interactions that occur within the hotel property. This research has shown that systems are therefore only being used as a guide.

On face value, this seems to mean the key question is how can automated revenue management systems be designed to encourage managers to see them as more than just a guide to human-led decision-making? Or even, are hotel companies currently wasting their money by investing large sums of capital in the development of automated revenue systems, if on the basis of user perception their full range of use will never be achieved when there is a continuing reliance on local data inputted by general managers outside of the systems? However, this research suggests that these might be the wrong questions to ask, because somehow, these questions suggest that the general managers, and to some degree the revenue specialists, are doing something wrong by valuing unique, smaller, micro insights into the customer reactions to price and value. One of the key issues emerging is that big data is “big” and potentially macro in nature and this is one of the key reasons general managers feel the need to keep individual control over the input of localised, unique data. General managers perceive that big data only covers broad trends rather than being sensitive to the intricacies of the local market which they see as so vital in making a reliable decision. This seems to be a valid point. Although some of the academic literature highlights the complexities and statistical intricacy of revenue management systems (Cetin et al., 2016), this does not translate into practice. It is the technology and not the human that is currently the barrier to increasing the reliability of big data analytics in automated revenue management decision-making. Connell and Voola (2007) and Hayne, Troup, and McComb (2011) had argued that big data required coordination and integration, but actually what this research has shown is that there is a need for big data covering broad trends and driven by analytics to be integrated

with other forms of local level data not just for there to be more big data. Within the hotel industry, discussions should perhaps focus less on data analytics and getting managers to trust big data led systems and more on how automated revenue systems can be widened out to incorporate a larger range of different local, qualitative inputs of data that is valued by both general managers and revenue specialists.

The second key finding to have an implication for industry practice is the dominance of market forces on the decision-making process. Given the amount of time general managers and revenue specialists take disseminating, discussing and going through the process of hybridising big and small data it seems to be a significant waste of resources if this data is not fully utilised in the decision-making process. Whilst it is perfectly correct for market forces in terms of demand factors to influence the price decision, as a basic understanding of economic principles would tell you, currently, managers are not taking a balanced approach. There should be a greater longer-term consideration of supply factors and managers should use the hybridised data they have as a context for understanding local market dynamics rather than omitting to interpret this detailed data when they come under perceived pressure to set a price. This research suggests that although automated systems are capable of making constant updates of prices and that changing prices across multiple distribution channels has been made instantaneous by technology, the better thing would be to slow down the process of decision-making. This would, in turn, make decision-making less reactive and less based on trial and error because there would be time to factor in all the hybridised data that has been generated as overall fewer price decisions would be being made. In fact, some managers in this research were already showing signs of awareness of the need to slow the pace of price changes but were looking at this from the impact on the evaluation of the fairness of prices from the customer viewpoint rather than from the perspective of the quality of the decisions they were making. Perhaps a strategic approach of quality over quantity should be the new mantra. Just because we can make multiple price changes easily, does not mean we should.

7.42 Implications for hospitality education

This research has also prompted a reflection on the delivery of revenue management education to students studying hospitality and hotel management

subjects in higher and further education. The clear impact of market forces on price decision-making and the need to understand the workings of the market in more depth, not just from a demand perspective but also a supply perspective, which many managers in this research failed to consider, leads to a belief that economic theory should become a more dominant topic in modules and courses that examine pricing strategy and revenue management. Essentially this research has led to the conclusion that the ability to make successful revenue management decisions must be underpinned by knowledge of micro-economic principles, with specific attention being paid to competitive forces and market analysis. This should encourage the managers of the future to engage a wider range of the data that they have available to them in assessing the market forces accurately and setting prices. However, this research has stressed that a significant involvement of human decision-making in pricing remains. Therefore any increase in economics teaching should consider not just neo-classical approaches to economics but should also incorporate insights into behavioural economic approaches. The challenge is in ensuring that hospitality students do not just learn the academic theory but understand how to apply it in practice so that their theoretical understanding is valuable to the industry.

Taking human behaviours in economic markets into account will work towards achieving this aim. If economic literacy centres on practical, real-life applications by humans then an understanding of human behaviours and reactions to economic theories must be included. There are lessons to be learned on revenue management from both paradigms, especially as this research has shown the importance of factoring in customer reactions to price and manager reactions to their perceptions of the strength and degree of stability in the market. Interestingly, Woodside's (2015) theory of behavioural pricing has begun to make further progress in behavioural economics, making it more applicable to business scenarios as it focuses on individual decision-making by managers, thereby illustrating real-life applications of behavioural economics. It argues that from a behavioural standpoint, knowledge of firm-level pricing decision processes is lacking, against a backdrop of literature on behavioural economics which focuses on behavioural finance at corporate decision-making level (Barberis & Thaler, 2003; Subrahmanyam, 2007). As already stated, this research has begun to close the gap in our understanding of pricing at a more practical and property level but it is felt that the realities of pricing and their

behavioural models should now be taken into the classroom to inform revenue management education.

7.5 Recommendations for future research

The focus of this research has been at the hotel property level to uncover the realities of the impacts of big data on hotel transient price decision-making processes and has certainly made some interesting and useful contributions to knowledge and understanding in this area. However, this research has the potential to develop and continue to make contributions to the academic literature on hotel revenue management and pricing. It is currently felt that this research could develop in three key areas. The first one being to examine changes over time in the perceptions of general managers and revenue managers that were observed in this research as undoubtedly there will be changes and improvements in automated revenue systems and artificial intelligence that may alter these perceptions in the future. A key question that remains is at what point, if ever, managers will consider these systems to be sensitive enough to factor in the uniqueness of customer reactions to price and value so that managers will be persuaded that the manual collection of small data is no longer needed. This would probably involve regaining access to the hotels used in this research as part of a longitudinal study.

The second strand to further research would also factor in that this current research has not explored perceptions of big data at a higher level within corporate revenue teams at hotel company head offices. Although this was not the aim of this research it would be fascinating to investigate whether these teams understand the way big data is perceived at the hotel property level and whether they realise its use is being reinterpreted with so much value placed on small data and local customer insights that are still generated through the general manager. This could contribute useful insights for the industry in aligning higher level data analytics at the corporate level with data practices on the ground in hotel properties. This research would probably be of most value if carried out within chain hotel companies and would rely on access being granted a high enough level within the business.

Finally, this research identified that within the economy hotel market the hybridisation of the data did not occur and it identified the reasons for this. However, it did not consider this in significant depth. Therefore, it would seem a valid extension of this

research to investigate further the use of different types of data from the typology of pricing data created in this research within the economy sector and then attempt to discuss if hybridised data is or could be generated in other ways where there is either an absence of specialist revenue support or a total centralisation of revenue management and pricing with very little input from the general manager. In addition it would also be interesting to investigate whether the lack of hybridisation of data impacts on the strength of the countervailing forces of the market in these types of hotels and also whether the typology of pricing data that has been created in this research exists in other related sectors such as the airline industry which like hotels is heavily driven by revenue management and pricing practices. Even a study of the retail sector could be useful to further test its reliability as a valid typology.

7.6 Chapter Summary

This chapter has reflected on the process of conducting this research and identified its key findings and contributions as well as considering the impacts of the research on industry and education. It has also looked to the future and suggested a pathway for developing this research and further advancing knowledge around the use of data in hotel pricing and revenue management. This thesis has kindled the beginning of an exciting research journey that will need to keep pace with the continual changes and developments in revenue management and in the data technologies that will continue to shape the hotel industry and will build on the researchers' current portfolio of publications (see appendix 6). However, it is worth finishing with one final and important reflection and this reflects back to the introduction of this thesis, which began with the following quotation from William Edwards Deming (1993):

“In God we trust: all others must bring data”.

This quote suggests the centrality of data, particularly big data, as did a significant amount of the extant commercial and academic literature on decision-making, pricing, and revenue management. Therefore, when considering this literature and when researching the use of big data in price decision-making it came as a surprise to find that not only was big data not the key driver of the process but also that data itself in any format was not fully used in the price decision-making process. This was not down to the typical reasons brought up in the literature such as information

overload, but to the pressures of the market. Therefore on reflection, it seems that perhaps on reflection William Edwards Deming should have written:

“In God we trust: all others must bring an understanding of market forces”.

Ultimately market forces proved more powerful than the big data.

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Appendix 1 - Data Management Plan

Project Name: Behavioural Pricing Theory and Manager Decision-Making Using Big Data - Dismantling Black Boxes

Principal Investigator / Researcher: Natalie Haynes

Project Data Contact: n.haynes@shu.ac.uk

Institution: Sheffield Hallam University

Description: The research aims to extend the theory of behavioural pricing through a study of big data's effects on manager's price decision-making behaviour at hotel unit level. Research data gathered from work shadowing field notes and semi-structured interview transcripts will be used to address the following specific research questions: 1. What are the issues that managers face in using Big Data in their room price decision-making and how are these manifested? 2. How do organizational and external pressures impact on the behaviours hotel unit managers' exhibit when interacting Big Data in the room price decision-making process? 3. How much influence do hotel managers perceive themselves to have over the use of Big Data in the room price decision-making process and how does this impact on their perceptions of influence over the price decision? 4. How do hotel managers' attitudes and behaviours towards Big Data shape the process of setting room prices?

DATA COLLECTION - What data will be produced?

Qualitative, observational data will be produced in this research project in several different forms. This data is captured in real-time and therefore is unique and irreplaceable. The formats will be both non-digital and digital. The non-digital data will come in the form of a field notebook, a memo notebook for recording both conceptual and methodological memos and a research diary. Field notes will be generated from three-day periods of overt work shadowing in six different hotel units. The digital data will take the format of audio files from my voice recorder, transcripts of interviews producing in MS Word and also more detailed write-ups of coding, concept and theoretical development, again in MS Word as well as detailed write-ups of the field notes. The UK Data Service (2016) supports the use of MS Word doc. or docx. for long-term data storage. I anticipate creating as a minimum six

interview transcripts and six sets of detailed field notes. The digital data will be sorted into three folders, entitled: 1. Work Shadowing Field Notes, 2. Interview Transcriptions and 3. Data Analysis, Coding and Memos. Each file will be labelled Observation 1 or Interview 2 with the date in the format of YYYY-MM-DD for ease of searching. A data collection schedule has also been produced to ensure the quality of data is maintained, for example it schedules the immediate digital write-up of field notes at the end of each day's observation in the field.

DATA DOCUMENTATION - How will your data be documented and described?

To ensure the data is understandable to others at a study and data level three key actions will be taken:

1. Study-level documentation - Contextual information about how the data was collected and supporting information on methodology, ethical issues and how data was collected and analysed will be recorded as methodological memos in a notebook. Utilising a notebook rather than a digital format allows for these memos to be easily created in the field.
2. Data-level documentation - As this research project is using a grounded theory approach many different codes and categories will be created throughout the data collection and data analysis. Therefore, a section in the memo notebook will be dedicated to the recording of these codes and concepts and their meaning. If these change over time, then the definitions will be updated. The date, the code and its definitions will also be recorded. This will allow people to clearly understand and track the development of the theory through the data, adding validity and integrity to the grounded theory generated as it will be clearer how the theory is actually grounded in the data.
3. Research Diary - Finally the researcher will make weekly records of the research progress and any personal reflections in a research diary but any procedural considerations will go in the memo notebook within the methodological memos.

I will also avoid the use of abbreviations in transcripts, field notes and file names in order that the data can be clearly understood by an outsider. If abbreviations are used, they will be fully explained and the definitions documented.

ETHICAL AND COPYRIGHT ISSUES - How will you deal with any ethical and copyright issues?

All respondents will be required to complete and sign a participant consent form which amongst other questions specifically asks them whether they are happy for the information collected, once anonymised, to be used for any other research purposes outside of the current PhD project. According to the Data Protection Act the data that I will be collecting will be neither personal data (as individuals will not be able to be identified in my study) and the data is also not sensitive (I will not collect sensitive personal data, such as race, religion, ethnic origin etc.). Therefore, research data will not need to be destroyed and there is no further need to comply with any other aspects of the Data Protection Act. The participant consent form also explains to respondents that they are able to stop the work shadowing process at any time to allow for confidential calls etc. No corporate confidential data will be collected or shared and respondents will be allowed access to field note write-ups and interview transcripts should they wish to check this. No personal or company names or any other identifying features will be used in the field notebook or in any other documentation. For research students, the copyright in the thesis submitted for examination remains with the candidate, but all other Intellectual Property rights lie with the University and/or the funder of the research project - including those over the research data produced for the thesis.

DATA STORAGE - How will your data be structured, stored and backed up?

The directory structure will see the digital data sorted into three folders, entitled: 1. Work Shadowing Field Notes, 2. Interview Transcriptions and 3. Data Analysis, Coding and Memos. Within the first folder each file will be labelled Observation 1, 2 etc. and in the second folder each file will be labelled Interview 1, 2 etc. In the final folder there will be six files created for the coding and memos for each individual hotel unit that is visited during the data collection. Each file will also be clearly dated using the format of YYYY-MM-DD for ease of searching. Versioning will not be required for field notes and interview transcripts as once created they will become static data, however, the coding and memos may evolve and therefore version numbers will be used to track these changes as well as possibly using the track changes options in MS Word.

During the research process, when the research diary, field and memo notebooks are not in use they will be locked in a filing cabinet within a locked office in the Stoddart building, City Campus, Sheffield Hallam University. When in the field the notebooks will either be kept on my person or will be secured in a hotel room safe. The terms of storage of the digital data folders and files I will primarily use Sheffield Hallam's Research Store (Q:\Research) for the back-up and storage of my data and I will shortly be requesting that a folder is set up for my research data in this store through IT Help at Sheffield Hallam University. Both I and my Director of Studies will have access to this data store. This will provide my primary back-up of master data, however, I will also utilise two further back-ups, following the 3-2-1 rule outline in the Online Academic CPD Module - Research Data Management. These will be

back-up every day during the data collection period to both a USB and an external hard-drive, both of which will be password protected, in line with the Sheffield Hallam University's Electronic Data Encryption Policy set out in 2016.

DATA PRESERVATION - What are the plans for the long-term preservation of data supporting your research?

The data that will be collected as part of this study has already been identified as low risk in terms of data protection and that the Data Protection Act would not demand its disposal for legal reasons. Therefore, following the Sheffield Hallam University guidelines, the research data will be kept for a minimum of ten years in the Sheffield Hallam University Research Data Archive (SHURDA). This allows for both the long-term storage of digital research data but also the non-digital memo and field notebooks that will be generated from the project. On completion of the thesis I may apply for a two-year embargo on the sharing of thesis and underpinning research data to allow for publication of the main findings, in line with the academic regulations and student policies for research degrees.

DATA SHARING - What are your plans for data sharing after submission of your thesis?

It is anticipated that the completed thesis may be of interest to future students, I, in order to extend research in this area, managers working with the hotel industry and peer researchers working in the area of behavioural pricing, revenue management, data analytics and behavioural economics. The thesis and underpinning data will be saved in the Sheffield Hallam Research Archive as per the universities requirements, although on completion of the thesis I may choose to apply for a two-year embargo on the sharing of the thesis and underpinning research data to allow for publication of the main findings, in line with the academic regulations and student policies for research degrees.

Appendix 2 - Evidence of open coding

This evidence of open coding relates to how the main category of "General Manager Involvement" was arrived at, which is illustrated in figure 4.6. For a more detailed explanation of the open coding process please refer to section 4.411 in the main body of the thesis. The following excerpts from the field notes and interview transcripts illustrate how the first open codes were identified that started thoughts on the emergency of a category around general manager involvement in the early stages of the grounded theory process. Open codes where highlighted in red during the coding process. Relevant open codes, such as autonomy and experience that relate to the main category of "General Manager Involvement" have now been highlighted in italics for ease of recognition.

Section Number	**Field Notes**	**Date Code Created**
48	Just after 3pm the GM goes back into Reslynx and checks the pick-up for tonight based on the lowering of the rate demand response/monitoring changes/impacts of decisions/checking and checks the business on the books again through the PMSmultiple checking of the same data/repetition. He reduces the rate for the other hotel in Rotherham to £35 as well and comments "sell, sell, sell" *autonomy*. sales focus/competitive/*personality* He also comments on the day of the week and says that "Monday is always a slow day for business and Tuesday is quite quick" *local knowledge*/mental storage/*experience*/hindsight. He seems to want to use a lowering of the rate to stimulate demand for tonight demand.	24/08/2017
Section Number	**Interview Transcript**	**Date Code Created**
	So what would you…how would you describe your role in sort of revenue management and setting prices for rooms then because obviously I've seen a little bit of what you do…how would you describe your role? And I presume you have no other revenue support...it's just you?	
9	It's um…and the current stage of our property's when you look at 31 bedrooms in operation or 51 bedrooms in operation…it's not a big hotelsize. It's classified as small businesses. It's not a major which is to have a sort of full department which is assisting you and everything, basically setting up strategies and so on and so*autonomy*. That doesn't exist unfortunately which is my background...which is in groups and everything which is that is nothing. Lately every single property I run is systemised...needs to be...not just on a manual where you have reservation agent whose taking the reservations...where you have actually reservations manager and so on and carries on. The guest themselves they can book themselves online as booking them. They can go on our	27/07/2017

	website...the prices everything is pre-set...system is filtered...just print registration card. Is only a matter of basically monitoring your competitors...the market and everythingmarket/*local knowledge/experience*. You know...the crowd...I know I'm targeting which is...my hotel is not a leisure hotel...people coming for weekends or leisure break or...it's mainly work and its mainly visiting if there are any events on-going*local knowledge*, so my role in here is not very challenging compared to a branded hotel as well or leisure hotels like holidays and resorts...is a different sector, which is as I said...you will be targeting companies and things like that. Your prices is actually...is putting you on top...where to be seen and known by the companieswinning/battle. You want to sell...they want to buy. They don't want to spend too much. So kind of a system...it works for itselfmarkets/demand.	

Appendix 3 - Evidence of the delineation of categories

As show in figure 4.6, in addition to the open coding process, the coding paradigm was being used at the same time to develop the open codes further so that ultimately through evolution of the grounded theory process a fully delineated category of "General Manager Involvement" could be arrived at. This process of applying the coding paradigm was supported through the use of memos written both on the open coding process and in a research diary. In essence the coding memos and those recorded in the research diary were used to develop thinking on the properties and dimensions of the categories, as well as considering the conditions, actions-interactions and consequences which are key elements of the coding paradigm in Straussian grounded theory. Examples of the delineation of the example category shown in figure 4.6 and the identification of the relevant elements of the coding paradigm in both coding memos and the research diary can be found below. These are snapshots of the data analysis process and ideas may have evolved from these examples with the introduction of more data but they serve to provide evidence of the process.

Example Coding Memos

What drives their instinctive attitude to RM - perhaps lack of a revenue background and previous experience/lack of trust in their IT systems/no RM support or heavy head office involvement so they make the decisions without having to have them checked by external third parties.

Consequences - instinctive attitude to revenue management driven by lack of specialist support

This GM is actually actively involved in rate setting due to the structure and ownership of the organisation. This structure or ownership might influence the way Big Data is used and the approach to RM.

Demand appears to drive the data that they look at and the channels that deliver that demand

Degree of involvement in the price decision may have an impact on the data that is reviewed and why

Suggests there are different degrees of automation. Here the GM needs to input data to ensure that it works.

Consider the idea of research in RM - who does it and how is it structured. Is data received passively from other sources or generated by the hotel - either formally or informally

Data storage - spreadsheets etc. or mentally stored is also another issue.

Satisfying - do only what they need to do to ward of threat, competition or risk…not about positive revenue growth - does having too much data cause managers to fall into this position of filtering only the data that shows there is a risk or a problem and therefore they focus on that.

Reliance on others is also a key issue - possible category.

Is there an element of tradition in hotel revenue management

Influence of guest on RM

Action without analysis could be a category

Actions- Interactions - degree of specialist revenue support

There seems to be certain pragmatism around actually using the resource available to you and delegating RM control to those people who have the expertise in certain area and the GM contributing where they feel they have the knowledge. The degree this happens depends on personal attitude and background etc. and knowledge base

Does how well the hotel is doing have an impact?

Unpredictable markets may lead to pragmatism in RM….we can't judge so why bother with the analysis - this type of attitude

She seems to be able to think longer-term - perhaps simplicity in the data used on a day -t day basis to change prices allows more freedom to consider the longer-term

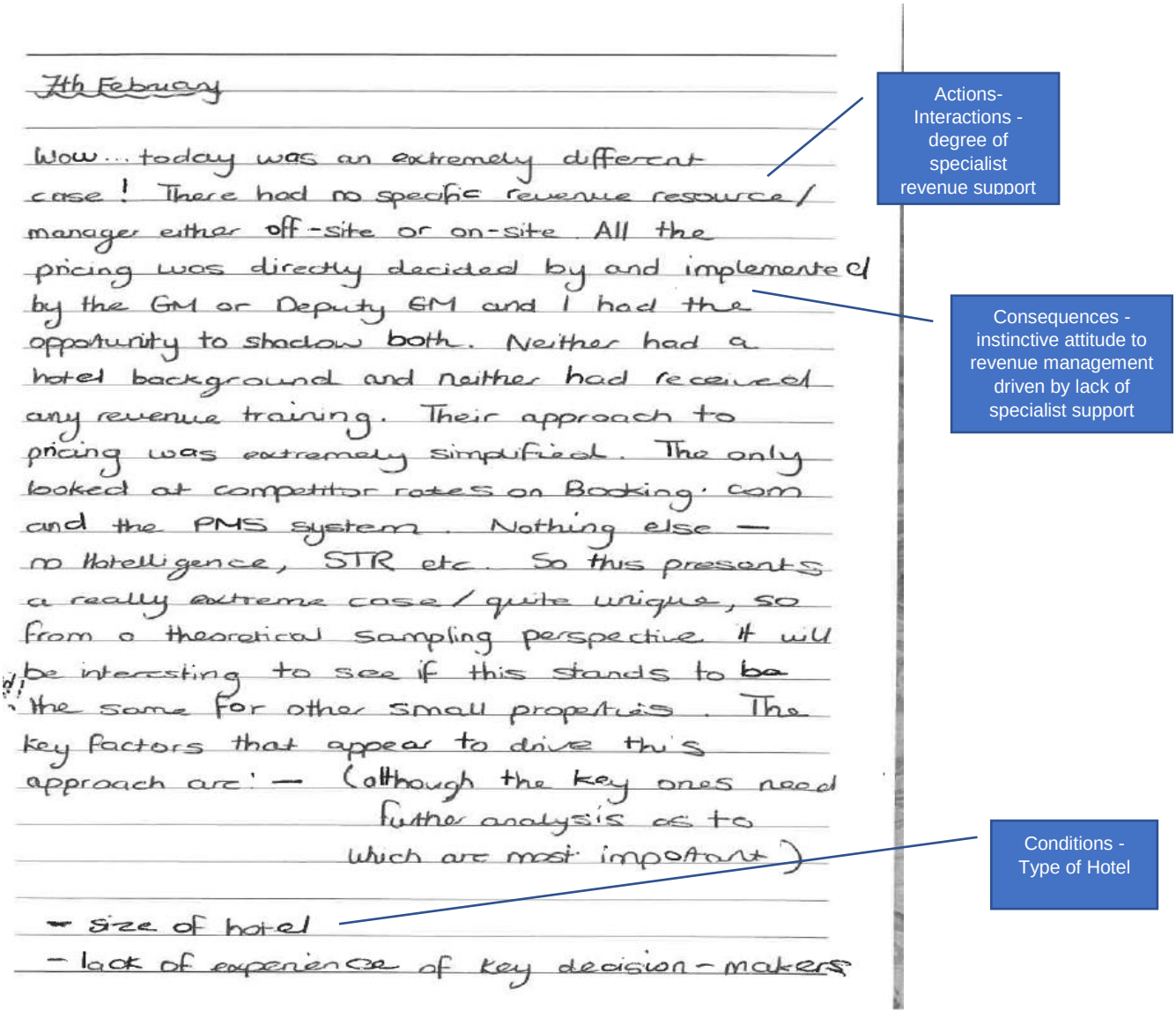
Conditions - Type of Hotel

The amount of analysis might also vary demanding on how much the hotel feels the need to defend or evidence it's position to management.

Independent hotels may rely more on metrics from third party sites e.g. Booking.com

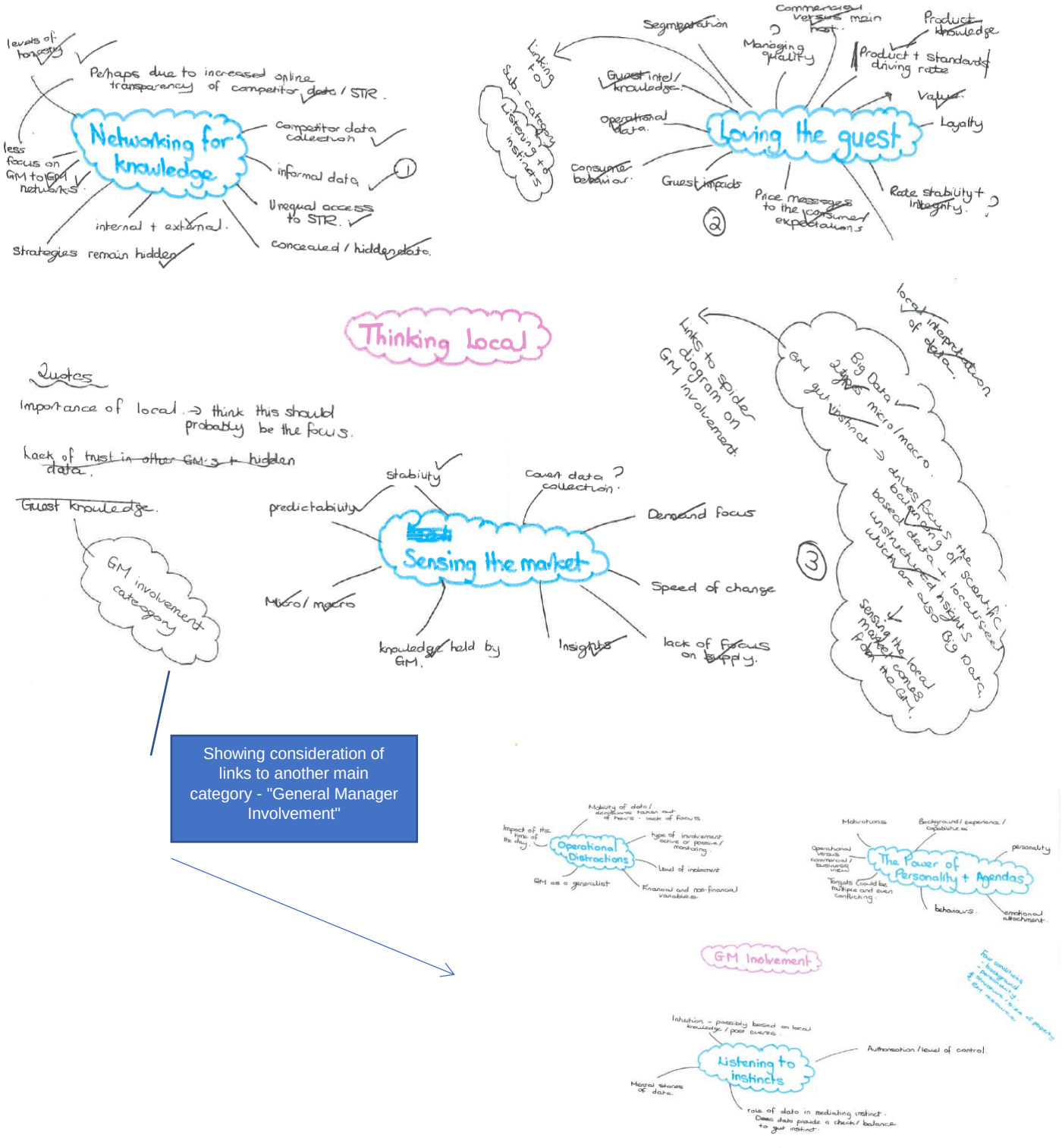
Speculation may be a category versus certainty

Example Research Diary Excerpt



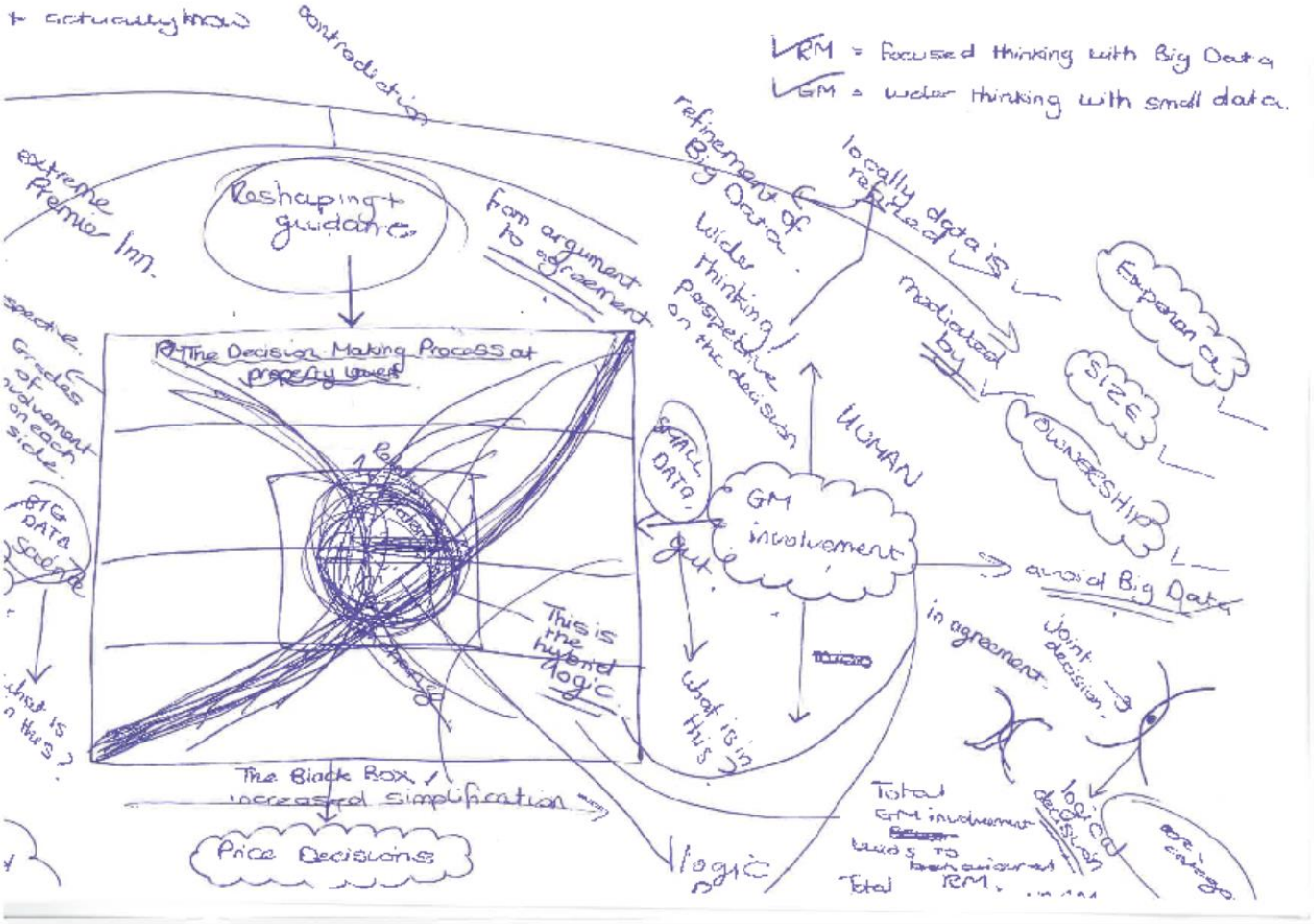
Appendix 4 - Evidence of axial coding

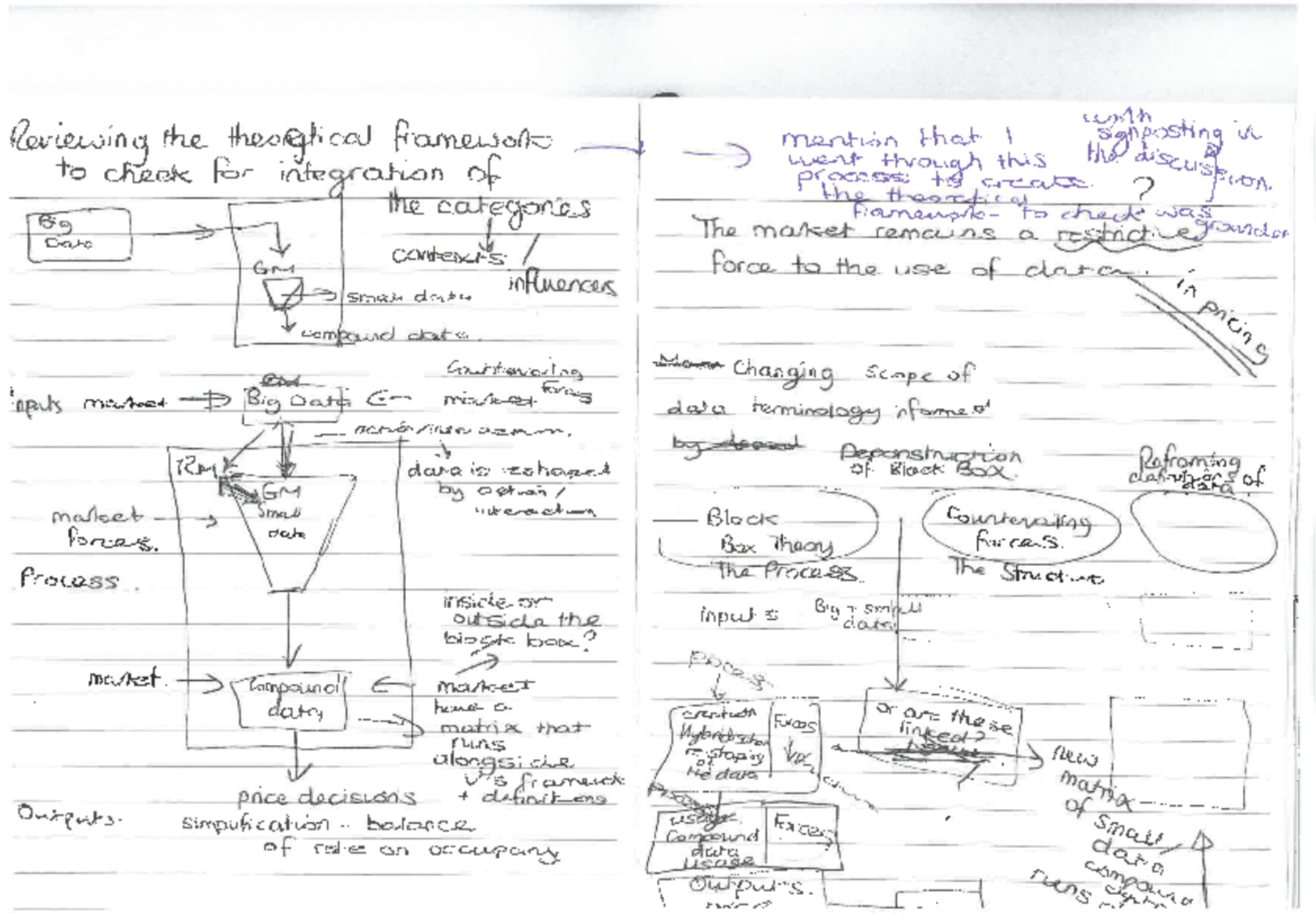
As shown in figure 4.6 once the categories, such as "General Manager Involvement" were fully delineated the relationships between the main categories and sub-categories could be considered as part of the process of axial coding. Full details of the axial coding process can be found in section 4.412 in the main body of the process. This was mainly achieved through the development of spider diagrams based upon the coding memos and also memos from the research diary that evolved over time. Some of the titles of the sub-categories were amended slightly during the final stages of analysis and write-up.

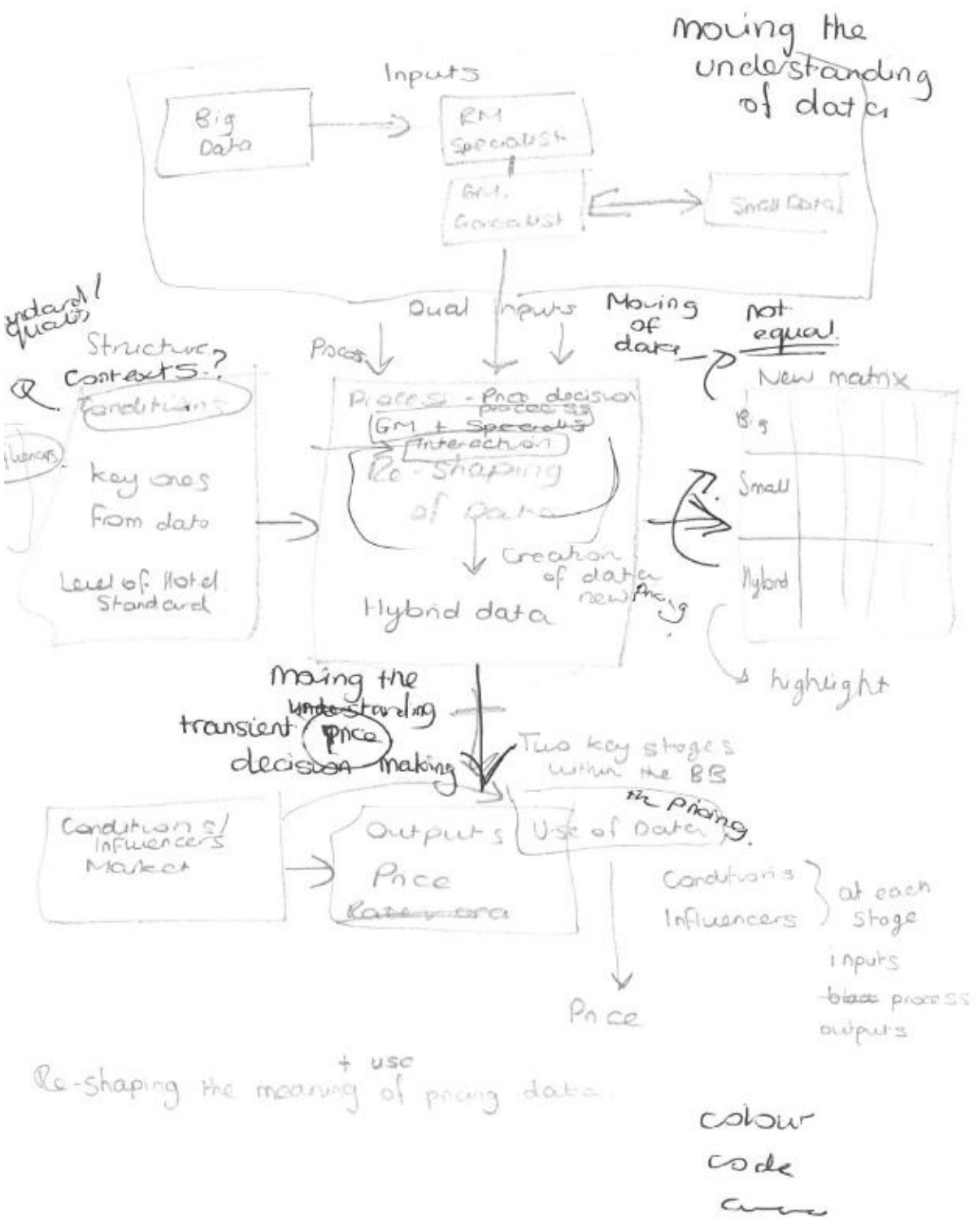


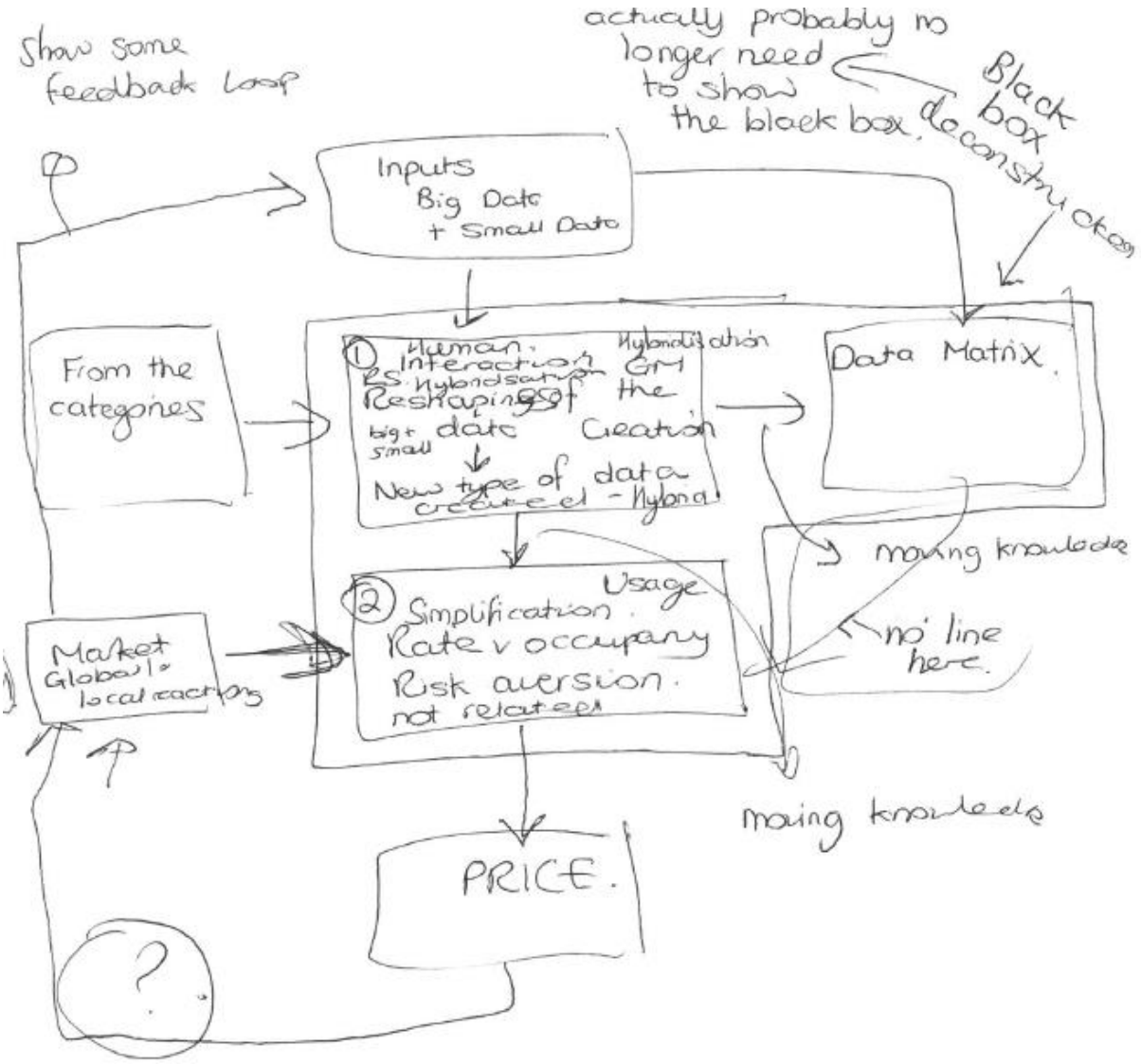
Appendix 5 - Evidence of selective coding - building the theoretical framework

The final stages of data analysis where the selective coding took place were extremely iterative and as explained in section 3.413 of the main body of thesis the core category and theoretical framework to deconstruct the black box was developed using a series of spider diagrams and rough sketches. These formed from the earlier open and axial coding and through repeated reflections on the memos and the research diary to ensure the framework was fully grounded in the data. Below are a few examples of those spider diagrams and sketches from this process.




Reviewing the theoretical framework to check for integration of the categories
contexts / influences
Big Data
GM
small data
compound data
inputs market
Big Data
countervailing market forces
data is reshaped by action / interaction
market forces
Process
inside or outside the black box?
market
compound data
market have a matrix that runs alongside
price decisions
Outputs
simplification - balance of rate on occupancy
mention that I went through this process to create the theoretical framework - to check was grounded
with signposting in the discussion
The market remains a restrictive force to the use of data in pricing
Changing scope of data terminology in terms of
Deconstruction of Black Box
Reframing definitions of data
Block Box theory The Process
Countervailing forces The Structure
inputs
Big + small data
or are these linked?
New matrix of small data compound
Compound data usage
Outputs


moving the understanding of data
Inputs
Big Data
RM Specialist
GM. Forecast
Small Data
Qual inputs
Moving of data
not equal
New matrix
Structure? Contexts?
Conditions
key ones from data
Level of Hotel Standard
Process - Price decision process
GM + Specialist Interaction
Re-shaping of data
Creation of data new pricing
Hybrid data
Big
Small
Hybrid
highlight
moving the understanding transient price decision making
Two key stages within the BB re pricing.
Conditions/ Influencers Market
Outputs
Use of Data
Price
Conditions
Influencers
at each stage
inputs
process
outputs
Price
+ use
Re-shaping the meaning of pricing data.
colour code



Moves knowledge in two directions.

Appendix 6 - List of Relevant Journal Publications

Haynes, N. (2016). The evolution of competitor data collection in the hotel industry and its application to revenue management and pricing. *Journal of Revenue and Pricing Management*, *15*(3-4), 258-263.

Haynes, N., & Egan, D. (2015). The future impact of changes in rate parity agreements on hotel chains: the long-term implications of the removal of rate parity agreements between hotels and online travel agents using closed consumer group booking models. *Journal of Travel & Tourism Marketing*, *32*(7), 923-933.

Haynes, N., & Egan, D. (2017). Revisiting the relevance of economic theory to hotel revenue management education and practice in the era of Big Data. *Research in Hospitality Management*, *7*(1), 65-73.

Haynes, N., & Egan, D. (2018). Manager perceptions of big data reliability in revenue management. *International Journal of Quality & Reliability Management*. DOI: IJQRM-02-2018-0056